The Contingent Effects of Prior Ties on Network Dynamics: Essays on the Formation and Dissolution of Interorganizational Relationships in the Venture Capital Industry

The Contingent Effects of Prior Ties on Network Dynamics: Essays on the Formation and Dissolution of Interorganizational Relationships in the Venture Capital Industry

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Abstract

This dissertation comprises three empirical chapters that investigate the limits of prior interorganizational ties in explaining patterns of tie formation and tie dissolution of interorganizational relationships in the context of the venture capital (VC) industry.

Existing empirical work has demonstrated that two actors have an increased likelihood of forming a direct relationship if both are connected indirectly via ties to the same third party, in part due to the introductions and referrals provided by the shared partner. In contrast, I propose that indirect ties via third parties can either facilitate or hinder the formation of direct relationships depending on the information that the third party provides. The first two chapters substantiate this claim in two empirical settings. In the first chapter, I examine how the success or failure of a VC firm's syndication affects the likelihood of securing funding from the Limited Partners of its syndication partners. In the second chapter (joint with Ranjay Gulati), I examine how a VC firm that has withdrawn from a syndicate is not only likely to be shunned in the future by its abandoned coinvestors, but is less likely to syndicate with third parties that are connected in some way to the abandoned coinvestors. In other words, withdrawals not only have dyadic repercussions, but have reputational consequences that ripple across interorganizational ties and have long-term implications on tie formation with third parties. Overall, those two chapters make

the case that we cannot fully understand the effects of interorganizational ties on future tie formation without knowing the content of the information flowing through those ties.

Whereas the first two chapters focus on elucidating the role of prior ties in tie formation, the final chapter examines the effects of prior ties on tie dissolutions. Prior research has highlighted that a history of collaborative relationships between two parties—also known as embeddedness—creates relational capital that increases the costs of tie termination and thus reduces the likelihood that either of party will withdraw from the relationship. Different theories have conflicting predictions, however, as to how economic shocks affecting the collaboration will affect the stabilizing role of embeddedness. To resolve this puzzle, I differentiate between general performance shocks (which affect all collaborations in a given domain) from specific performance shocks (which apply only to the focal collaboration). Drawing on the idea that actors are more likely to discount ambiguous signals when they have the psychological motivation to do so, I propose that general performance shocks will increase, and specific performance shocks will attenuate, the effects of embeddedness on collaboration stability. I empirically verify my argument in the context of VC firm withdrawals from syndicates, and demonstrate how these effects are shaped by prior ties with the syndication partners, the valuations of the focal industry (i.e., the general performance signals), and the valuation of the focal portfolio company (i.e., specific performance signals). This third study highlights that while social factors are indeed important for predicting tie dissolutions, we can only truly appreciate their role in the context of the economic forces buffeting the collaboration.

Table of Contents

Acknowledgements .... **vii**

List of Tables .... **xii**

List of Figures .... **xiii**

Introduction **1**

1 The Presence of the Tie or the Content of the Tie: Venture Capital Syndication Networks and Limited Partner Investment Decisions **6**

1.1 Introduction 6

1.2 Theory and hypotheses 10

Information flows and triadic closure *10*

Information valence and new tie formation *13*

Intermediary performance and information valence *15*

Availability of alternative sources of information *17*

1.3 Research context 19

1.4 Data and variables 24

Data *24*

Dependent variable *26*

Independent variables *26*

Control variables *29*

1.5 Method 32

1.6 Results 34

Main results *34*

Post-hoc analyses *43*

Robustness tests *46*

1.7 Discussion and conclusion 47

2 After the Break-Up: The Relational and Reputational Consequences of Withdrawals from Venture Capital Syndicates **55**

2.1 Introduction 55

2.2 Research context 59

2.3 Theory and hypotheses 62

The relational consequences of withdrawals *62*

The global reputational consequences of withdrawal *64*

The local reputational consequences of withdrawal *65*

Interaction of local and global reputational consequences of withdrawal *67*

2.4 Data and variables 71
Data *71*
Dependent variable *75*
Independent variables *75*
Control variables *77*
2.5 Method 79
2.6 Results 82
Main results *82*
Robustness tests *90*
Post-hoc analyses: Alternative channels of information diffusion *92*
Post-hoc analyses: Circumstances of the withdrawal *92*
2.7 Discussion and conclusion 93
3 When Does the Glue of Social Ties Dissolve? Collaboration Embeddedness and Performance Signals in Withdrawals from Venture Capital Syndicates 102
3.1 Introduction 102
3.2 Theory and hypotheses 106
Embeddedness, expectations and attachments *106*
Performance signals and embeddedness *108*
3.3 Research context 113
3.4 Data and variables 116
Data *116*
Dependent variable *118*
Independent variables *118*
Control variables *119*
3.5 Method 122
3.6 Results 125
Main results *125*
Robustness tests *132*
3.7 Discussion and conclusion 133
References 137

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To Xiaolu for her love and support

through all my years at Harvard

List of Tables

Table 1.1: Summary statistics and correlations for all key variables 35

Table 1.2: Conditional logit model predicting new tie formation – test of main effects............. 37

Table 1.3: Conditional logit model predicting new tie formation – test of interaction effects..... 40

Table 1.4: Conditional logit model predicting new tie formation – post-hoc analyses 45

Table 2.1: Summary statistics and correlations for all key variables 83

Table 2.2: Rare event logit model predicting the likelihood of syndication................................ 85

Table 3.1: Summary statistics and correlations for all key variables 126

Table 3.2: Conditional logit model (firm, industry, year fixed-effects) predicting probability of withdrawals from syndicates... 128

Table 3.3: Probit model (industry and year fixed effects) predicting probability of withdrawal from syndicates. 130

Table 3.4: Predicting down-rounds using an ordinary and instrumental variable probit............ 134

List of Figures

Figure 1.1: Theoretical framework 19

Figure 1.2: Referral calls of a fund-of-fund LP during a due diligence on a VC fund................ 22

Figure 1.3 Effects of successful versus unsuccessful ties on the probability of LP investments . 38

Figure 1.4: Effects of successful ties via high-performance versus low-performance intermediaries on the probability of LP investments 41

Figure 1.5: Effects of failed ties via high-performance versus low-performance intermediaries on the probability of LP investments 42

Figure 2.1: Theoretical framework 71

Figure 2.2: Predicted probability of syndication over different values of the social overlap with abandoned and non-abandoned partners of the alter (sets the other value at zero). 88

Figure 2.3: Predicted probability of syndication over different values of focal VC firm's overall withdrawal rate. Sets the other VC firm's social overlap with the abandoned coinvestors of the focal firm at either zero or one standard deviation above mean. 89

Figure 2.4: Predicted probability of syndication over different values of the focal VC firm's overall withdrawal rate. Sets the other VC firm's social overlap with the non-abandoned coinvestors of the focal firm at either zero or one standard deviation above mean...................... 90

Figure 3.1: Theoretical framework 113

Figure 3.2: Interaction between embeddedness in the syndicate and book-to-market ratio deviation from the industry mean in predicting withdrawals from syndicates 131

Figure 3.3: Interaction between embeddedness in the syndicate and down-round valuation in predicting withdrawals from syndicates 131

Introduction

In many settings, organizational success depends heavily on engaging in collaborations such as strategic alliances (Doz & Hamel, 1998), investment banking syndicates (Eccles & Crane, 1988), or venture capital syndicates (Lerner, 1994). Such collaborations allow organizations to pool their resources toward a common goal and share business opportunities that they would not be able to access on their own. As such, the ability to collaborate with the right partners is a critical competitive advantage (Gulati, 2007). A variety of studies across empirical settings have demonstrated that the positioning of organizations within the interorganizational network is a crucial predictor of several outcomes such as survival (e.g., Malter, 2012), performance (e.g., Hochberg, Ljungqvist, & Lu, 2007; Shipilov & Li, 2008), and innovation (e.g., Ahuja, 2000a). Taking a more global perspective, several studies have highlighted the role of the overall tie configuration of a network for understanding the performance of all the organizations within it (Sytch & Tatarynowicz, 2014a; Uzzi & Spiro, 2005).

Given the importance of the interorganizational relationship structure for understanding the performance outcomes of both individual organizations and entire network communities, it is important to understand the drivers of network evolution: the processes of tie formation, tie dissolution, and how these processes are interrelated. Chapter 1 of this dissertation examines how the history of tie formation affects future tie formation within a network; Chapter 2 considers how the history of tie dissolution affects future tie formation; and Chapter 3 investigates how the history of prior ties affects future tie dissolution. In these chapters, the dissertation touches on two key ideas of theoretical interest to organizational and network scholars. First, how is the effect of social relationships on tie formation shaped by the information flowing across them? Second, how do social relationships affect the processing of information; in particular, what information to attend to and what information to discount?

In predicting future tie formation, scholars have generally emphasized the role of the social context established by the prior relationships. For example, actors are disproportionately likely to prefer repeat relationships to selecting ties with third parties (Gulati, 1995b; Li & Rowley, 2002). Furthermore, two actors are more likely to establish an indirect relationship if they are already connected via shared partners (Chung, Singh, & Lee, 2000; Gulati & Gargiulo, 1999), a phenomenon known as triadic closure (cf. Simmel, 1950). Much of the organizational literature attributes the latter effect to the flow of referrals and endorsements passed by the shared partner, which presumably alleviates the parties' concerns about collaborating with one another (e.g., Gulati, 1995b). The implicit assumption, which to date remains unchallenged, is that the information transmitted is unambiguously positive. Chapters 1 and 2 question this assumption and argue that in situations in which a shared partner is likely to report negative information on one of the parties, the tie is less likely to form than the baseline of no indirect tie at all. Different types of relationship disruptions, such as a failure to syndicate as discussed in Chapter 1 or a VC firm's decision to withdraw from a syndicate as discussed in Chapter 2, have more than just dyadic implications. They also engender negative information that ripples across the interorganizational network and limits the focal VC's ability to engage in exchange with third parties that have been exposed to the negative information.

In Chapter 1, I focus on the investment decisions of the capital providers to venture capital (VC) funds—known as Limited Partners or LPs—and how these decisions are affected by the structure and content of the syndication networks. In particular, I examine the conditions under which an LP is likely to invest in syndication partners of the VC firms in which it has previously invested. Conventional network theory predicts an increased likelihood of such investments due in part to the LP's easier access to information through the shared partner. I argue, however, that the content of such information is more important than its availability. A successful collaboration between two VC firms will result in transferring positive information and will increase the probability of an LP investment. In contrast, a failed collaboration will lead to transferring negative information and will reduce the likelihood of such investments below what one would expect in the absence of a connection. Furthermore, when the intermediary VC has a superior track record of performance, the effects of the positive and negative information that it passes along are magnified. In contrast with the commonly held assumption that collaborating with highly prominent actors provides unambiguous signaling benefits, my findings suggest that such collaborations are a high-risk, high-rewards proposition. The prominence of collaborators can open a lot of doors if they are satisfied with the relationship, but can likewise close many doors if the collaboration fails.

Chapter 2 (co-authored with Ranjay Gulati) examines the consequences when VC firms withdraw from investment syndicates. Existing research and our qualitative evidence both suggest that participating in VC syndicates comes with the expectation that involvement will continue; however, there has been limited attention to whether violations of that expectation will affect the ability of a VC firm to engage in future syndications. We explore the consequences of VC firm withdrawals from syndicates on three levels. At the relational level, we predict that the withdrawal can disrupt the relationship with the coinvestors and reduce their willingness to syndicate with the withdrawing firm in the future. At the global reputational level we hypothesize that the firm's publicly available track record of withdrawals can signal its lack of reliability and make prospective syndication partners wary of entering into a relationship. At the local reputational level, we propose that abandoned coinvestors may spread negative private information to their immediate network contacts, reducing the likelihood that they will enter into a syndicate with the withdrawing firm. In addition to unpacking the various consequences to withdrawal and elucidating the underlying mechanisms, we also show that the local and global consequences of withdrawal attenuate each other's effects. This is due to the redundancy in the content of the information that each provides.

While Chapter 2 looks at how the history of tie dissolutions affects future tie formation, in Chapter 3 I consider the opposite question: how the history of prior ties (also known as embeddedness) affects future tie dissolutions. Prior research has considered that the history of prior relationships is associated with creating valuable relationship capital that facilitates future exchanges (e.g., Greve, Baum, Mitsuhashi, & Rowley, 2010). The presence of such relational capital increases the cost of terminating the collaboration in a way that may harm the overall relationship between the parties (Guler, 2007). To date, however, we understand little as to how the emerging negative signals of the collaboration's performance will affect the actors' willingness to break ties. On the one hand, performance challenges can trigger greater pressures from collaborators to hold ranks and thus increase the holding power of embedded ties (Guler, 2007; Sgourev & Zuckerman, 2011). On the other hand, relational cohesion is threatened when the relationship does not deliver the expected economic value (Li & Rowley, 2002; Ring & Van de Ven, 1994; Rowley, Greve, Rao, Baum, & Shipilov, 2005). As such, the effects of embeddedness on tie stability tend to be lower when performance challenges merge.

In Chapter 3, I resolve this puzzle by differentiating between the general performance signals that are relevant to all collaborations within a given domain from the specific performance signals that are relevant only to the focal collaboration. I propose that general performance signals are more ambiguous; thus, actors are more likely to be discounted by actors who are psychologically motivated to preserve the relationships with their collaborators. In contrast, specific performance signals are unambiguously related to the venture, cannot be easily discounted, and give actors the cover to resist pressures of their collaborators not to break rank. This argument is consistent with my analyses of the withdrawal behavior of VC firms from syndicates in the 1985–2009 period. A VC's prior ties with its syndication partners reduces its likelihood to withdraw, especially when the industry of the syndicate is suffering from poor valuation on the financial markets and is therefore offering diminished exit opportunities. On the other hand, the effects of embeddedness on withdrawals disappear when the company in which the syndicate invested stumbles and suffers from reduced valuation itself.

Together, the three empirical chapters of this dissertation paint a nuanced picture of the role that the history of prior relationship plays in the processes of tie formation and dissolution. Prior collaborations may facilitate or hinder the formation of future ties, depending on the course of those prior collaborations. Pre-existing relationships with the VC coinvestors play a large role in preventing withdrawals from syndicates in the face of market-wide shocks, but have virtually no effect in the face of syndicate-specific shocks. These results serve as a reminder that even taken-for-granted network effects can vary dramatically across different circumstances and should, I hope, stimulate further research into the contingencies in the effects of interorganizational relationships.

Chapter 1

The Presence of the Tie or the Content of the Tie: Venture Capital Syndication Networks and Limited Partner Investment Decisions

1.1 Introduction

Securing exchange opportunities with the right external actors—whether investors, alliance or syndication partners, customers, or clients—is essential for virtually any organization to survive and thrive. As a result, the factors that drive an organization's decisions when selecting partners have long been of central concern to organizational theory. Early research in this area has focused on the forces of strategic interdependence that force organizations to cooperate in order to mitigate environmental uncertainty and ensure firm survival (Pfeffer & Nowak, 1976; Pfeffer & Salancik, 1978). Other work has emphasized the quality of the match as determined by the complementarity and compatibility of the resource and knowledge bases of the prospective partners (Eisenhardt & Schoonhoven, 1996; Mitsuhashi & Greve, 2009; Stuart, 1998). Yet another research stream has focused on how the network's prior structure affects how new relationships form in the future (Ahuja, 2000b; Baum, Shipilov, & Rowley, 2003; Gulati & Gargiulo, 1999; Walker, Kogut, & Shan, 1997).

A central finding of this latter stream of research is that two actors are more likely to establish a tie with one another if they share a common partner; this phenomenon is known as triadic closure (Simmel, 1950). Originally applied in the domain of interpersonal relationships (Granovetter, 1973; Heider, 1958), since the 1990s triadic closure has been applied increasingly to a wide range of interorganizational phenomena from alliances (Gulati, 1995b; Walker et al., 1997) to investment banking syndication (Chung et al., 2000) to venture capital syndication (Sorenson & Stuart, 2001, 2008). It is foundational to many models of long-term industry network evolution, particularly the tendency toward the development of densely interconnected clusters of local relationships (Baum et al., 2003; Gulati & Gargiulo, 1999; Sytch, Tatarynowicz, & Gulati, 2011).

A key theoretical model used to explain triadic closure is the flow of referrals and endorsements through interorganizational ties. In general, network theorists assume that collaborative ties between organizations are associated with positive relationships (cf. Sytch & Tatarynowicz, 2014b: 585). At the dyadic level, collaborative ties are thought to foster familiarity, trust, and social attachments between the participants (Larson, 1992; Lawler, Thye, & Yoon, 2000; Uzzi, 1997). This assumption about dyad-level interactions is often carried over in theorizing about higher-level network processes; for example, shared partners often act as brokers to bring together collaborators through referrals and endorsements. Such brokerage potentially alleviates each party's concerns about the other's capabilities and intentions (Chung et al., 2000; Gulati, 1995b; Uzzi, 1996).

This view, however, is difficult to reconcile with evidence that many interorganizational collaborations fail to perform to expectations.[1] We know that performance issues can undermine the quality of the relationship (Ring & Van de Ven, 1994), reduce the likelihood of subsequent exchange (Li & Rowley, 2002; Schwab & Miner, 2008), and breed mutual distrust and conflict (Azoulay, Repenning, & Zuckerman, 2010; Chung & Beamish, 2010; Faems, Janssens, Madhok,

[1] A frequently cited statistic is that more than 50% of strategic alliances do not achieve their objectives (Kale & Singh, 2009); more than one-third of venture capital syndicate-backed portfolio companies eventually end in bankruptcy or liquidation (author's analysis of the VentureXpert data).

& Van Looy, 2008). It is unlikely that such negative experiences would result in endorsements; indeed, to the contrary, they may dissuade indirectly connected parties from working together. To date, however, little research has examined how the outcomes of exchange relationships between two organizations has broader effects beyond the focal dyad.

The core objective of the present paper is to build a theory of how the flow of positive or negative information across indirect ties affects the formation of new exchange relationships. It does so by examining how dyadic-level performance outcomes affect triadic-level tie formation. I start with a simple model in which a shared partner (the "intermediary") passes on its private knowledge regarding an evaluated organization (the "evaluatee") to an evaluating organization (the "evaluator"). I argue that the valence of the information passed along through an indirect tie is contingent on the success or the failure of the prior interactions between the evaluatee and the intermediary. I suggest that successes lead to the flow positive information and increase the probability of a direct tie forming between the evaluator and the evaluatee, and failures have the opposite effect. I then investigate two contingencies that may increase the evaluator's reliance on the private information passed on by the intermediary, whether it is positive or negative. First, I propose that the evaluator's reliance on both positive and negative information will depend on the intermediary's credibility or the extent to which the evaluator believes the intermediary has both the ability to discern high quality in its exchange partners and the incentives to communicate such information truthfully. One way that organizations develop such credibility is through a track record of superior performance. Second, I examine how the presence of alternative sources of information—whether public sources of information such as the presence of an established track record of the evaluatee or alternative private sources of information resulting from the evaluator's embeddedness into the interorganizational network—attenuates the reliance on the positive and negative information transmitted through the indirect ties.

I test those ideas in the context of the matching between venture capital (VC) firms and their capital providers, also known as limited partners (LPs). Although both organizational theorists and finance scholars have long studied the investment and syndication patterns of VC firms (e.g., Hochberg, Lindsay, & Westerfield, 2013; Hochberg, Ljungqvist, & Lu, 2010a; Podolny, 2001; Sorenson & Stuart, 2001, 2008; Trapido, 2007), so far limited attention has been paid to the VC's upstream relationships with the LPs, which tend to be large financial institutions such as foundation and university endowments and public and private pension funds (for recent exceptions, see Hochberg, Ljungqvist, & Vissing-Jorgensen, 2010b; Hochberg & Rauh, 2013). Selecting high-performing VCs is critical to such institutions due to the high dispersion of returns within the industry (Kaplan & Schoar, 2005). Within this empirical context, I focus on the effect of the LP–VC_A–VC_B indirect ties—in which an LP has a prior investment with VC_A, which has a syndication relationship with VC_B—on the LP's decision to subsequently invest in VC_B. I argue that the information the intermediary, VC_A, will pass to the LP, and the LP's subsequent VC selection decision, will depend critically on the outcome of the co-investments between the two VCs.

The present paper challenges two core assumptions of network theory. First, in contrast to the generally presumed tendency toward triadic closure, I argue that indirect ties can either facilitate or impede the formation of direct ties, depending on the content of the information flowing through the ties. Second, the present research highlights a previously unexplored trade-off to having high-credibility exchange partners. Although partners' credibility can magnify the benefit of their endorsement if they are satisfied with the relationship, they can also be effective at closing doors if a relationship turns sour. This finding stands in contrast to the conventional wisdom that collaborating with high-credibility partners amounts to unambiguous endorsements that can enhance an actor's standing and desirability as an exchange partner (e.g., Stuart, Hoang, & Hybels, 1999).

1.2 Theory and hypotheses

Information flows and triadic closure. Triadic closure—defined as the tendency of actors sharing ties with the same actor to disproportionately form and maintain ties among themselves—dates back to Simmel (1957) and is one of the oldest concepts in sociology. It is central to balance theory (Heider, 1958) and has been critical to many of the assumptions of network theory. For example, Granovetter's (1973) influential work on weak ties is based on the premise that triads with weak ties are less likely to close. Triadic closure is one of the elementary processes of network evolution and is at the heart of creating small worlds (Baum et al., 2003; Watts, 1999). In interorganizational network research, triadic closure has been documented in a variety of settings, including strategic alliances in several industries (Gulati & Gargiulo, 1999; Powell, White, Koput, & Owen-Smith, 2005), venture capital syndication (Sorenson & Stuart, 2001), and investment banking syndication (Baum et al., 2003). While much of this research has focused on horizontal networks in which all three members of the triad play the same role, evidence is mounting regarding closure in what Shipilov and Li (2012) call "multiplex triads;" that is, triads in which one of the actors is a different type of organization than the other two. For example, a shared client can introduce two investment banks (Shipilov & Li, 2012), or a VC firm can facilitate an alliance between two of its portfolio companies (Lindsey, 2008).

A key explanation behind triadic closure is the flow of information across the interorganizational ties. Some of this information can increase the visibility of the indirectly connected actors in the search space. For example, venture capitalists use introductions from common acquaintances as a tool to winnow down their deal flow to a manageable short list (Wang, 2010). Shared partners can transmit timely information on collaborative opportunities and thus facilitate matching between the actors to which they are connected (Gulati, 1995b; Obstfeld, 2005). Finally, referrals flowing across interorganizational ties can alleviate the adverse selection concerns of the indirectly connected parties about one another's quality and motivations. Referrals carry reputational consequences for the referring party, which may lose its partners' trust if the matches it facilitates go badly (cf. Smith, 2005).

There are two key challenges, however, to attributing triadic closure to information flows. Conceptually, just the presence of an indirect tie does not guarantee that the information flowing across it assuages the parties' concerns about one another. Indeed, one can easily imagine that indirect ties can transfer negative information, which can subsequently exacerbate the two parties' mutual distrust (cf. Burt & Knez, 1995). To explain triadic closure by ex ante information flow, therefore, researchers must assume implicitly that most of the information transmitted by indirect ties is positive. Such an assumption is not always tenable. Many collaborations can result in conflicts and strained relationships among the collaborating parties (Azoulay et al., 2010; Doz, 1996); therefore, it is likely that an actor that has experienced a relationship breakdown with a collaborator is not going to endorse it to its other partners.

The second challenge is separating the effects of indirect ties from those of homophily, that is, preferring exchange partners that share some characteristic with the focal actor (McPherson, Smith-Lovin, & Cook, 2001). Evidence suggests that organizations cluster in the interorganizational network in part because of similarities in industry positioning, research and development interests or geographic locations (Stuart, 1998; Trapido, 2007). If homophily is a major driver of partner selection, then two organizations with a tie to a shared partner are more likely to be similar to one another and thus more likely to establish a future connection merely by virtue of their similarity. Existing research on triadic closure generally either ignores the question of such homogeneities (e.g., Walker et al., 1997) or alternatively tries to control for them by incorporating observable dyadic-level measures of similarity, industry positioning, or dyadic distance (Gulati, 1995b; Gulati & Gargiulo, 1999; Lindsey, 2008; Mitsuhashi & Greve, 2009). Even this latter approach, however, cannot resolve issues surrounding unobserved dimensions of similarities or differences that are relevant to the collaboration decisions. As such, empirical research risks misattributing triadic closure to the presence of shared partners, while in fact it is driven by the hemophilic preferences of the actors (Baum, Cowan, & Jonard, 2010; Shalizi & Thomas, 2011).

We can address both of these challenges by shifting the focus from the mere absence or presence of ties to the valence of the information—positive or negative—that is transmitted through these ties. Simultaneously considering the effects of both positive and negative information on tie formation can potentially show previously unexamined limits to a taken-for-granted stylized fact—that triads tend to close—while at the same time reinforcing the confidence in the underlying theoretical mechanism predicated on information flows. Demonstrating both the positive and negative effects of indirect ties on direct tie formation can also alleviate uncertainties regarding unobservable homogeneities driving triadic closure. While unobservable homogeneities may be an alternate explanation for direct tie formation when positive information is transferred across indirect ties, they cannot account for the diminished likelihood of tie formation when negative information travels along the same route.

Information valence and new tie formation. My starting point is a simple triadic model. An evaluated organization (the "evaluatee") seeks to enter into a relationship with an evaluating organization (the "evaluator"). Given its concern with the unobservable quality of the evaluatee, the evaluator seeks information from a shared partner (the "intermediary") whose opinion it trusts and who has private knowledge of the evaluatee through a prior collaboration.[2] The key theoretical question becomes what are the factors that determine the valence—positive or negative—of the information the intermediaries transmit and subsequently influence the evaluator's decision. For three major reasons, I propose that the performance of the collaboration between the intermediary and the evaluatee will play a key role in determining the valence of the information being transferred to the evaluator.

First, a simple outcome-based learning model can predict that the intermediaries would base their assessments of the evaluatee's quality partially on the outcome of their collaboration. Much of the existing research has focused on how failure can signal low quality or compatibility, which reduces the expected value and thus the likelihood of future collaborations with the same partner (Li & Rowley, 2002; Schwab & Miner, 2008). In contrast, successes lead to positive assessments of the collaborator and an increased willingness to engage in an exchange (Lawler et al., 2000; Ring & Van de Ven, 1994). I suggest that this effect generalizes as well to the

[2] The roles of the evaluator and the evaluatee may be clear cut when the selection is one-sided, for example when multiple service providers compete for a relationship with the same organization. The roles may be more ambiguous, however, in cases when the matching is a mutual decision and both sides play the role of evaluator and evaluatee simultaneously, for example in strategic alliances or venture capital syndication. One of the attractive features of the present manuscript's empirical setting is that the roles are clearly defined: LPs are the evaluators, firms in which the LPs have invested are the intermediaries, and the firms competing for new investments from the LPs are the evaluatees.

evaluations transmitted to third parties such as the evaluator (for a related argument in the context of job referrals, see Smith, 2005).

Second, successes and failures can affect the quality of the relationship between the evaluatee and the intermediary. Field studies of interorganizational collaborations suggest that performance struggles can undermine the quality of the relationship between two partners. This can lead to a vicious circle of diminishing trust, mutual recriminations, and increasingly negative attributions of the partner's capabilities and intentions (Arino & de la Torre, 1998; Doz, 1996; Faems et al., 2008). In contrast, successful exchanges can promote growing trust and attachment between collaborating partners (Larson, 1992; Ring & Van de Ven, 1994). The quality of the relationship, in turn, colors the attributions actors make of their collaborators' capabilities and intentions (Uzzi, 1997). Subsequently, we can expect these biases to carry over in the recommendations the intermediaries pass to the evaluators.

Third, intermediaries can have strategic reasons to pass negative information to evaluators when a collaboration fails. Such failures can reflect badly on the capabilities of both the intermediary and the evaluatee. To the extent that the intermediary cares about its own standing with the evaluator, it is incentivized to minimize its own responsibility and overstate the evaluatee's role in the failure.[3] Together, these three mechanisms lead to the following predictions:

> ***Hypothesis 1a:*** *Collaboration successes between the intermediary organization and the evaluatee will increase the likelihood of new tie formation between the evaluatee and the evaluator.*

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[3] This factor may be particularly important in the present study's setting given that the evaluators are ultimately investors in the intermediary VCs and hold them accountable for any failure.

Hypothesis 1b: *Collaboration failures between the intermediary organization and the evaluatee will decrease the likelihood of new tie formation between the evaluatee and the evaluator.*

Intermediary performance and information valence. Fundamentally, referrals and endorsements are acts of certification; as such, they depend on the certifying actor's credibility. Here, I define credibility as the likelihood that a recipient will accept and act upon an informational signal from an actor. Credibility is tied intimately to the perceived quality of the organizational actor. For example, Stuart and colleagues (1999) contended that prominent backers of young ventures, such as strategic alliance partners, venture capitalists, and investment banks have greater capabilities to evaluate high-quality firms and incentives to avoid affiliating with low-quality firms lest they jeopardize their own standing (see also Milanov & Shepherd, 2013). The decision by such prominent actors to enter into an exchange relationship with a focal organization is thus interpreted as a credible endorsement that alleviates uncertainties about the focal organization's underlying quality and enhances its ability to secure future exchange partners (see also Lee, Pollock, & Jin, 2011; Ozmel, Reuer, & Gulati, 2013).

To this perspective, the present study adds the idea that the credibility of organizations matters not only when they publicly certify their partners by initiating any form of exchange, but also when they privately certify partners through information they pass to other members of their own network. Such private certification allows for different valence of the information that is passed through the interorganizational tie: from positive endorsement to lukewarm referral to negative criticism. Importantly, I expect that the intermediary credibility will magnify the effect of both positive and negative information passed through the interorganizational ties. In other words, while much of the research on interorganizational tie formation has assumed that the credibility of one's exchange partners confers unambiguous advantages in terms of forming new relationships, I contend that high credibility collaborators can be a double-edged sword; indeed, they can open doors if they are satisfied with the collaboration, but can slam them shut if they are not happy with it.

There are many ways for organizations to build credibility in the marketplace. In settings in which quality is uncertain and ambiguously defined, audiences may look for indirect signals of the actor's quality such as the deference shown by its peers in the marketplace (Benjamin & Podolny, 1999; Podolny, 1993). In settings with greater performance transparency, however, the primary way of signaling quality, and thus establishing credibility, is a track record of organizational achievements, such as winning prestigious awards (Hallen, 2008; Rao, 1994), receiving patents (Hsu & Ziedonis, 2013), or participating in high-profile IPOs (Lee & Wahal, 2004). In the present paper, I focus on the track record of performance as a key component of credibility due to its high salience within the venture capital industry, which is my setting of interest.[4] Therefore, I predict the following:

> ***Hypothesis 2a:*** *The past performance of the intermediary will increase the positive effect of collaboration successes between the intermediary and the evaluatee on the likelihood of new tie formation between the evaluatee and the evaluator.*
>
> ***Hypothesis 2b:*** *The past performance of the intermediary will increase the negative effect of collaboration failures between the intermediary and the evaluatee on the likelihood of new tie formation between the evaluatee and the evaluator.*

[4] Venture capitalists routinely decorate their walls with plaques commemorating their exits, and with virtually no exceptions both venture capitalists and limited partners shared the sentiment of one venture capitalist that ""The exits you have had are the coin of the realm and the key to being taken seriously… You are only as good as your last exits."

Availability of alternative sources of information. In conducting due diligence on a potential exchange partner, actors draw on several sources of information, both public and private. The information flowing across indirect ties is but a single piece of this process. The availability of alternative sources of information should reduce the influence of shared partners, whether their information is positive or negative. In particular, I focus on two possible alternative sources of information: (1) the publicly available track record of the evaluatee and (2) the access of the evaluator to other sources of private information on the evaluatee.

Uncertainty about the quality and motivations of the exchange partner is a key driver of relying on private sources of information; therefore, any factor that reduces uncertainty can undermine the effect of positive and negative information. In particular, as organizations age, they accumulate a track record of performance that can serve as at least one publicly observable data point on their unobservable characteristics. Organizational age reduces actors' use of indirect signals of quality such as affiliating with high-quality actors (Stuart et al., 1999) or the human capital of the founders (Hallen, 2008). Similarly, the presence of performance track record will similarly reduce the need to rely on the private signals of performance, whether positive or negative:

> ***Hypothesis 3a:*** *The length of the evaluatee's track record will decrease the positive effect of collaboration successes between the intermediary and the evaluatee on the likelihood of new tie formation between the evaluatee and the evaluator.*
>
> ***Hypothesis 3b:*** *The length of the evaluatee's track record will decrease the negative effect of collaboration failures between the intermediary organization and the evaluatee on the likelihood of new tie formation between the evaluatee and the evaluator.*

Even in accessing private information, organizations are not constrained to relying on a particular relationship. More centrally located organizations are positioned better to access the word of mouth information flowing from the network and aggregating data from multiple sources as opposed to relying on a narrow set of indirect ties (Gulati & Gargiulo, 1999; Robinson & Stuart, 2007). As a result, more central organizations are able to execute global searches for exchange actors beyond their local cluster of relationships more effectively (Sorenson & Stuart, 2001). To the extent that they can access private information from several sources, central actors may rely less on the positive and negative information from the narrow set of shared partners with a prospective counterparty. Thus:

> ***Hypothesis 4a:*** *The centrality of the evaluator in the interorganizational network will decrease the positive effect of collaboration successes between the intermediary organization and the evaluatee on the likelihood of new tie formation between the evaluatee and the evaluator.*

> ***Hypothesis 4b:*** *The centrality of the evaluator in the interorganizational network will decrease the negative effect of collaboration failures between the intermediary organization and the evaluatee on the likelihood of new tie formation between the evaluatee and the evaluator.*

Figure 1.1 illustrates the conceptual model. Relatively to a baseline of no indirect ties, a successful relationship between an intermediary and the evaluatee will increase the probability of a tie forming between the evaluator and the evaluatee (Hypothesis 1a). In contrast, a failed relationship between an intermediary and the evaluatee will decrease the probability of a tie forming between the evaluator and the evaluatee (Hypothesis 1b). I also expect that higher performance of the intermediary will increase the credibility of any information it passes and will thus magnify both effects (Hypotheses 2a and 2b). Finally, I predict that both effects will be attenuated by the presence of alternative sources of information. Such information can come from the length of the evaluatee's public track record (Hypotheses 3a and 3b) or from the evaluator's centrality in the interorganizational network and thus its ability to tap into word of mouth information circulating about the evaluatee (Hypotheses 4a and 4b).

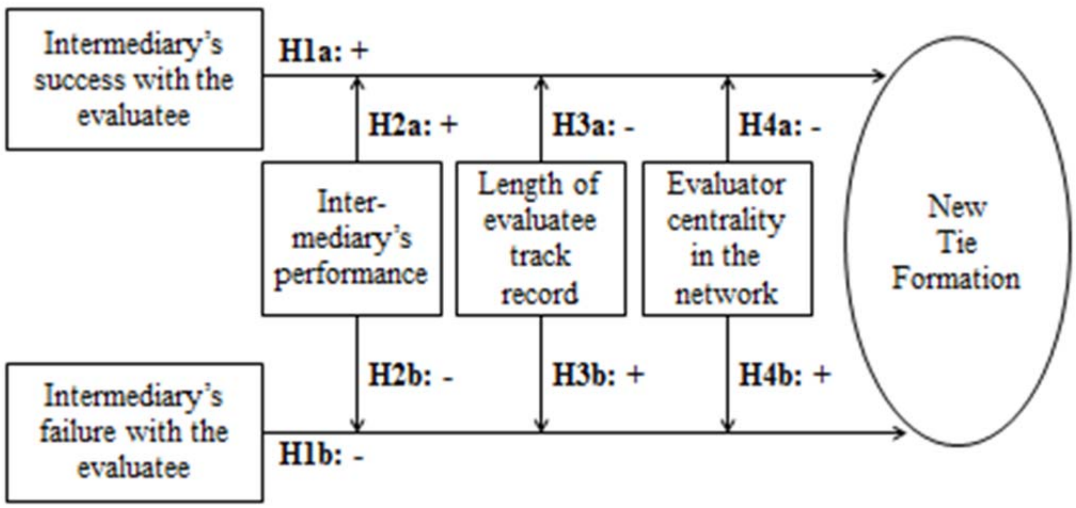

Figure 1.1: Theoretical framework

1.3 Research context

I investigate the mechanisms of triadic closure in the context of the investment decisions of limited partners (LPs) investing in venture capital (VC) firms. The VC industry can be conceived as a value chain in which capital cycles from the original investors (LPs) to the capital intermediaries (VC firms) to the investment targets—companies in need of financing—and then hopefully back to the LPs following a successful exit. The LPs include a variety of deeppocketed capital providers, including university and foundation endowments, private and public pension funds, the investment offices of wealthy individuals or families, and funds of funds. Such investment entities specialize in constructing portfolios of VC investments for individuals and institutions that cannot afford a well-diversified portfolio.[5]

Successful VC firms aim to raise a new fund every three years, typically attracting a mix of new and repeat investors. Top firms such as Kleiner Perkins and Sequoia typically have more willing investors and typically ration the access to their funds.[6] Beyond that small group of elite VCs and the LPs that have access to them, the fundraising process is a challenge for both sides. One venture capitalist noted that "the fundraising process takes me at least as much time—and certainly more stress—than the investing side. This is the one time I feel what it is to be in the shoes of the entrepreneur pleading for money." On the LP side are the challenges of evaluating the most promising investments. Funds are typically raised before the final results of the previous two or three funds are revealed, and interim performance figures are sensitive to accounting assumptions and virtually unrelated to the final performance (Hochberg et al., 2010b). As a result, soft information obtained from other sources can play an important role in the investment decision.

Despite the importance of the fundraising process both for the LPs and the VCs, relatively little systematic research has been conducted on the determinants of the LP investment

[5] VC firms are required to limit their number of individual investors to maintain their private status and thus be exempted from the SEC's public security regulations. As a result, the minimum size of a commitment is typically in the millions or dozen of millions of dollars. Given the high idiosyncratic risk of these investments, diversifying across multiple VC firms is critical. This is why industry insiders consider that a well-balanced VC portfolio requires several hundreds of millions of dollars. Furthermore, the evaluating, selecting, and overseeing multiple VC firms requires skilled personnel, which may be prohibitively expensive overhead for smaller institutional investors. Funds of funds therefore provide the benefits of diversification at the expense of an additional layer of fees.

[6] Some VCs may turn down LPs if they are significantly oversubscribed, that is, they are over the target level of funding. I account for this effect by controlling for the oversubscription ratio of the VC fund (i.e., the ratio between the amount raised versus the original target).

decisions. Much of the work has focused on the patterns of LP reinvestments and has documented the information advantage that fund insiders have compared to new investors (Hochberg et al., 2010b; Lerner, Schoar, & Wongsunwai, 2007). More recent work has focused on the role that geographic proximity plays in the LP investment selection. Specifically, LPs have been shown to overinvest in VCs in the same state to the detriment of their performance (Hochberg & Rauh, 2013). To date, however, I am unaware of any research examining the role of interorganizational networks in the fundraising process.

My interviews with seven VC principals and five LPs suggest the important role of network ties in alleviating the adverse selection concerns of the LPs. In particular, LPs can consult three major sources in the course of the due diligence process (see Figure 1.2): (1) other LPs currently invested in the fund, (2) executives of portfolio companies in the fund, and (3) other VCs that have co-invested in the fund. Each of these sources provides an important source of information. Other LPs that have invested in a VC firm can contribute their unique perspective as insiders to the fund with a privileged view of both its investment strategy and its treatment of its investors (Lerner et al., 2007). Furthermore, other investors are much more likely to have a broad view of the overall market and how the VC in question compares to others from the investors' perspectives. Second, LPs typically call founders and executives from portfolio companies financed by the venture capitalist, sometimes specifically selecting both successes and failures, to understand their reputation in the entrepreneurial community and their effectiveness in supporting their ventures. Finally, LPs talk to as many venture capitalists who have syndicated with the portfolio companies in question. Said one LP: "[Other VCs] provide the best sort of feedback, because they see the VC in action, both at the negotiating table and in the boardroom." Another LP emphasized, "My starting point when I conduct a due diligence is to check whom they have been working with… And if I happen to know some [of their syndication partners], they are the first people I call." All of the VC principals with whom I talked emphasized that they regularly fielded due diligence questions from LPs about VCs with which they have worked and consider it important to provide their honest assessment (positive or negative). Notably, they are fully aware that their own reputations with the LPs might be affected by the perceived quality of their recommendations. In a due diligence report one LP provided, conversations with VCs accounted for five of 14 due diligence calls, with LPs and entrepreneurs accounting for four and two calls, respectively.

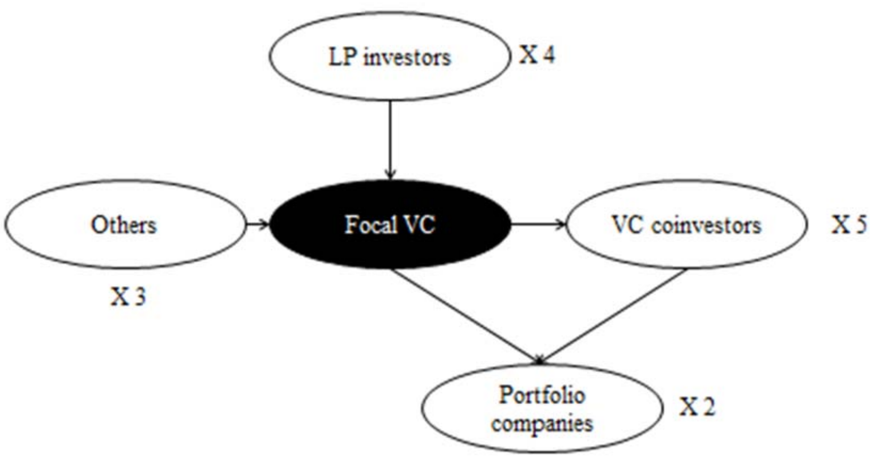

Figure 1.2: Referral calls of a fund-of-fund LP during a due diligence on a VC fund

Based on a confidential due diligence memorandum provided to the author. Others include retired founding members of the VC fund as well as its legal counsel.

For my empirical analyses, I focus on VCs in which the LP has already invested that have syndicated with the focal VC firm. While LPs can and do call other VCs, they are particularly likely to trust the opinions of VCs in their portfolio. Such are more likely to have a pre-established relationship of trust, which is especially critical for transmitting sensitive information on their past, present, and most likely future partners. Furthermore, LPs are keenly aware of their position of dependence of their own VCs and their incentives to provide high-quality appraisals. As one LP noted, "These are my service providers, after all, so I can expect them to answer the call."

A distinct advantage of this setting is the unambiguous mapping of all the key analytical constructs within the theory. The LPs can be considered the evaluators, for whose attention the individual VCs (the evaluatees) compete,[7] whereas the intermediary is the VC that has a syndication relationship with the evaluatee (another VC) and an investment relationship with the focal LP. The ultimate performance of the interaction between the intermediary and the evaluatee is easily observable and unambiguously assignable; indeed, an exit such as an IPO or an acquisition is regarded universally as a success, whereas a bankruptcy or liquidating a portfolio company is clearly a failure. By comparison, the different roles in the triad are much more difficult to disentangle in horizontal networks (e.g., investment banking syndicates or corporate strategic alliances), where any single member can play simultaneously the role of evaluator, evaluatee, and intermediary. Furthermore, many settings lack transparent data on relationship performance. For example, strategic alliance research has long been hampered in its ability to

[7] Sometimes VCs may turn down LPs if they are significantly oversubscribed, that is, over the target level of funding. At the highest end of the market, top firms such as Sequoia and Kleiner Perkins are extremely sought after to the extent that LPs can compete with one another for an allocation. I account for this effect by controlling for the oversubscription ratio of the VC fund (i.e., the ratio between the amount raised versus the original target).

assess alliance performance due to the nonpublic nature of the data and the multitude of objectives beyond financial metrics (e.g., Zollo, Reuer, & Singh, 2002).

1.4 Data and variables

Data. I aggregated two major datasets: the data on VC investment and syndication activities was drawn from the widely used VentureXpert database by Thompson Reuters, whereas the data on LP to VC investment was drawn from the Private Equity Intelligence (Preqin) database. I discuss the two datasets and the aggregation procedure in the following paragraphs.

VentureXpert has been tracking venture capital fundraising, investments, and exits since the 1970s and is commonly used for research in both finance (Hochberg et al., 2007, 2010a) and economic sociology (Podolny, 2001; Sorenson & Stuart, 2001, 2008). It lists the investors in each funding round of a particular portfolio company; from this information I constructed a symmetrical matrix of prior syndication relationships between two VC firms, in which the ij^{th} entry denotes the number of times VC firm, i, co-invested with VC firm j within a preceding period of some length. Consistent with prior research (e.g., Sorenson & Stuart, 2008), I report a 5-year rolling window, but the results reported are robust to 3-year and 7-year rolling windows as well.

The VC industry has historically been rather secretive about funding sources, which explains the very limited prior research on LP investments. The few authoritative studies on the topic typically secured access under strict confidentiality agreements into the investment portfolios of a small number of large institutional investors (Lerner & Schoar, 2004; Lerner et al., 2007). To fill this gap in industry data, Preqin began assembling a dataset on specific investors from three sources. As a starting point, it used Freedom of Information requests (or the equivalent in other countries) to procure investment-level data from publicly owned LPs. A significant number of the large LPs in the US fall into this category, including public pension plans such as the California Public Employees' Retirement System (also known as CalPERS and is among the largest LPs in the United States) or the endowments of public universities (e.g., the University of Michigan endowment). Preqin complemented this core of legally disclosable data with two sets of surveys, one to the VC firms raising the funds and one to the privately owned LPs. The final Preqin database triangulates and checks across these different sources to reduce the selection biases in any single method. Finance scholars have recently started using the Preqin dataset and have confirmed the exhaustive nature of the dataset relative to older sources of data (e.g., CapitalIQ, VentureOne, and VenturEconomics).[8]

Starting with the Preqin core dataset, I filtered the data as follows. First, I used only dyads in which both the LP and the VC were based in the US helped ensure homogeneity of the institutional environment. Second, for data availability reasons, I limited my attention to the period January 1997 to December 2007.[9] Third and finally, I excluded a large number of classes such as real estate, hedge funds, natural resources, and mezzanine financing that are clearly outside the VC industry.[10]

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[8] Hochberg and Rauh (2013) created a combined dataset of LP investments of all these three databases plus Preqin. Alone or in combination with the other datasets, Preqin contributed 89% of all data points in the database; more than half of the database entries came from Preqin alone, without appearing in any of the other databases.

[9] There are several reasons for the choice of this timing window. Preqin started collecting data in 2001-2002, which are the years of the first available snapshots of the LP portfolios. Because the life cycle of VC funds is around 10 years, I conclude that the first year for which reliable VC investments is available started in 1992. I use the first five years to construct the initial rolling window network, as typical in interorganizational network research (Gulati, 1995b; Podolny, 2001; Sorenson & Stuart, 2001). This left me with 1997 as the first year on which to conduct the analyses.

[10] The classes excluded are Co-investment, Direct Secondaries, Distressed Debt, Fund of Funds, Mezzanine, Natural Resources, Secondaries, Special Situations, Timber, and Turnaround.

Because no common identifier exists between VentureXpert and Preqin, I used a fuzzy textual matching algorithm, the Datamatch© software. It compares the similarity between any two-word strings, ignoring known noise such as common abbreviations (e.g., Ltd., vs. Limited). I carefully checked each match to ensure accuracy, consulting the VC firms' websites as applicable. As a final check on the integrity of the matching, I resolved any discrepancies in the address information available on each firm by consulting both databases. In all, I was able to confidently match 60% of the firms (668 of 1127) within the scope of the research; these firms accounted for 70% of the individual funds raised and 75% of the LP–VC dyads. Supplemental analyses suggest that the sample is biased toward larger VCs raising funds in the most important states to the VC industry such as Massachusetts, California, and New York. In my robustness tests, I examine the extent to which this bias may affect the present study's findings.

Dependent variable. The dependent variable used across all analyses is an indicator of whether the LP–VC tie was realized, that is, whether the LP invested in the new fund being raised by the new VC firm.

Independent variables. The core independent variables relate to the count of VC-mediated ties between the focal LP and the VC firm. Due to the highly skewed nature of the variables, all of them are logged. The naïve structural embeddedness variable of *VC-mediated ties count* is the logged number of different VCs in which the LP has invested within the prior five years and which have one or more syndication experiences with the focal VC across the same time frame. I count only the number of discrete paths, that is, a single mediating VC counts as one indirect tie, even if it has had multiple syndication experiences with the focal VC.

I then differentiate between *VC-mediated indirect ties count–failure* as the aggregate count of indirect ties in which at least one of the deals resulted in a bankruptcy or liquidation of the portfolio company. Similarly, *VC-mediated indirect ties count–success* designates the aggregate count of indirect ties in which at least one of the deals resulted in a successful exit—either an IPO or an acquisition—of the portfolio company.[11] Hypothesis 1a predicts that the latter type of ties will have a positive effect on the probability of the focal LP investing in the focal VC. Hypothesis 1b predicts that the former type of ties will have a negative effect on that same probability. For parsimony, I exclude neutral relationships (ones in which all portfolio companies are still listed as active) from the subsequent analyses. Notably, they do not change anything if they are included, and in all of the specifications for which I ran robustness tests, their effect was statistically indistinguishable from zero. Furthermore, I follow the precedent of the finance literature (Gompers, Mukharlyamov, & Xuan, 2012a) in allowing both successes and failures to occur at any time, not just prior to the year of the focal investment. While this approach was adopted for data availability reasons (i.e., I have the dates of the successful IPOs but not of acquisitions or bankruptcy filings), it is also a conservative test of the proposed private information transfer mechanism. Venture capital firms become aware relatively quickly of prospects for collaboration and may convey this in private information to their LPs, even if the portfolio company has not yet failed or succeeded. The LPs that rely solely on public information would not have access to such information. I also examined an alternative specification in which I only include syndicates that have completed their final round before the LP's investment in the focal VC. The premise of this approach is that the prospects of such syndicates—positive or

[11] Such definition allows some ties, including simultaneously successes and failures, to be double-counted as both successful and unsuccessful VC-mediated indirect ties. In this way, I assume that the LP will receive both a positive and a negative piece of information from the connection. An alternative approach, in which I exclude all indirect ties including both successes and failures, yielded substantively identical results to those reported.

negative—are clearer than prospects for ongoing syndicates. The results using this alternative specification are substantively unchanged.

To test the moderating effects of intermediary performance, I calculated the IPO rates of all VC firms based on the number of IPOs they exited over the prior five years divided by their total number of investments over the same period. I then divided the VCs into two groups based on whether they are within or outside the top quartile of all VCs for that particular year.[12] Initial public offerings have long been considered the most high profile type of exit, are monitored carefully by industry participants, and aspired to by firms striving to bolster their standing in the industry (Lee et al., 2011; Lee & Wahal, 2004). I used a 2×2 matrix that included the intermediary VC performance on one dimension and the outcome of the collaboration of the intermediary VC and the focal VC on the other dimension. From this, I derived four different VC-mediated indirect tie counts: (1) *high performance intermediary and failure*, (2) *low performance intermediary and failure*, (3) *high performance intermediary and success*, and (4) *low performance intermediary and success*. When these four variables are incorporated into the model, testing Hypotheses 2a and 2b becomes a simple test of differences of coefficients. Hypothesis 2a predicts that *high performance intermediary and failure* will have more of a negative effect than *low performance intermediary and failure*. Meanwhile, Hypothesis 2b predicts that *high performance intermediary and success* will have a more positive effect than *low performance intermediary and success.*

[12] The top quartile choice was motivated by two factors. First, it is a highly salient cut-off within the VC industry. For example, major databases such as Preqin report the firm standing by quartiles. Second, it ensured the maximum variance within the split variables, because the intermediaries in the top quartile in the IPO rate accounted for approximately half of the VC-mediated indirect ties. The results are robust, however, if I use alternative cut-offs such as median or mean.

For Hypotheses 3a and 3b, I use the age of the VC firm defined as years elapsed since it raised its first fund, as a moderator of the effects of both successful and failed VC-mediated indirect ties. Older firms have a longer history of investing that LPs can scrutinize to understand the VC's investment strategy and capabilities better. Firm age is especially important considering that the outcome of many investments is not fully known for several years. As such, interpreting the track record of very young firms is very challenging. Finally, for Hypotheses 4a and 4b, I use the number of different VCs in which the LP had invested in over the past five years as a moderator. Although those VCs might not have direct experience with the evaluated VC, they can provide valuable access points to the word of mouth information circulating in the VC networks regarding a particular firm (cf. Gulati & Gargiulo, 1999 regarding centrality in the interorganizational network and word of mouth).

Control variables. To credibly estimate the structural effects, I incorporated a wide variety of controls at the level of the focal VC firm, as well as the focal LP–VC dyad.

To incorporate the track record of the VC firm, I include the number of funds previously raised by the same VC firm (logged to correct for over-dispersion) and the logged number of years elapsed since its first fundraising. I also incorporate three indicator variables denoting the size quartile of the focal VC firm: lower quartile equates to smaller size, with the top (4^{th}) quartile being the omitted category. I use two sets of variables to measure the performance of the focal VC firm. I first include the outcomes of all the portfolio companies in which the VC has invested over the prior five years: portfolio company IPO rate, portfolio company acquisition rate, and portfolio company failure rate. I also use the average performance quartile of the previous funds raised by the same VC firm as reported by Preqin. In cases where the average performance quartile is missing (approximately 20% of the cases), I impute it from all the other independent variables using STATA's *impute* procedure. For this variable, lower values indicate better performance (i.e., funds in the first quartile are the best-performing funds, whereas the funds in the fourth quartile are the worst performers). With the influence of these controls partialed out in the regression, I can claim that the count of successful versus failed VC-mediated indirect ties does not reflect the unobservable, true quality of the VC firm. I also incorporate the focal firm's (logged) degree centrality in the VC syndication network to control for the fact that more central firms are more likely to have more indirect ties to the VCs, but can also be more attractive because their centrality in the VC network can signal quality (Podolny, 2001).

Not all VCs are equally available for new investments. In particular, VCs often suffer from scalability issues, because its existing partners can manage only a limited number of investments, and new partners cannot be added quickly without jeopardizing quality (Gompers & Lerner, 1999). As a result, VC firms often set targets for the new fund; if fund-raising exceeds these targets, it is called oversubscribed. And yet, oversubscribed funds do not automatically stop accepting new investments. Conversations with venture capitalists suggest that most firms aim to be slightly oversubscribed by a factor of 1.1 or 1.2 of their target to signal their desirability in the market. Being oversubscribed more than that becomes problematic. Conversely, undersubscribed funds are generally desperate for new investors due to the stigma this situation entails. Correspondingly, I control for the VC's availability to new investors by calculating its *oversubscription ratio* defined as the total funds raised divided by the fund target. In cases where no fund target is available, I assume that the fund is exactly subscribed. I log the ratio to make it symmetric around zero; an undersubscribed firm will have negative logged ratio, whereas an oversubscribed firm will have a positive logged ratio.

I also incorporate a large number of dyadic controls, in particular to remove the influence of proximity or homophily from the effects of indirect ties (Sorenson & Stuart, 2001; Stuart, 1998). I include an indicator variable equal to 1 if the LP and the VC are located in the same state. This variable controls for the documented tendency of LPs to invest disproportionately in geographically proximate VCs (Hochberg & Rauh, 2013). I also obtain substantively identical results using the logged distance between the LP and the VC; however, the two geographic measures are correlated too heavily to be used together in the same model.

I also control for the preferences of the LPs as implied by their existing portfolio. In the case of *average industry overlap*, we first calculate the dyadic industry overlap between the focal VC and each of the other VCs using the following formula, where p_{ik} is the proportion of VC firm *i*'s investments in industry *k* over the prior five years:[13]

$$Dyadic\ Industry\ Overlap_{ij} = \sum_{k=1}^{K} MIN(p_{ik}, p_{jk})$$

The dyadic industry overlap measure between two VC firms ranges from 0 to 1, with 1 indicating identical distribution of investments across industries. I then average the overlap measure between the focal VC and all VCs with which the LP has invested over the prior five years, which results in an index of how similar the industry specialization of the focal VC is to the "average" VC that the LP has chosen previously. Similarly, I compute *average state overlap* based on the average overlap in state-by-state investments to control for the geographic investment specialization of the VCs in which the LP has invested previously. Finally, I compute

[13] I use VentureXpert's standard Minor Industries classification with ten categories: Biotech, Communications and Media, Computer Hardware, Computer Software, Semiconductors/Other Electronics, Industrials/Energy, Internet Specific, Medical/Health, Consumer Related, and Others.

the *average stage overlap* based on the average overlap in the stages of the investments between the focal VC and the other VCs in the LP's portfolio.[14] Together, these three variables should account for the industry, geographic, and stage preferences of the LPs.

Finally, I control for the presence of *LP-mediated indirect ties* between the focal LP and VC. These ties are formed when an LP that has prior co-investments with the focal LP has also invested previously in the focal VC. This is a potentially important channel for referrals, because LPs are highly interested in the perspective of other institutional investors who have first-hand experiences with the VCs of interest. Prior co-investment ties between two LPs means that their key personnel likely sit on the same LP boards, which facilitates the exchange of private information. Another reason an LP-mediated tie could be potentially important is because it can serve as an attention-focusing mechanism. To the extent that structural equivalence increases the perception of competition and mutual monitoring (Burt, 1987; White, 1981), LPs are likely to keep track of their co-investment partners' investments. If a peer has invested in a particular VC firm, it may be regarded as social proof of its worth, which merits closer investigation. In the present study, I do not attempt to differentiate between those specific mechanisms, but strive to account for them all by controlling for the LP-mediated indirect ties.

1.5 Method

I derived the dataset used for the core analyses on new tie formation using the factual–counterfactual set-up common for investigating dyadic tie formation (e.g., Sorenson & Stuart, 2008). Existing LP–VC dyads define the universe of factual pairings. For each factual dyad, I define the universe of counterfactual dyads in which the same LP is matched with other VCs that

[14] I use the standard VentureXpert classification of investment round stage as Seed/Start-up, Early Stage, Growth, and Late Stage.

(1) raised new funds in the same calendar year and (2) belong to the same fund classification.[15] Because I am interested in new tie formation, I exclude from the analysis all pairs—factual or counterfactual—in which the LP and the VC have had prior investment ties. I also drop from consideration all first-time funds, because new firms start with no prior syndication experiences, which leaves my core independent variable undefined. All in all, this reduced dataset includes 3,601 factual and 61,869 counterfactual observations, including 610 LPs investing in a total of 709 discrete funds.

I used a conditional logit model, also known as the McFadden Choice Model, to predict the factual observation within each group. In effect, this model estimates an unobserved utility function associated with each observation within the set and selects the observation with the highest value. Because it only considers within-group variation, the model effectively incorporates fixed effects at the group level. Commonly, conditional logit models are used to analyze tie formation in the interorganizational networks literature due to their ability to control for all unobservables shared across a particular choice set (e.g., Sorenson & Stuart, 2008). Given that my counterfactual sampling strategy keeps the same LP, year, and fund type fixed across groups, all variables fixed within any of those levels of analyses—or permutations thereof, such as LP eigenvector centrality in a given year—are absorbed by the fixed effects and are thus not included in the model. I also used robust standard errors clustered at the group level.

Conditional logit models are not sensitive to differences in the number of alternatives across decisions; therefore, I have allowed the number of counterfactuals to vary from 1 to 44 per group depending on the number of other VCs that raised funds of the same type in the same

[15] The major classifications are general VC (~40%), early-stage VC (~17%), and late-stage VC/buyout (~40%) of the observations. Several smaller classes account for the remaining 3%.

year. In unreported robustness analyses, however, I replicated my findings using only three or five randomly selected counterfactuals, consistent with other studies in the literature (Jensen, 2006).

1.6 Results

Main results. Table 1.1 presents the descriptive statistics and the correlations for the core dataset that predicts new tie formation. The correlations between most of the independent variables and the dependent variable is largely as predicted. Prior fund count and fund age are positively correlated with the odds of matching, as does the fund size subscription ratio and the past performance of the funds the focal firm raised. All of the homophily measures—same state location between the VC and the LP and the similarity of the VC to other firms in the LP's portfolio—are also positively associated with matching.

Some independent variables have moderately high correlations; for example, fund count, firm age, and firm logged degree centrality in the syndication network are all correlated at above 30%, as are the structural and the homophily measures. Not surprisingly, the different subdivisions of the VC-mediated ties are highly correlated with the variables that they aggregate to. For example, *low performance intermediary and failure* and *high performance intermediary and failure* are both highly correlated with the aggregated *VC-mediated indirect ties count–failure* variable. Such problematic pairs, however, never enter the model together. Overall, the correlations are not sufficiently high to create significant issues. No model specification reported exhibits a Variance Inflationary Factor of above five, which is substantially lower than the value of 10 typically accepted as the upper acceptable bound (Kutner, Nachtsheim, & Neter, 2004).

Table 1.1: Summary statistics and correlations for all key variables

Variables	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12
1. Realized LP-VC tie (=1)	0.06	0.23	1.00											
2. VC prior fund count (logged)	1.35	0.60	0.06	1.00										
3. VC firm age (logged)	2.14	0.82	0.07	0.56	1.00									
4. VC 1st size quartile (=1)	0.37	0.48	-0.10	-0.33	-0.29	1.00								
5. VC 2nd size quartile (=1)	0.29	0.45	-0.02	-0.04	0.00	-0.49	1.00							
6. VC 3rd size quartile (=1)	0.20	0.40	0.03	0.15	0.14	-0.39	-0.32	1.00						
7. VC firm 5-year IPO exit rate	0.16	0.16	-0.01	0.02	0.00	-0.05	0.11	-0.01	1.00					
8. VC firm 5-year M&A exit rate	0.46	0.21	0.00	-0.07	-0.21	0.04	-0.07	0.03	-0.47	1.00				
9. VC firm 5-year failed investment rate	0.17	0.16	0.00	-0.05	-0.06	0.12	-0.05	-0.07	-0.10	-0.14	1.00			
10. VC firm Bonacich centrality	1.33	1.89	0.02	0.44	0.40	-0.25	-0.04	0.10	0.15	-0.09	-0.02	1.00		
11. Average Bonacich centrality of VC firm's existing LPs	2.25	1.69	0.03	0.16	0.03	-0.24	0.03	0.14	0.05	-0.02	-0.01	0.16	1.00	
12. Subscription ratio (logged)	0.01	0.20	0.04	0.09	0.03	-0.22	0.08	0.09	-0.02	0.05	-0.03	0.02	0.08	1.00
13. VC and LP collocated in same state (=1)	0.12	0.32	0.05	-0.01	-0.01	-0.05	0.01	0.04	0.03	0.01	-0.02	0.03	0.00	0.02
14. Distance between VC and LP (logged km)	6.12	2.29	-0.02	0.01	0.03	0.02	-0.01	-0.03	-0.02	-0.02	0.01	0.05	0.02	0.00
15. LP-VC industry specialization overlap	0.29	0.20	0.03	0.14	0.15	-0.07	-0.01	0.01	-0.05	-0.08	0.07	0.22	0.03	0.00
16. LP-VC state specialization overlap	0.21	0.16	0.04	0.15	0.19	-0.14	0.01	0.04	0.01	-0.12	0.00	0.29	0.09	0.04
17. Geographic distance between VC and LP investments (logged km)	5.99	2.51	0.00	-0.01	0.04	0.00	0.00	-0.01	-0.04	0.00	-0.06	0.05	-0.05	0.01
18. Lp-mediated indirect tie count (logged)	1.19	1.14	0.07	0.48	0.21	-0.31	0.00	0.13	-0.01	0.00	-0.03	0.24	0.40	0.09
19. VC-mediated indirect tie count (logged)	0.47	0.70	0.04	0.20	0.24	-0.14	0.01	0.05	0.04	-0.09	0.00	0.41	0.07	0.01
20. VC-mediated indirect tie count - failure(logged)	0.16	0.39	0.03	0.19	0.19	-0.11	-0.01	0.03	0.03	-0.04	0.09	0.39	0.10	0.01
21. VC-mediated indirect tie count - success(logged)	0.39	0.63	0.04	0.20	0.23	-0.14	0.00	0.05	0.06	-0.07	0.00	0.43	0.08	0.02
22. VC-mediated indirect tie count - high rep. intermed. & failure(logged)	0.11	0.31	0.02	0.15	0.16	-0.08	-0.02	0.03	0.05	-0.04	0.08	0.36	0.08	0.01
23. VC-mediated indirect tie count - low rep. intermed. & failure(logged)	0.01	0.10	0.01	0.10	0.08	-0.04	0.00	-0.01	0.01	0.00	0.03	0.17	0.05	0.01
24. VC-mediated indirect tie count - high rep. intermed. & success(logged)	0.28	0.51	0.04	0.16	0.18	-0.12	0.00	0.04	0.09	-0.06	0.02	0.40	0.07	0.02
25. VC-mediated indirect tie count - low rep. intermed. & success(logged)	0.19	0.42	0.04	0.21	0.22	-0.13	0.00	0.06	-0.01	-0.04	-0.03	0.35	0.07	0.01

Variables	Mean	Std. Dev.	13	14	15	16	17	18	19	20	21	22	23	24
13. VC and LP collocated in same state (=1)	0.12	0.32	1.00											
14. Distance between VC and LP (logged km)	6.12	2.29	-0.89	1.00										
15. LP-VC industry specialization overlap	0.29	0.20	0.02	0.01	1.00									
16. LP-VC state specialization overlap	0.21	0.16	0.09	-0.03	0.66	1.00								
17. Geographic distance between VC and LP investments (logged km)	5.99	2.51	-0.02	0.06	0.53	0.44	1.00							
18. Lp-mediated indirect tie count (logged)	1.19	1.14	0.01	-0.01	0.31	0.32	0.33	1.00						
19. VC-mediated indirect tie count (logged)	0.47	0.70	0.09	-0.03	0.43	0.49	0.30	0.35	1.00					
20. VC-mediated indirect tie count - failure(logged)	0.16	0.39	0.08	-0.03	0.33	0.36	0.19	0.31	0.73	1.00				
21. VC-mediated indirect tie count - success(logged)	0.39	0.63	0.10	-0.03	0.42	0.47	0.28	0.35	0.95	0.66	1.00			
22. VC-mediated indirect tie count - high rep. intermed. & failure(logged)	0.11	0.31	0.08	-0.03	0.29	0.33	0.16	0.26	0.64	0.88	0.60	1.00		
23. VC-mediated indirect tie count - low rep. intermed. & failure(logged)	0.01	0.10	0.01	0.00	0.11	0.11	0.06	0.14	0.28	0.39	0.29	0.22	1.00	
24. VC-mediated indirect tie count - high rep. intermed. & success(logged)	0.28	0.51	0.09	-0.03	0.38	0.43	0.24	0.31	0.87	0.64	0.91	0.63	0.22	1.00
25. VC-mediated indirect tie count - low rep. intermed. & success(logged)	0.19	0.42	0.09	-0.04	0.30	0.34	0.21	0.29	0.78	0.55	0.81	0.42	0.36	0.55

Table 1.2 helps develop our understanding of the main effects predicted by Hypotheses 1a and 1b—that success in the syndication between the focal firm and the intermediary VC will increase the probability of an LP investing in the focal VC, whereas failure will decrease the probability of investing. Models 1 and 2 present the simplest conditional logit models in the absence of any controls, first including just the overall indirect ties measures. All of the positive effects of triadic closure load on indirect ties that are associated with success, whereas the ties associated with failure are statistically indistinguishable from 0. Models 3 and 4 introduce the monadic and dyadic controls, respectively. The change in the coefficients is especially noteworthy in Model 4, where the positive effects of successful VC-mediated ties are reduced by half, whereas the effects of failed VC-mediated indirect ties become significantly negative and quite substantive. Reassuringly, the results suggest that omitting the effects of observed homogeneities biases upward the effects of both successful and unsuccessful indirect ties by almost equivalent amounts, and does not affect the difference in the effect of the successful and the unsuccessful indirect ties.

Models 5 and 6 show that the reported pattern holds in the presence of all controls. Model 7 tests the same conditional logit model with a reduced sample, in which only three counterfactuals per group are selected at random as some prior research (Jensen, 2006) has done. Again, both the positive and the negative effects remain stable. Finally, Models 8 and 9 ensure that the findings are not a consequence of the chosen functional form—logit versus linear—or a consequence of the fixed effects of the conditional logit. Model 8 tests the data with a simple cross-sectional logit, whereas Model 9 uses a cross-sectional linear probability model, which has the advantage of making the coefficients easier to interpret.

Table 1.2: Conditional logit model predicting new tie formation – test of main effects

	Conditional Logit							Logit	OLS
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
VC-mediated indirect tie count (logged)	0.520***				0.161***				
	(14.02)				(3.40)				
VC-mediated indirect tie count - failure(logged)		0.0106	-0.162**	-0.132*		-0.175**	-0.187*	-0.178**	-0.0105**
		(0.19)	(-2.75)	(-2.32)		(-2.95)	(-2.57)	(-3.23)	(-3.22)
VC-mediated indirect tie count - success(logged)		0.598***	0.304***	0.394***		0.301***	0.328***	0.213***	0.0121***
		(13.69)	(6.07)	(8.27)		(5.90)	(5.56)	(5.86)	(5.87)
VC firm age (logged)			0.256***		0.284***	0.283***	0.264***	0.259***	0.0123***
			(8.52)		(9.19)	(9.17)	(7.15)	(8.89)	(9.67)
VC prior fund count (logged)			-0.200***		-0.302***	-0.300***	-0.273***	-0.277***	-0.0132***
			(-5.16)		(-6.64)	(-6.59)	(-5.10)	(-6.46)	(-6.20)
Fund subscription ratio			0.376**		0.389***	0.391***	0.343*	0.363**	0.0141***
			(3.21)		(3.34)	(3.35)	(2.57)	(3.13)	(3.34)
Fund average performance quartile on prior funds			-0.105***		-0.0875**	-0.0843**	-0.0771*	-0.175***	-0.00787***
			(-3.94)		(-3.23)	(-3.11)	(-2.43)	(-6.84)	(-6.96)
VC 1st size quartile (=1)			-1.459***		-1.423***	-1.417***	-1.430***	-1.568***	-0.0942***
			(-22.97)		(-21.29)	(-21.26)	(-18.37)	(-24.77)	(-23.96)
VC 2nd size quartile (=1)			-0.934***		-0.910***	-0.910***	-0.861***	-0.962***	-0.0741***
			(-17.14)		(-16.38)	(-16.40)	(-12.81)	(-18.10)	(-18.29)
VC 3rd size quartile (=1)			-0.678***		-0.648***	-0.655***	-0.666***	-0.686***	-0.0585***
			(-13.40)		(-12.52)	(-12.72)	(-10.66)	(-13.28)	(-13.27)
VC firm 5-year IPO exit rate			0.0598		0.0861	0.0590	0.314	-0.150	-0.0114*
			(0.42)		(0.61)	(0.42)	(1.86)	(-1.32)	(-2.15)
VC firm 5-year M&A exit rate			-0.108		-0.118	-0.126	0.0105	-0.377***	-0.0180***
			(-0.99)		(-1.07)	(-1.14)	(0.08)	(-4.13)	(-4.17)
VC firm 5-year failed investment rate			0.274		0.172	0.206	0.320	-0.0704	-0.00202
			(1.76)		(1.07)	(1.29)	(1.76)	(-0.59)	(-0.41)
VC firm degree centrality in the syndication network (logged)			-0.0180		-0.0154	-0.0212	-0.0193	-0.0626***	-0.00380***
			(-0.88)		(-0.71)	(-0.99)	(-0.78)	(-5.00)	(-5.73)
VC and LP collocated in same state (=1)			0.773***	0.790***	0.795***	0.795***	0.793***	0.559***	0.0348***
			(12.50)	(13.38)	(12.87)	(12.86)	(11.07)	(12.39)	(10.71)
LP-VC industry specialization overlap				0.607***	0.419*	0.401*	0.292	0.391**	0.0185**
				(3.40)	(2.27)	(2.18)	(1.34)	(2.67)	(2.63)
LP-VC state specialization overlap				0.162	-0.622**	-0.629**	-0.298	-0.398*	-0.0205**
				(0.85)	(-3.07)	(-3.11)	(-1.34)	(-2.45)	(-2.68)
LP-VC stage specialization overlap				-0.00755	-0.00514	0.00195	-0.0653	-0.261*	-0.0126*
				(-0.05)	(-0.04)	(0.01)	(-0.39)	(-2.31)	(-2.39)
Lp-mediated indirect tie count (logged)				0.266***	0.101***	0.102***	0.0816**	0.0976***	0.00594***
				(12.92)	(3.99)	(4.03)	(2.96)	(5.61)	(5.64)
Constant								-1.552***	0.147***
								(-13.14)	(23.95)
Observations	65465	65465	65465	65465	65465	13054	65470	65470	65470

Conditional model grouped on a factual LP × VC pairing and the associated counterfactuals; fixed effects for LP, fund type, vintage. T-stats in parentheses (clustered around same groups as the conditional logit).

* $p<.05$, ** $p<.01$, *** $p<.001$

The magnitude of the coefficients is quite substantive economically, considering that the baseline probability of a realized match in the sample is approximately 5%. The linear probability model suggests that going from 0 to 1 successful VC-mediated indirect tie increases the probability of matching by 0.8% (up to 5.8%), while going from 0 to 1 failed VC-mediated indirect tie decreases the probability of matching by 0.7% (down to 4.3%). Figure 1.3 illustrates the equivalent probabilities based on the logit specification in Model 6 and, for comparison, adds the estimated effect of a total count of VC-mediated ties based on Model 5.[16] It is clear that the positive main effects of triadic closure conceal a significant effect of heterogeneity based on the valence of the information flowing through the indirect ties; thus, both Hypothesis 1a and 1b are supported

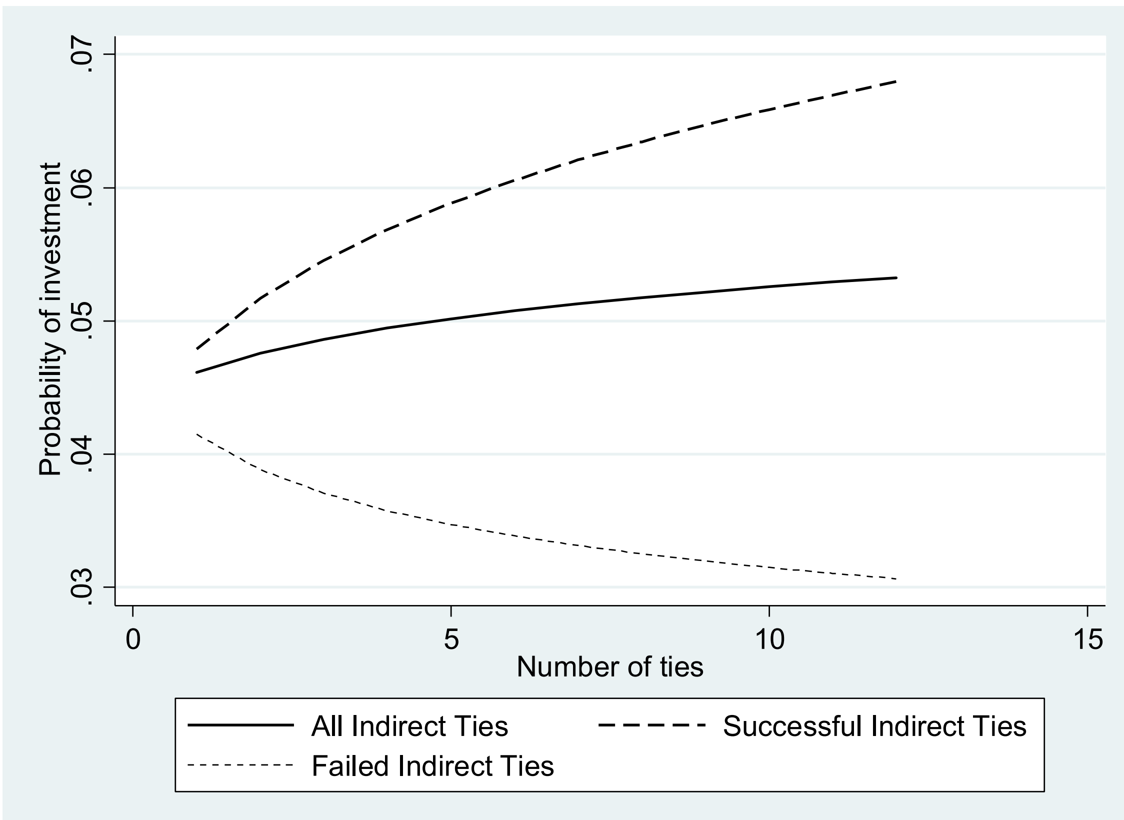

Figure 1.3 Effects of successful versus unsuccessful ties on the probability of LP investments

Based on a logistic model with the same set of variables as Models 5 and 6, Table 1.2

[16] Note that I cannot present the predicted probabilities according to the conditional model, because it only outputs selection within-group; the utility scores it assigns to each observation cannot be converted into probabilities. Therefore, the graphs presented on Figure 1.3, Figure 1.4 and Figure 1.5 are based on a simple logistic model. The estimated coefficients of these specifications were all substantively similar to the conditional logit results.

Table 1.3 elaborates on the interactions predicted in Hypotheses 2 through 4. It is based on the full conditional logit model, with all control variables incorporated but unreported for brevity. Model 1 starts with the standard indirect VC-mediated ties measure, whereas Model 2 breaks down the results by successful versus failed relationships (those two specifications are identical to Table 1.2, Model 5 and 6, respectively). Model 3 tests Hypothesis 2 that the performance of the intermediary—defined as belonging to the top quartile of all funds in terms of realized IPO rate over the preceding five years—would reinforce the positive effects of successful indirect ties and the negative effects of unsuccessful indirect ties. Statistically, the coefficient for *high performance intermediary and failure* is significantly more negative than the coefficient for *low performance intermediary and failure*; conversely, the coefficient for *high performance intermediary and success* is significantly more positive than the coefficient for *low performance intermediary and success*. In fact, the outcome of the syndication between the focal VC and the intermediary VC seems to make no discernible difference on likelihood of an LP investment when the intermediary VC is low-performing. The overall pattern of findings is consistent with the basic argument that the performance of the intermediary reinforces the effect of the information flowing across the indirect tie, regardless of whether that information is positive or negative. Figure 1.4 and Figure 1.5 illustrate the differences of the effects of successful versus unsuccessful indirect ties depending on the performance record of the intermediary.

Models 4 and 5 explore the role of alternative sources of information. Hypothesis 3 predicts that the effect of private information transmitted through an indirect tie—whether positive or negative—will be attenuated for older firms with more extensive track records. Model

Table 1.3: Conditional logit model predicting new tie formation – test of interaction effects

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VC-mediated indirect tie count (logged)	0.161***					
	(3.40)					
VC-mediated indirect tie count - failure(logged)		-0.175**		-0.0366	-0.231**	-0.111
		(-2.95)		(-0.53)	(-2.78)	(-1.18)
VC-mediated indirect tie count - success(logged)		0.301***		0.408***	0.418***	0.512***
		(5.90)		(7.36)	(6.59)	(7.68)
VC-mediated indirect tie count - above mean rep. intermediary & failure (logged)			0.321***			
			(5.47)			
VC-mediated indirect tie count - below mean rep. intermediary alter & failure (logged)			0.0853			
			(1.33)			
VC-mediated indirect tie count - above mean rep. intermediary & success (logged)			-0.282***			
			(-3.55)			
VC-mediated indirect tie count - below mean rep. intermediary alter & success (logge			0.0281			
			(0.37)			
VC-mediated indirect tie count - failure × firm age (both logged and centered)				-0.158+		-0.147+
				(-1.78)		(-1.66)
VC-mediated indirect tie count - success × firm age (both logged and centered)				-0.213***		-0.214***
				(-4.19)		(-4.16)
VC-mediated indirect tie count - failure × LP centrality (centered)					-0.109**	-0.0993**
					(-3.00)	(-2.71)
VC-mediated indirect tie count - success × LP centrality (centered)					0.0651	0.0722
					(1.33)	(1.47)
Observations	65465	65465	65465	65465	65465	65465

Conditional model grouped on a factual LP × VC pairing and the associated counterfactuals; fixed effects for LP, fund type, vintage. Same control variables as in Table 1.2.T-stats in parentheses (clustered around same groups as the conditional logit).

* *p*<.05, ** *p*<.01, *** p<.001

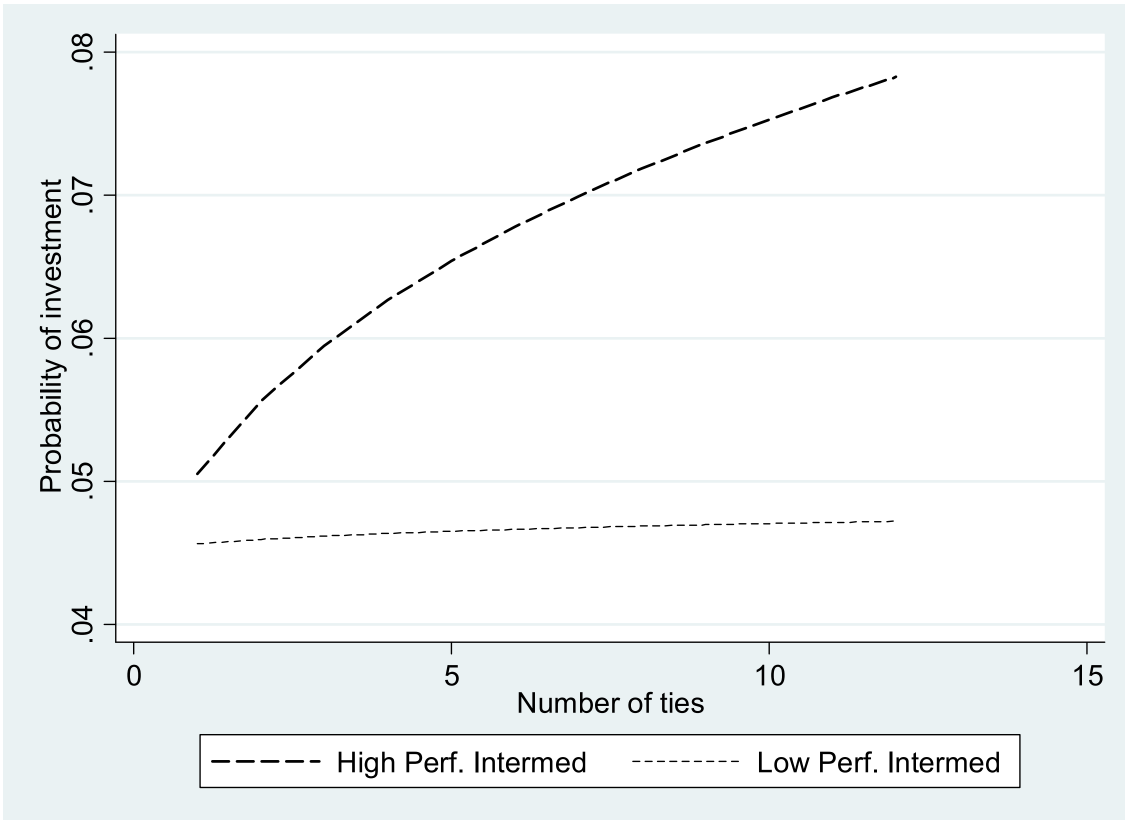

Figure 1.4: Effects of successful ties via high-performance versus low-performance intermediaries on the probability of LP investments

Based on a logistic model with the same set of variables as Models 3, Table 1.3

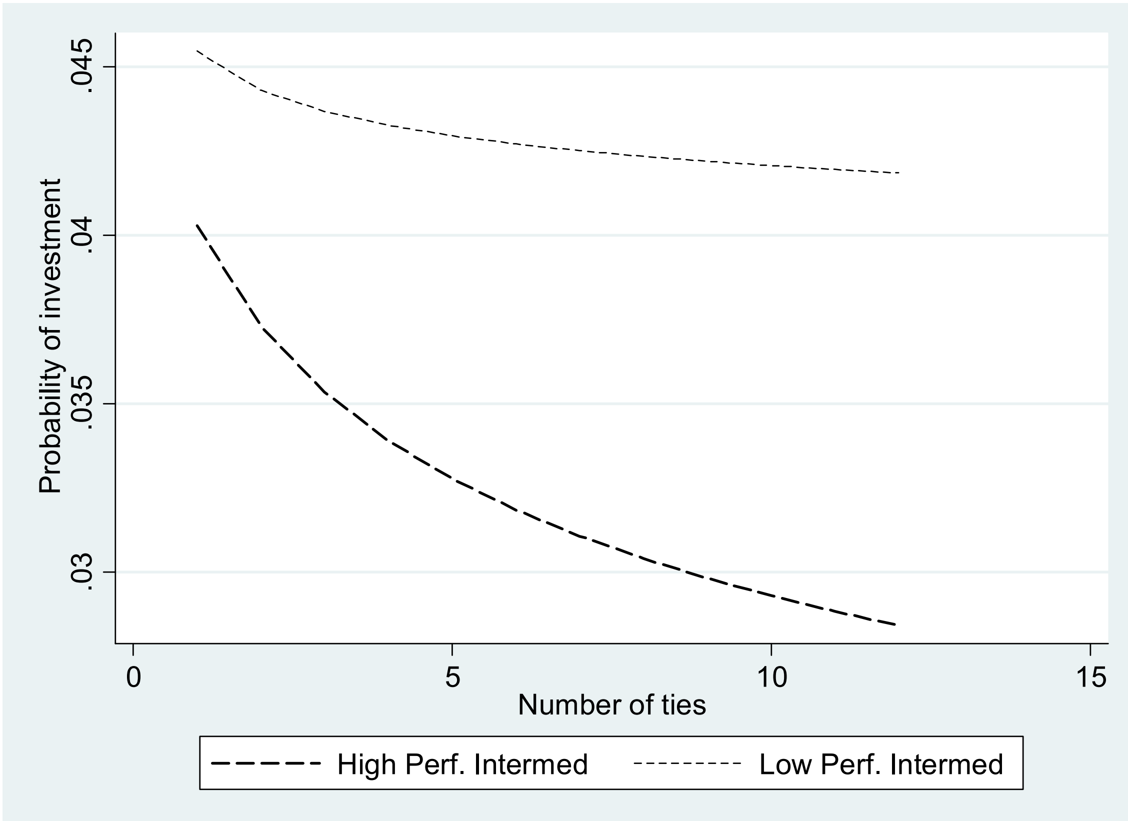

Figure 1.5: Effects of failed ties via high-performance versus low-performance intermediaries on the probability of LP investments

Based on a logistic model with the same set of variables as Models 3, Table 1.3

5 presents the interaction of the successful versus failed VC-mediated indirect ties and focal VC firm age. The results show that it is only the effect of the latter that decreases with firm age, thus providing support for Hypothesis 3a but not for Hypothesis 3b. In fact, contrary to expectations, the negative effect of failed VC-mediated indirect ties is attenuated for younger firms, although the interaction is only marginally significant.

Hypothesis 4 predicts that LPs with a connection to a greater number of VCs have access to wider information and are less likely to be affected by both successful and failed VC-mediated ties. The relevant interaction coefficients in Model 6 both have the predicted signs, but only the interaction with successful VC-mediated ties reaches statistical significance. Overall, the results for both Hypotheses 3 and 4 suggest that LPs may treat positive information differently than negative information, a notion on which I elaborate in the *Discussion*.

Post-hoc analyses. I also conducted two sets of split sample analyses to explore how the results change depending on the type of VC (generalist/early-stage VC versus late-stage VC/buyout firms) and the historical period (the bubble period of pre-2001 versus 2002-2007). Table 1.4 compares split sample analyses along these two dimensions with the baseline model (Model 6, Table 1.2).

Not all investments are equally risky. Earlier stage organizations suffer from an unproven business model, poorly established execution routines, and a limited track record of performance. Not surprisingly, they tend to fail more frequently than established organizations (Aldrich & Auster, 1986). Consequently, tolerance for failure is ingrained in the early-stage entrepreneurial cultures of places such as Silicon Valley (Saxenian, 1994). In contrast, later-stage companies are presumed to be much more stable, and failure can be interpreted as a bigger blow for their investors. As such, I investigated whether successful versus failed indirect ties have different effects for earlier stage versus later stage VCs. Models 2 and 3 in Table 1.4 present a split-sample analysis for late-stage VCs versus VCs in all other stages (generalist and early-stage VCs), respectively. Interestingly, whereas the positive effects of having successful VC-mediated ties is very similar in the two samples, the negative effects of failed VC-mediated ties are concentrated in the late-stage VC sample. In other words, whereas success is always valued, failure is discounted in the segments of the market in which it is expected to be more common.

The second set of split-sample analyses focuses on how the historical period moderates the effects of positive versus negative ties. Many of my conversations with industry practitioners focused on the dramatic break that the dotcom crash in 2001 brought to investment patterns in the industry. Said one limited partner, "[Prior to 2001], it was a feeding frenzy. All the VCs were posting great returns from all those IPOs, and LPs were crazy about getting a piece of the action, getting into any fund. There was a lot of herding and not a lot of thinking going on then… The crash burned a lot of people, and LPs have since have gotten a lot more careful as to where they're putting their money." I would therefore expect that the role of VC-mediated ties, which are activated primarily during the due diligence process, is greater after the 2001 crisis. Comparing the split samples reported in Models 4 and 5 in Table 1.4 is consistent with this idea. Both successful and failed VC-mediated ties have a substantively and statistically significant effect on LP decisions, but only after 2001. Interestingly, the results also suggest LPs were herded in the pre-2001 period; indeed, an LP was much more likely to invest in a VC if it had prior co-investment ties to any of its past LPs. This effect disappears altogether in the post-2001 period, potentially indicating the increased role of independent due diligence.

Table 1.4: Conditional logit model predicting new tie formation – post-hoc analyses

	Full Sample	Late Stage VCs only	Non-Late Stage VCs	Pre-2001	Post-2001
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
VC-mediated indirect tie count - failure(logged)	-0.175**	-0.569***	0.0815	-0.0411	-0.321***
	(-2.95)	(-4.26)	(1.17)	(-0.49)	(-3.67)
VC-mediated indirect tie count - success(logged)	0.301***	0.378***	0.319***	0.111	0.444***
	(5.90)	(4.81)	(4.70)	(1.44)	(6.39)
VC firm age (logged)	0.283***	0.416***	0.131**	0.276***	0.214***
	(9.17)	(8.88)	(2.82)	(6.22)	(4.58)
VC prior fund count (logged)	-0.300***	-0.157*	-0.270***	-0.460***	-0.163**
	(-6.59)	(-2.50)	(-3.85)	(-5.78)	(-2.85)
Fund subscription ratio	0.391***	0.948***	0.0869	1.010***	0.381**
	(3.35)	(5.19)	(0.64)	(4.00)	(2.78)
Fund average performance quartile on prior funds	-0.0843**	-0.194***	0.0411	-0.112**	-0.0229
	(-3.11)	(-4.36)	(1.12)	(-2.74)	(-0.62)
VC 1st size quartile (=1)	-1.417***	-1.640***	-1.183***	-1.474***	-1.239***
	(-21.26)	(-16.19)	(-12.88)	(-15.66)	(-13.10)
VC 2nd size quartile (=1)	-0.910***	-1.414***	-0.467***	-0.925***	-0.862***
	(-16.40)	(-16.40)	(-6.38)	(-11.52)	(-11.18)
VC 3rd size quartile (=1)	-0.655***	-0.905***	-0.451***	-0.614***	-0.700***
	(-12.72)	(-11.92)	(-6.57)	(-8.31)	(-9.71)
VC firm 5-year IPO exit rate	0.0590	0.339	0.720*	0.516	-0.282
	(0.42)	(1.93)	(2.16)	(1.94)	(-1.49)
VC firm 5-year M&A exit rate	-0.126	-0.0478	0.492*	0.0450	-0.218
	(-1.14)	(-0.34)	(2.03)	(0.22)	(-1.61)
VC firm 5-year failed investment rate	0.206	0.402	0.344	0.0528	0.328
	(1.29)	(1.88)	(1.08)	(0.20)	(1.59)
VC firm degree centrality in the syndication network (logged)	-0.0212	-0.00272	-0.111**	0.0244	-0.0347
	(-0.99)	(-0.10)	(-2.64)	(0.75)	(-1.13)
VC and LP collocated in same state (=1)	0.795***	0.670***	0.963***	0.772***	0.821***
	(12.86)	(8.14)	(10.03)	(8.71)	(9.37)
LP-VC industry specialization overlap	0.401*	0.768**	0.366	0.0633	0.403
	(2.18)	(2.62)	(1.53)	(0.20)	(1.74)
LP-VC state specialization overlap	-0.629**	-1.244***	-0.498	-0.944**	-0.401
	(-3.11)	(-3.66)	(-1.81)	(-3.11)	(-1.44)
LP-VC stage specialization overlap	0.00195	-0.200	0.517*	0.301	-0.117
	(0.01)	(-1.04)	(2.01)	(1.33)	(-0.61)
Lp-mediated indirect tie count (logged)	0.102***	0.0179	0.135**	0.331***	0.00679
	(4.03)	(0.58)	(3.25)	(7.11)	(0.22)
Observations	**65086**	**25863**	**39223**	**36914**	**28172**

Conditional model grouped on a factual LP × VC pairing and the associated counterfactuals; fixed effects for LP, fund type, vintage. T-stats in parentheses (clustered around same groups as the conditional logit).

* *p*<.05, ** *p*<.01, *** p<.001

Robustness tests. I conducted several tests to ensure the robustness of the reported results. The results are robust to different time windows for deriving the network statistics and performance variables (seven or three years in addition to the basic five years). Classifying firms into high performance versus low performance, which is core to testing Hypothesis 2, provides similar results whether done by mean, median, or first quartile cutoffs. I also varied the counterfactual set, and all results remain robust if I restrict each group to just five or three randomly selected counterfactuals, rather than allowing the number to vary based on actual availability of funds on the market.

I also explored the effects of lost observations due to my inability to find matches for some firms in both databases. To do so, I first created a model incorporating all VC firms from the VentureXpert database to predict whether they also appear in the Preqin database. I used a range of independent variables, including dummies for fundraising years, states in which they are located, size of funds raised, and fund types. I used the fitted probabilities in two ways. I incorporated them as an independent variable in the regression models to test directly for bias. Although its effect was negative as one would expect (i.e., the reduced probability of getting matched in both datasets is also associated with reduced likelihood of being selected by an LP), it did not materially affect any of the relevant coefficients. Second, I weighted the observations in the logit model by the inverse of the match probability, a standard procedure to make the sample more similar to the overall population. Again, no meaningful changes in the coefficients were detected.

1.7 Discussion and conclusion

The present study examines how the valence of information flowing through interorganizational ties affects the role of indirect ties in forming interorganizational relationships. The preference for indirectly connected others is so widely documented that it is virtually a taken-for-granted stylized fact of organizational theory (Ahuja, 2000b; Baum et al., 2003; Gulati & Gargiulo, 1999). Here, I shift the emphasis from *whether* a tie exists to *what* kind of information the tie conveys. My results show that triadic closure between one VC's LPs and another VC is clearly observable when the collaboration between the VCs was successful. In contrast, if the collaboration failed, the likelihood of the LP–VC matching via the indirect tie is lower than if no indirect tie existed at all. In other words, just as positive information from shared partners can open doors, negative information from shared partners can slam doors shut.

I also examined some of the key contingencies to this information diffusion process. The intermediary's credibility ultimately determines the extent to which actors take the information seriously or seek it at all.[17] The track record of organizational achievements, in this case successful IPOs, is a key component of credibility to the extent it signals superior ability to evaluate exchange partners and minimizes the incentives to strategically overstate the partner's responsibility for failures. Consistently with this argument, I found that only indirect ties via high-performance intermediaries had a positive effect (in cases of success) or negative effects (in cases of failure) on the match between the focal VC and LP. Furthermore, the outcome of the

[17] Although both mechanisms can explain the lower effect of connections through lower credibility actors, some anecdotal evidence suggests that the latter mechanism dominates in the present study's setting. VCs rarely provide active referrals, that is, suggest other VCs for the LPs to consider. Most often, they provide passive referrals responding to an LP's inquiries about a particular VC in which the LP is already interested. Some LP interviewees suggested that they would not waste their time calling a VC if they did not think that they would take the VC's suggestions seriously, regardless of what information they receive.

collaboration between the two VCs makes no discernible difference on the effect of the tie when the intermediary is low performing.

These findings, while fully consistent with the information transfer model that I propose, oppose the predictions of established organizational theory. The prevailing view that the actor's prominence confers a "halo" on its exchange partners predicts positive effects of the intermediary VC's performance on the likelihood of a match between the LP and the focal VC, regardless of the outcome of the collaboration between the two VCs (Lee et al., 2011; Podolny, 2005; Stuart et al., 1999). This explains why successful indirect relationships via prominent intermediaries promotes triadic closure, but not why failed indirect relationships via prominent intermediaries tend to preclude triadic closure. A second view, rooted in the idea of the Matthew effect (Merton, 1968) might predict that highly prominent collaborators receive disproportionate credit for the successes and inadequate responsibility for the failures. Indeed, this view can explain why collaboration failures with high-performance intermediaries are particularly harmful to the likelihood of LP–VC matching, but cannot explain the benefits of successes involving high-performance intermediaries.

If positive or negative information transferred across credible interorganizational ties is the key driver underlying LPs' investment decisions, we can reasonably believe its effect will be attenuated by the availability of alternative information sources regarding the evaluated VC. The evidence pointing to this proposition is mixed. I find that LP's access to other sources of information about the evaluated VC—proxied by the length of the evaluated VC's track record and the extent of the LP's prior investments in the VC industry—reduce the effect of successful indirect ties on the LP's investment decision. Notably, however, neither of these sources of information reduces the negative effect of failed indirect ties on the probability of matching. One possible explanation could be the negativity bias, which has been well-documented by cognitive psychologists; indeed, the tendency of negative information tends to have a greater effect on cognition and behavior than comparable positive information (for a review, see Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Rozin & Royzman, 2001). In particular, negative information retains its salience and is less likely to be diluted than positive information as the overall amount of information increases. This is exactly the pattern I document in the present study.

Just the existence of social ties does not mean that such ties would be necessarily activated during the due diligence process (Gulati, Lavie, & Madhavan, 2011). My post-hoc analyses suggest that the effect of both successful and unsuccessful indirect ties only became pronounced in the post-2001 period. One possible explanation may be that successes were less salient during this time period, when high-profile exits were common. This argument, however, cannot explain why the salience of the failures would also be lower. A more plausible explanation, consistent with the views industry interviewees expressed, is that LPs were generally much less careful about due diligence in the pre-2001 world and therefore were less likely to seek advice from indirectly connected VC firms. Such findings thus suggest the importance of considering the extent to which actors actively tap the resources available to them through interorganizational ties. This question is of increasing interest at the individual level (Smith, Menon, & Thompson, 2012; Smith, 2005; Srivastava, 2013) but rarely considered in the interorganizational setting (for an exception, see Gulati et al., 2011).

Finally, the post-hoc analyses also suggest that the consequences of various types of successes and failures cannot be considered separately from the expectations of the participating actors. In particular, failed indirect relationships do not reduce the probability of matching between LPs and VCs specializing in earlier stage companies, presumably because the failure of such companies is considered common. In contrast, failed indirect relationships figure heavily in LPs' selection of late-stage funds, which are investing in more established companies that are less expected to fail outright.

The key contribution of the present research is that it shifts attention away from the mere presence or absence of indirect ties toward investigating the content of the information those ties transfer across the marketplace. Allowing the coexistence of both positive and negative information as a function of the outcome of relationships between collaborators challenges some taken-for-granted assumptions of organizational theory. In contrast to the default assumption of a tendency toward triadic closure, I demonstrate that the presence of indirect ties via shared partners can either facilitate or hamper a firm's ability to form direct ties depending on the outcome of the relationships among the shared partners and the focal actors. My findings also underscore the importance of information valence in relation to intermediary performance. Previous research has largely assumed that connecting with alters of high credibility is unambiguously desirable, because it confers a powerful endorsement on the focal organization (Milanov & Shepherd, 2013; Stuart et al., 1999). Instead, the present paper suggests that connections to high credibility actors is more of a high-risk, high-reward proposition rather than an unmitigated blessing. Collaborating successfully with such alters can certainly open doors, as they privately endorse the organization with their own exchange partners. A failure of the relationship, however, can just as easily slam the same doors shut. Overall, such findings suggest that without knowing the valence of the information flowing through seemingly similar collaborative ties, we know little about their ultimate effects on behavior.

More broadly, the present paper contributes to the growing interest in understanding factors that drive the heterogeneity of social ties. Unavoidably, network researchers must assume some level of homogeneity in the effects of social ties in order to parsimoniously examine social structures (cf. Zuckerman, 2010).[18] Excessive focus on the *structure* of the network, however, can potentially crowd out an appreciation for the *content* of the interorganizational ties (Mizruchi, 1996; Stinchcombe, 1990). A key challenge for network theorists, therefore, is to balance the need for parsimony while also appreciating the contingencies of network effects. Previous years have seen a growing interest in understanding the factors that drive the heterogeneity of tie effects in the interorganizational setting. For example, our understanding is growing regarding how factors such as the age of the ties (Baum, McEvily, & Rowley, 2012; McEvily, Jaffee, & Tortoriello, 2012), the level of resource co-specialization the ties require (Gimeno, 2004), or interpersonal relationships among the organizational actors that represent the nodes (Gulati & Westphal, 1999; Vissa & Chacar, 2009) can dramatically transform the effects of interorganizational ties. The present research highlights another source of heterogeneity—the valence of the information flowing across interorganizational ties—that is critical to understanding network evolution.

Closer attention to the content of the interorganizational relationships also helps better understand the underlying mechanisms behind network processes. It makes explicit a key assumption of interorganizational theorists—that social ties can transfer information that facilitates matching organizational actors—and develops it into a theoretical framework of how indirect ties can make establishing direct ties more or less likely. In addition to highlighting the

[18] The homogeneity assumption is key to the parsimony of network analysis. As Zuckerman (Zuckerman, 2010: 4) noted: "In order to call [a collection of dyads] a network we need to be able to say that the links are of the same type throughout the network. Put differently, the drawing of a social network depends on an act of … standardization, whereby particular or individual features of the dyads are eliminated and all links are rendered comparable."

important role of the valence of the information transferred through the interorganizational ties, the theoretical framework also emphasizes how the credibility of the intermediary and the availability of alternative sources of information play a role. The results also demonstrate the asymmetrical effect of information saturation on the effects of positive or negative information. This negativity bias is well known to cognitive psychologists, but to my knowledge is entirely absent from discussions in the organizational literature.

Carefully delineating the underlying mechanisms of triadic closure can also alleviate concerns that this widely documented phenomenon can be attributed to the information transferred across indirect ties rather than unobserved homogeneities between actors. Network theorists are increasingly concerned that some of the evidence of network effects could be confounded by unobserved homogeneity between the actors (Shalizi & Thomas, 2011). In the case of triadic closure in particular, one plausible concern would be due to the tendency of VCs to syndicate with those similar along some dimension, such as investment preferences or geographic location (Sorenson & Stuart, 2001; Trapido, 2007) combined with the preferences of the LPs to invest in VCs that are similar along that dimension. The present study's results alleviate these concerns for two reasons. Conceptually, such an alternative mechanism does not explain the dramatic flip in the effects of indirect ties depending on the outcome of the collaboration between the two VCs. If the effects of indirect ties is merely an artifact of the similarity between actors, then the information flowing between them should not make a difference to their effects. Empirically, the present results demonstrate that omitting the effects of observed homogeneities biases upward the effects of both successful and unsuccessful indirect ties by almost equivalent amounts. If anything, the present study's estimates of the negative effects of failed indirect ties can be considered conservative if my controls do not capture the full extent of the LPs' investment preferences.

The present research opens three major avenues for future research. First, researchers can examine the generalizability of claims made here to other domains of interorganizational collaboration such as strategic alliances. On the one hand, the theoretical mechanisms on which the present paper is built are highly generalizable and applicable to a range of domains. The key assumptions are: (1) quality uncertainty exists about the exchange partner, which is diminished by private information transferred through interorganizational ties and (2) variations in the outcomes of collaborations can generate variations in the valence of the information flowing through the social ties. On the other hand, certain unique features of the VC industry may amplify the observed effects. VC firms are small and cohesive (rarely exceeding a dozen principals) and are thus more likely to act as unitary actors that form coherent impressions of a particular VC and pass it on to all of their LPs. In contrast, some large corporations may have multiple, highly autonomous divisions that might not necessarily share all relevant experience about a particular partner internally, let alone with all external partners.[19] Thus, the internal cohesion within an organizational actor can play a key role in its effectiveness as a conduit of private information (cf. Vissa & Chacar, 2009).

Second, although this research focuses on documenting the effects of relationship performance and triadic closure, the implications of its key theoretical claim—that interorganizational relationships can spread negative information just as they spread positive information—are much more far-reaching. For example, future research could examine how the

[19] The lack of internal sharing of alliance experiences among divisions is a key reason for the importance of centralized alliance management function for the performance of alliances (Kale, Dyer, & Singh, 2002)

identity of collaborators shapes the long-term implications of successes and failures on organizational life chances. The results suggest that more central collaborators can spread both positive and negative information to a greater number of alters; more credible collaborators can make their alters more likely to act on the information they receive. Consequently, actors that have a greater proportion of their successes with highly central or highly credible counterparties are likely to have higher chances of securing future exchange partners than those that have a higher proportion of their failures with highly central and/or credible counterparties.

Finally, future research can measure the existence and the content of the information flow directly. Although the idea that LPs call on VCs when they are conducting due diligence on the VCs' co-investments is consistent with qualitative accounts and the archival evidence provided by the investment decisions. However, future research can go further by measuring the presence and the content of the information from which LPs draw various sources directly and how it affects their investment decisions. Such research will not only conclusively demonstrate the mediating role of information flows in the investment selection process, but also shed light on the underlying interpretation processes. Under what conditions do successes (or failures) lead to transferring positive (or negative) information to the LPs? Under what conditions does this information affect the LPs' investment decisions? Measuring the information flows directly can potentially disentangle those two distinct steps that underlie the investment decisions.

Chapter 2

After the Break-Up: The Relational and Reputational Consequences of Withdrawals from Venture Capital Syndicates

(With Ranjay Gulati)

2.1 Introduction

Organizational theorists have long been interested in the drivers of collaboration partner selection in various settings, such as strategic alliances (Ahuja, 2000b; Gulati, 1995b), investment bank syndicates (Podolny, 1994; Shipilov & Li, 2012), and venture capital (VC) syndicates (Sorenson & Stuart, 2008; Trapido, 2007). Much of this research has been concerned with how the history of prior tie formation can facilitate the development of future collaborative ties. The literature's overwhelming consensus is that prior collaborations facilitate the development of trust and social attachments that increase the likelihood that actors will select their partners for future collaborations (Dyer & Singh, 1998; Gulati, 1995b; Li & Rowley, 2002). Indirect ties via shared partners can also serve as conduits for introductions, referrals, and endorsements, increasing the likelihood that indirectly connected actors will form direct connections with each other (Gulati & Gargiulo, 1999).

The view that the history of prior relationships enables the formation of new relationships implicitly relies on the assumption that all collaborations proceed as planned and thus strengthen the bond connecting the collaborating parties.[20] Increasing evidence, however, shows that not all

[20] A rare exception to this view at the interorganizational level is the work of Li and Rowley (2002), who found that poor performance of an investment banking syndicate reduces the likelihood that the participating investment banks

collaborations end well. For example, by some accounts more than fifty percent of strategic alliances dissolve before achieving their objectives (Kale & Singh, 2009), and other field studies have suggested that some of those dissolutions are acrimonious affairs, resulting in mutual frustration, strained relationships, and deep distrust between the former collaborators (Arino & de la Torre, 1998; Doz, 1996; Faems et al., 2008; Gulati, Sytch, & Mehrotra, 2008). Similarly, in a different context, the withdrawal of VC firms from syndicates with other VC firms is highly disruptive for the portfolio companies, and field studies suggest that it can poison relationships with the abandoned coinvestors (e.g. Guler, 2007). A heightened appreciation of the importance of tie dissolutions has led to a growing effort to understand their antecedents (Greve et al., 2010; Greve, Mitsuhashi, & Baum, 2013; Polidoro, Ahuja, & Mitchell, 2011). To date, however, few studies have examined the consequences of tie dissolutions on future tie formation.

Understanding the consequences of dissolutions is important because the relationship disruptions they cause can undermine the taken-for-granted relationships between past and future tie formation. At the dyadic level, scholars typically assume that past collaborations are associated with growing familiarity and trust that facilitate future exchange. Allowing for tie termination, however, can help us uncover that not all ties are created equal and that some may indeed subsequently unravel. This, in turn, can undermine trust, cause the relationship to deteriorate, and reduce the likelihood of repeat collaborations. At the triadic level, actors often select alters with whom they shared a past collaboration partner, in part because positive referrals flow through the mutually trusted third party. Referrals flowing through the indirect tie may turn

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would collaborate in the future. At the interpersonal level, Labianca and colleagues explored the antecedents and consequences of conflict and negative reputation among coworkers (Labianca & Brass, 2006; Labianca, Brass, & Gray, 1998).

negative, however, and thus reduce the likelihood of collaboration between the two parties if either of them terminates the relationship with the shared partner.

Tie dissolutions also have important implications for our understanding of organizational reputation. Existing research has widely assumed that an organization's centrality in the interorganizational network can act as a positive signal of its attractiveness as a collaboration partner (Ahuja, Polidoro, & Mitchell, 2009; Gulati & Gargiulo, 1999). In contrast, we propose that the withdrawal of an organization from an ongoing collaboration can send the opposite signal: that it is an unreliable and thus undesirable partner. Such inferences can form the basis of a negative reputation that could limit an organization's ability to form future relationships. Conceptualizing tie dissolutions as reputation-impairing events allows us to distinguish between the effects of different sources of negative information. For example, we can learn how a focal actor's willingness to form a tie with a particular alter[21] is affected by 1) publicly available negative information, based on the alter's publicly observable history of tie dissolution; and 2) privately-sourced negative information, based on the focal actor's social connections to actors whom the alter has previously abandoned and who are therefore especially likely to pass on negative information about the alter. We can also examine the extent to which the negative information from private sources amplifies or attenuates the effects of the publicly available negative information: a question to which existing theory offers no settled answer.

We set our study in the context of VC firm withdrawals from venture capital syndicates, defined as the joint investment of two or more VC firms in a portfolio company that involves significant financial contributions and managerial oversight and guidance. Such syndicates have

[21] For consistency, in the remainder of the paper, we take the perspective of the actor who selects a collaboration partner ("the focal actor") and consider the "alter" the actor that is evaluated as a potential partner.

long been of interest to both finance (Hochberg et al., 2007, 2010a; Lerner, 1994) and organizational scholars (Podolny, 2001; Sorenson & Stuart, 2001, 2008). Typically, venture capital investments are disbursed in rounds conditional on the portfolio company's progress (Gompers, 1995a). Venture capital firms can withdraw at any stage of the collaboration; however, prior research has indicated that significant pressures exist from the coinvestors to remain in the syndicate even if its chances of success deteriorate (Guler, 2007). The present work is the only research to date that examines an important consequence of withdrawal decisions: the ability of VC firms to enter into future syndication relationships.

We explore the consequences of such withdrawals on three levels. First, at the relational level, we predict that the withdrawal can lead to a disruption with the relationship with the coinvestors and reduce their willingness to syndicate with the withdrawing firm in the future. Second, at the global reputational level we hypothesize that the publicly available track record of the firm's withdrawals can signal its lack of reliability and cause prospective syndication partners to be more wary of entering into a relationship with it. Third, at the local reputational level, we propose that abandoned coinvestors may spread negative private information about the withdrawing firm, reducing the likelihood that their immediate network contacts will enter into a syndicate with it.

In addition to unpacking the differential consequences to withdrawal and elucidating their underlying mechanisms, we examine the extent to which the local and global reputational consequences of withdrawal reinforce or attenuate each other. Existing theory offers conflicting predictions. On the one hand, the negative private information available from abandoned coinvestors can draw attention to, and validate, any existing publicly available negative information (e.g., Haunschild & Beckman, 1998). On the other hand, negative public and private information can offer redundant content and thus have diminishing marginal effects on firm behavior. Our study allows us to provide a definitive answer to this unresolved issue in the literature.

2.2 Research context

The VC industry has played an important role in supporting entrepreneurship and innovations in a range of industries, including biotechnology, information technology, and energy (Gompers & Lerner, 2001). It functions as a gatekeeper, selecting promising new ventures (called portfolio companies) for continued investment and support. It also serves as an intermediary, linking capital providers—large institutions such as endowments, foundations, and pension funds—with young, nonpublic companies that need funds. Such young companies potentially can return the investment many times over in the case of an initial public offering (IPO) or an acquisition by an established industry actor. Finally, VCs can provide significant nonfinancial support for their portfolio companies, including strategic guidance and direction (Gorman & Sahlman, 1989), connections with prospective customers, suppliers, alliance partners or acquirors (Lindsey, 2008), as well as signaling the value of the portfolio company in the larger marketplace (Lee et al., 2011; Stuart et al., 1999).

VC firms commonly form syndicates and invest in the same portfolio company for several reasons. Syndication allows them to share the financial risk and diversify their portfolio more effectively by spreading their capital over a larger number of companies (Wilson, 1968). Coinvestors are also expected to contribute nonfinancial resources, such as participating in the due diligence process, sitting on the company's board, providing management advice and coaching, and promoting the company within their own networks (Gorman & Sahlman, 1989).

Pooling the resources and capabilities of a variety of investors increases the probability of success for the syndicate (Hochberg et al., 2013), but requires the trust and commitment that all participants will meet their obligations (Sorenson & Stuart, 2008). As a result, VCs are highly selective in choosing their syndication partners, and they present a compelling setting to study the formation of interorganizational relationships.

Traditionally, organizational and finance scholars have drawn on two major drivers of syndication partner selection. First, scholars have focused on the resources that can increase the attractiveness of a VC as a syndication partner, such as deep reserves of capital (Hochberg et al., 2013), extensive experience in the industry of the portfolio company (Lerner, 1994), status in the interorganizational network (Piskorski & Anand, 2011), or the human capital of the individual venture capitalists (Gompers et al., 2012a). The guiding logic of this stream of research is that better endowed VCs can be expected to make higher-quality contributions and would thus be more likely to be invited to syndicates. The second stream of research focuses on how mechanisms such as trust or familiarity explain the preference for similar or structurally proximate VCs. For example, VCs have a marked preference for syndicating with past coinvestors or VCs that are close in the syndication network (Sorenson & Stuart, 2001).Venture capital firms also disproportionately select coinvestors with similar geographic and industry specialization (Trapido, 2007). At the interpersonal level, VCs tend to invite disproportionately more coethnics and former classmates to join their syndication deals (Gompers et al., 2012a).

Although scholars have conducted extensive work on what drives syndication, there has been little attention to withdrawals from syndication relationships. Venture capital firms disburse investments in rounds, with each conditional on the venture achieving specified milestones. Staging an investment limits investors' commitments at the outset, when uncertainty is highest, and keeps a tight leash on an entrepreneur who depends on subsequent cash infusions (Gompers, 1995a). Legally, a VC firm is free to terminate its participation at any round, even though significant incentives are included in syndication agreements to prevent defections.[22] Importantly, syndication contracts in the US almost universally include the right of a VC firm to participate in each future round at the rate of its prior stake in the company. This means that a firm can never be excluded from the syndicate against its own wishes.[23]

Limited empirical research has examined the antecedents and consequences of VC withdrawals from syndicates. Townsend (2011) explored the effect of VCs' liquidity constraints on their ability to continue participating in syndicates and the negative effect of such withdrawals on the performance outcomes of otherwise high-quality companies. In an important early exploration of this question, Guler (2007) documented how pressures from coinvestors and concerns about disrupting valuable relationships may keep VCs from abandoning underperforming deals. Guller's work, however, leaves as an open question whether such pressures indeed translate into real penalties following the withdrawal. The present research aims to answer this question directly.

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[22] Such penalties can take the form of "pay-to-play" provisions, which require a VC to maintain its financial contributions in order to retain its seat on the portfolio company's board. Alternatively, dilution provisions specify that a defector's ownership share in the portfolio company will be diluted significantly in the subsequent round.

[23] Informal discussions with several venture capitalists and industry experts suggest that withdrawals by participating VCs in a venture from subsequent rounds can occur for three major reasons. First, a VC firm may lose confidence in the prospects of the portfolio company or decide that its limited capital is useful for other purposes. Second, a VC firm may be too resource constrained to participate in the round. Third, some smaller firms tend to specialize exclusively in earlier stages and thus may have agreed upfront to withdraw in the later rounds. In the present study, we are interested in withdrawals of the first type, because they involve the VC's conscious decision to part ways with its coinvestors. In the present study's data and methods section, we discuss approaches to ensure that the other two possible drivers of withdrawal do not impact our results.

2.3 Theory and hypotheses

The relational consequences of withdrawals. In prior studies, organizational scholars have focused on how the history of exchange relationships deepens the ties between collaborators, which leads to the development of trust and social attachments that increase the probability of tie renewal (Gulati & Sytch, 2008; Seabright, Levinthal, & Fichman, 1992). Researchers have become increasingly aware, however, that this process is contingent on a positive experience with the exchange partner. Dissatisfaction with the collaboration can serve as a negative relationship shock (Azoulay et al., 2010; Chung & Beamish, 2010) that makes repeated collaborations less likely (Li & Rowley, 2002; Schwab & Miner, 2008). Along similar lines, we propose that a firm withdrawing from a syndicate can also be considered a negative shock that will reduce the likelihood of syndication with the coinvestors. We posit this for two reasons.

Direct experience of withdrawals can lead the coinvestors to question the reliability of the withdrawing VC firm: an attribute that venture capitalists care deeply about. Unexpected withdrawals can be highly disruptive to the collaboration because they create a funding shortfall, deprive the venture of managerial expertise, and send a negative signal that can potentially hobble the syndicate's ability to recruit new outside investors (Townsend, 2011). Withdrawals can thus jeopardize the capital and time that the remaining collaborators have invested in the venture. As a result, the track record of reliably providing support to prior investments can be a criterion by which VCs evaluate their prospective partners. According to an interviewed VC principal, VCs "want a good partner, someone who would stick with the company through thick and thin." Abandoned coinvestors can take the focal VC's withdrawal as a direct signal of its character and are more likely to expect a withdrawal from that VC in the future. Naturally, this would make the VC a less attractive syndication partner for the abandoned coinvestors.

Beyond the pure signaling value of withdrawals, a withdrawal can undermine the quality of the relationship between the withdrawing VC and its syndication partners. Syndication between VC firms involves close collaborations between the principals that each VC nominates to represent it at the board of directors (e.g., Gorman & Sahlman, 1989). The trust and the interpersonal attachments existing between the principals of VC firms thus play a major role in syndication decisions (Gompers et al., 2012a; Rider, 2012). Exchange theorists have proposed that the process of successful exchange generates positive emotions that the individual participants attribute to the relationship and their collaboration partners (Lawler, 2001; Lawler & Yoon, 1998); such attributions, in turn, lead to deepening attachments and a willingness to continue the exchange even if more attractive alternatives were available (Lawler et al., 2000). In the present study, we propose that terminating exchange relationships could have the opposite effect; that is, the withdrawal is likely to generate negative emotions that become attached to the relationship and might increase the aversion of the abandoned principals to engaging again with the withdrawing partner. An interpersonal relationship breakdown can easily translate into an interorganizational relationship breakdown. Given that VC firms are tightly knit and cohesive entities, and typically every major investment decision can be vetoed by any single partner, the interpersonal relationships disrupted by withdrawal can lead to a diminished likelihood of future syndication between the abandoned VC firms and the withdrawing firm.

In summary, experiencing a withdrawal can have signaling implications (i.e., re-evaluation of the reliability of the withdrawing firm) as well as interpersonal relationship implications (i.e., worsened relationship between the principals involved on both sides). Taken together, these two mechanisms suggest that the withdrawal might have relational costs,[24] including the decreased likelihood of the withdrawing VC to secure future syndications with the abandoned partners. This leads to the following hypothesis:

> ***Hypothesis 1****: A focal VC firm is less likely to engage in syndication with alters that have previously withdrawn from a greater proportion of their syndicates with the focal VC.*

The global reputational consequences of withdrawal. Although some withdrawal consequences—such as the relationship deterioration—are clearly dyadic, a withdrawal from a VC syndicate may have broader repercussions; namely, implications for the exchange partner's reputation for reliability. Here, we use the classic definition of reputation as "a set of attributes ascribed to a firm, inferred from the firm's past actions" (Weigelt & Camerer, 1988: 443). The starting point is the idea that the true attributes of interest are unobservable but can be inferred from the firm's past actions or achievements. These inferences, in turn, inform actors' decisions regarding whether to conduct an exchange with an organization (e.g., Dollinger, Golden, & Saxton, 1997; Sullivan, Haunschild, & Page, 2007).

Our interviews suggested that within the VC context, the reliability of expected support is a crucial consideration when selecting syndication partners. In assessing the likelihood of continued support, VCs tend to look both at the hard data of the prospective partner's ability to participate in future rounds, as well as the soft data of the partner's willingness to consistently support the syndicate, including the history of and reasons for withdrawals. Withdrawals can raise many concerning questions about a VC's reliability, for example, how difficult is it to work with and how committed it is to supporting its portfolio companies. The proliferation of industry

[24] Our choice of terminology derives from Gulati's (1995) use of the term: just as "relational embeddedness" refers to the existence of a prior relationship and how it can facilitate the formation of repeat alliance ties, the relational costs of withdrawal refer to how the direct experience of a withdrawal can diminish the likelihood of future syndication.

databases covering VC investment, syndication, and withdrawal decisions—such as VentureXpert, Preqin, and Pitchbooks—means that most withdrawal decisions will be globally observable. Thus, a repeated track record of withdrawing from syndicates can create a global signal of unreliability that can affect all prospective syndication partners.

Venture capitalists are acutely aware that their withdrawal decisions can affect their overall reputation and access to future syndication partners. As one VC firm principal volunteered, "[you] want a VC who is a **good** partner, who would stick to the company through thick and thin…Most of us work with other VCs at some point, so it is very bad to develop a **reputation** for being a bad partner" (emphasis added). Another VC echoed this sentiment, "[It] is critical to support the company in good times and bad, and the partners who withdraw from the syndicate at the first signs of bad news are often not so much sought after."

We therefore propose in Hypothesis 2 that withdrawals can be considered a globally-observable, reputation-impairing event that can reduce the attractiveness of a particular VC to all prospective syndication partners:

> ***Hypothesis 2****: A focal VC firm will be less likely to enter into syndicates with alters that have withdrawn from a larger proportion of their syndicates.*

The local reputational consequences of withdrawal. A global reputational perspective assumes that all relevant information about the alter is universally accessible and sufficiently salient to all participants in the system. This is a common assumption within much of the research on corporate reputation. For example, studies examining the link between reputation and organizational characteristics (such as financial performance or good citizenship behavior) typically assume that the entire polled audience was aware of all such characteristics (e.g., Fombrun & Shanley, 1990). While such public information has the advantage of comprehensiveness and ease of accessibility, scholars have increasingly recognized that much of the reputation-relevant information can only be obtained through private contacts and thus may be only accessible to actors with the right connections (Hillmann & Aven, 2011; Raub & Weesie, 1990).

In our context, the indirect connections of a focal VC firm to the prospective alters via a shared syndication partner are likely to be especially important for the due diligence process for two major reasons. First, a shared syndication partner is likely to have first-hand information about both the prospective alter and inside details of the collaboration. For example, conversations with principals from VCs abandoned by a prospective alter can provide rich details of what happened behind closed doors. This is information that is unlikely to be available in the public record, yet it is important for making sense of the reasons behind a withdrawal and the likelihood that the alter will withdraw from future collaborations. Second, syndication partners are purportedly trustworthy data providers. The intense collaborations in the course of syndication are conducive to the development of deep, trust-based relationships that facilitate the transmission of sensitive private information (cf. Uzzi, 1997). Furthermore, private contacts are considered a credible source of information, because they put their own reputation at risk (Gulati & Gargiulo, 1999: 1447). The venture capitalists with whom we talked were acutely aware of the reputational costs of misrepresentations. As one noted, “It is a small world, and if someone lies to you, it will come back to bite them in the end.”

Shared syndication partners can therefore serve as a trusted source of rich, private information about the prospective alter. Existing research has largely assumed that such information would generally allay the focal firm’s concerns about collaborating with the alter and increase the probability of forming a direct relationship between them (Gulati, 1995b; Gulati & Gargiulo, 1999). We depart from this implicit assumption by proposing that the private information flowing across the indirect ties is not necessarily positive, and its valence will be shaped by the experiences of the shared partner with the alter. As we argued in our motivation for Hypothesis 1, experiencing a withdrawal can lead the abandoned actor to question the reliability of the alter; such negative attributions can be reinforced further by the relationship breakdown that can accompany the withdrawal. As a result, the abandoned former syndication partners of the alter are more likely to pass on negative information to their own network contacts, reducing the likelihood that they would engage in syndication with the withdrawing party. [25] This leads us to propose Hypothesis 3:

> ***Hypothesis 3****: A firm is less likely to syndicate with an alter if it has more connections to abandoned former syndication partners of the alter.*

Interaction of local and global reputational consequences of withdrawal. Our argument so far has proposed two distinct reputational consequences of withdrawal. The global reputational consequences are caused by the public information on an alter's history of withdrawals, which serves as a negative signal that affects all VC firms considering a syndication partner; the local reputational consequences are driven by negative private information, which only spreads to those with connections to the abandoned coinvestors. Although a significant body of work has touched on those two separate mechanisms—global reputation engendered by an overall track record of behavior (e.g., Dollinger et al., 1997; Rao, 1994; Sullivan et al., 2007) versus transferring private information across interorganizational ties (Gulati & Gargiulo, 1999; Shane & Cable, 2002)—there is little understanding of how these two mechanisms interactively affect tie formation behavior. In fact, existing theory gives conflicting

[25] Although we do not formally formulate it as a hypothesis, we fully expect that connections to non-abandoned former coinvestors of the alter will increase the likelihood of syndication. Because our empirical strategy rests on disaggregating the connections to abandoned and non-abandoned syndication partners, we will have the opportunity to directly compare the two coefficients.

predictions: some perspectives suggest that negative public and private information will strengthen one another's effects; other perspectives suggest that negative public and private information will attenuate each other. We review those two conflicting predictions in turn.

Simultaneous access to both public and private information about an actor's past withdrawals can shape the behavior of recipients of that information in ways where each is amplified by the presence of the other. A firm's exposure to negative private information about an alter can magnify the effect of existing negative public information via two key mechanisms. First, cognitive limitations in the way we look at large bodies of information means that private information can increase the salience of similar publicly available information. Organizational actors are attention constrained and generally attend to only a fraction of the overall information to which they are exposed (Ocasio, 1997). When faced with information overload, they tend to zero in on the pieces of information related to what they already know (Piezunka & Dahlander, Forthcoming). Private information tends to be vivid and easy to retain, especially when it is told in person and is drawn from the interlocutor's first-hand experience (Nisbett & Ross, 1980). As a result, it can form the cognitive filter through which venture capitalists selectively process the much larger sea of publicly available information. Similar explanations have been proposed in other settings; for example, Haunschild and Beckman (1998: 840) argued that business press coverage of acquisitions focuses attention on the M&A activities of a company's interlock partners and thus increases their influence on decision-making.

Second, we know that when actors receive supportive information from multiple sources, they tend to believe that the information is more credible (Nisbett & Ross, 1980). In our context, this means that negative private information and negative public information can enhance one another's credibility when they offer a convergent view of an actor. Private information provides richer inside details that allow compelling sense-making around a small number of cases; in contrast, public information covers an entire track record of behavior, but gives few of the rich details needed to translate the raw facts into a character assessment. When simultaneously exposed to consistently negative public and private information, recipients of that information have greater confidence in drawing negative inferences about the prospective alter and generalizing those inferences to the alter's entire track record.

Together, the two mechanisms support our fourth hypothesis:

> ***Hypothesis 4a****: The negative effect of an alter's overall history of withdrawals on the probability of syndication with a focal VC firm will be stronger if the focal VC firm has more connections to abandoned former syndication partners of the alter.*

An opposing perspective to the above hypothesis predicts that public and private sources of negative information do not amplify one another but rather attenuate the other's effect. There are several reasons for this claim. First, accumulating similar information from different sources can have diminishing marginal effects on behavior (cf. Ozmel et al., 2013; Schwab, 2007). As stated in Hypotheses 2 and 3, each of these sources of negative information *individually* may undermine the focal firm's willingness to form future collaborations with an alter by raising doubts about its reliability. However, *together* those two signals may exhibit diminishing marginal effects because the transmissions are redundant. Learning theorists have argued that "information from multiple sources has a substitutional effect if these sources provide redundant or duplicate information" (Schwab, 2007: 238). Such substitution effects have been documented in several settings, from CEOs' M&A decisions (Haunschild & Beckman, 1998) and alliance partner selection (Ozmel et al., 2013) to consumer reactions to product recalls (Rhee & Haunschild, 2006). These same processes can apply readily to the VC relationships as well.

A second reason negative private information may reduce the effects of negative public information relates to the satisficing behavior of organizations. Organizational theorists have long known that instead of undertaking an exhaustive search to uncover all relevant information, organizations typically stop the information collection process when they have determined that they have acceptable amounts of information (March & Simon, 1958; Simon, 1955). Such satisficing behavior may be relevant in the course of due diligences of prospective syndication partners, especially given the intense time pressures to which venture capitalists are routinely subjected. After receiving a few negative assessments from abandoned syndication partners of the alter, the decision makers at the focal VC firm may decide to eliminate the alter from consideration and thus do not exploit the remaining trove of public information about its behavior (see Schwab, 2007 for a related argument).

Both the redundancy and satisficing mechanisms point in the same general direction; that is, exposure to negative private information about the alter will reduce the focal VC firm's sensitivity to negative public information about the alter. This leads to formulating the following hypothesis:

> ***Hypothesis 4b****: The negative effect of an alter's overall history of withdrawals on the probability of syndication with a focal VC firm will be weaker if the focal VC firm has more connections to abandoned former syndication partners of the alter.*

Figure 2.1 illustrates an overview of our hypotheses. Hypotheses 1 looks at the relational consequences of withdrawals; that is, a focal VC firm is less likely to syndicate with an alter that has previously withdrawn from one of its syndicates. Hypothesis 2 examines the global reputational consequences of withdrawal and predicts that a focal VC firm will be more averse to syndicating with an alter that has withdrawn from a greater proportion of its prior syndications. Hypothesis 3 proposes that a focal firm's connections to previously abandoned syndication partners of the alter will reduce the likelihood of syndication. Finally, Hypotheses 4a and 4b present the conflicting predictions that a focal firm's connections to previously abandoned syndication partners of the alter may either reinforce or attenuate the negative effect of the alter's proportion of past withdrawals on the likelihood of syndication.

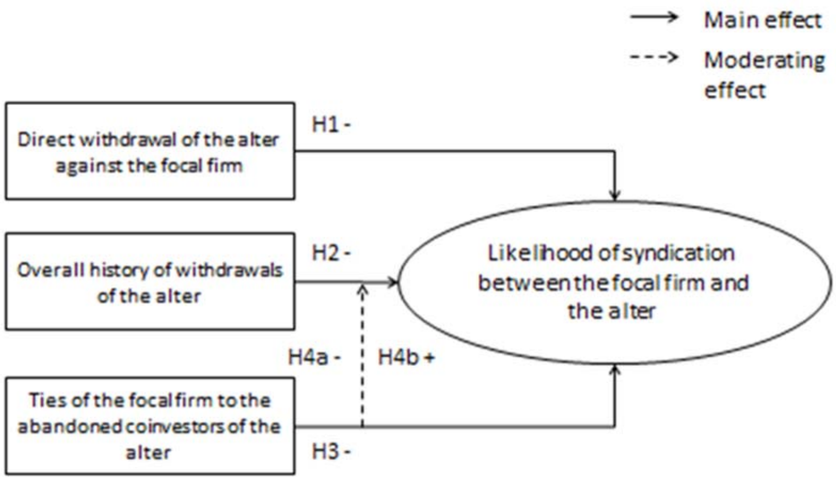

Figure 2.1: Theoretical framework

2.4 Data and variables

Data. Our core data were drawn from Thomson Reuter's VentureXpert database, which has tracked venture capital fundraising, investments, and exits since the 1970s. VentureXpert is used widely for research in both finance (Hochberg et al., 2007, 2010a) and economic sociology (Podolny, 2001; Sorenson & Stuart, 2001, 2008). Our data cleaning process entailed several steps. To focus on the dynamics of the US venture capital market, we excluded all non-US VC firms and investments. We also eliminated entities that VentureXpert had not identified as dedicated venture firms,[26] and we eliminated funds that had made no investments over the preceding 5-year period.

Identifying withdrawals was a critical step in the data cleaning. Following Townsend (2011), we defined a withdrawal as the permanent disappearance of a VC firm from the ranks of coinvestors. If a firm merely skipped a round but renewed participation at a later point, we continued to count it as a syndicate participant. We did this for two reasons. First, some of the omissions were apt to be due to data errors. Second, even if a firm indeed failed to participate in an investment (i.e., due to liquidity issues), its readmission suggested that it was granted a temporary reprieve by its coinvestors. When none of the original members of a syndicate participated in a follow-up round—for example, if they were bought out by another syndicate—they were not counted as withdrawing. In cases of a complete change in syndicates, we simply stopped tracking that particular company. Finally, we did not include withdrawals following a successful exit such as an IPO or acquisition.

A possible concern with our coding of withdrawals is that it does not distinguish prenegotiated withdrawals in which a VC committed to participate solely in an early round—and thus exits with the prior approval of its coinvestors—from withdrawals that happened over the coinvestors' objections. The former scenario is especially likely if a particular firm's strategy

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[26] In particular, such criterion excludes Corporate Venture Capital (CVC), the venture arm of major corporations. We made this decision for two reasons. First, CVCs typically invest primarily for strategic reasons (such as access to technology) rather than financial reasons (such as bringing the company to IPO). Their incentives often include acquiring crucial resources of the portfolio company at the lowest price; thus, they can be misaligned with the entrepreneur's or the other VC investors' objectives (Hallen, Katila, & Rosenberger, In Press; Katila, Rosenberger, & Eisenhardt, 2008). Second, CVCs syndicate less frequently (Hochberg et al., 2010a), in part because as sole investors, they can have stronger control over the portfolio company and its resources. For these and other reasons, excluding CVCs from analyses of VC syndication is common practice (Hochberg et al., 2007; Sorenson & Stuart, 2001, 2008; Trapido, 2007).

focuses primarily on early stage investments. Although it is difficult to reconstruct systematically the reasons a firm has withdrawn from a syndicate based on the archival data, we made several efforts to grapple with the following possible alternative rationale for exit. First, if certain firms withdraw as a matter of strategy, then we expect that they will have withdrawn from a large proportion of their syndicates. In our sensitivity analyses, therefore, we excluded all firms belonging to the top decile in terms of overall withdrawal rate (i.e., have withdrawn from more than 35% of their syndicates). Second, because the tendency to engage in pre-negotiated exits is likely to be a part of a firm's long-term strategy—and thus relatively time-invariant[27]—we also explored in our robustness checks whether adding firm fixed effects would change our main results. Finally, it bears emphasizing that any pre-negotiated withdrawals that are not controlled for in our two robustness tests will likely bias our estimates of the reputational and relational consequences of withdrawal toward zero and therefore make our results more conservative.

Our aim was to identify the individual- and relationship-level factors that drive the probability of a given pair of active funds establishing a connection in a given year. In setting up our dyadic dataset, we first created all possible dyads of firms active in a given year. To eliminate spurious pairs, we examined only pairs that invested in the same industry and the same geographic region during the focal year. Using this approach, we found approximately 1.2 million potential pairs, approximately 41,000 of which were actually realized. Analyzing all these observations, however, led to autocorrelation, because each firm is represented in a large number of counterfactual pairings. It also led to low variance of the dependent variable, which biases the coefficients in logit and probit models (Jensen, 2003; King & Zeng, 2001; Trapido, 2007). We then followed standard practice by taking a random sample of the unrealized dyad

[27] Generally, firm investment strategies are fixed in the investment prospectus and are therefore relatively stable during the 10-year life of the fund.

years to achieve a 5:1 ratio of realized to unrealized observations (Jensen, 2003; Sytch & Tatarynowicz, 2014b). This resulted in a final dataset of 250,730 observations. Following Jensen (2003), we also ensured that all our results were robust to ratios of 3:1 and 10:1 of controls to cases.

The present study's dataset is based on unique dyads; that is, the specification of one firm as the first member of the dyad and the other as the second member is determined randomly and consistent throughout all annual observations of the pair. The ordering of the firms in the dyad made no difference for any of the variables. The dyadic attributes (such as the distance between the two investment portfolios or the number of prior connections) are independent of ordering, and the node-specific attributes (such as centrality or the number of times one member of the dyad has withdrawn from the other's syndicates) were summed and presented as a single coefficient following standard practice (Gulati & Gargiulo, 1999; Stuart, 1998; Trapido, 2007).[28] To test Hypotheses 4a and 4b, which require the interaction between each firms' social overlap with the abandoned coinvestors of the alter on the one hand, and the overall withdrawal rate of the alter on the other hand, we first computed the product of the two variables (mean-centered to avoid multicollinearity issues) from the perspective of each firm, and then summed it across the dyad.

[28] The justification for summing all node-specific attributes is as follows. Let Y_{ij} be the dyadic outcome of interest for actors *i* and *j*; $\boldsymbol{X}_i$ is the vector of node-specific attributes for actor *i*; $\boldsymbol{X}_j$ is the vector of node-specific attributes of actor *j*; and $\boldsymbol{X}_{ij}$ is a vector of dyadic attributes. Y_{ij} is predicted by these three vectors, therefore,

$$Y_{ij}=f(\boldsymbol{b}_1 \boldsymbol{X}_i + \boldsymbol{b}_2 \boldsymbol{X}_j+\boldsymbol{b}_{12} \boldsymbol{X}_{ij})$$

Because the order of the firms is determined randomly, and the dependent variable Y_{ij} is symmetric (i.e., $Y_{ij}= Y_{ji}$), the monadic attributes of each firm in the dyad should have equal effect on the dependent variable, that is, $\boldsymbol{b}_1=\boldsymbol{b}_2=\boldsymbol{b}$. Substituting in the equation shows that we can obtain the coefficient vector b by summing the monadic attributes:

$$Y_{ij}=f(\boldsymbol{b} \boldsymbol{X}_i + \boldsymbol{b} \boldsymbol{X}_j+\boldsymbol{b}_{12} \boldsymbol{X}_{ij})=f(\boldsymbol{b}(\boldsymbol{X}_i+ \boldsymbol{X}_j)+ \boldsymbol{b}_{12} \boldsymbol{X}_{ij})$$

Dependent variable. To test our hypotheses, we chose an indicator equal to 1 if the two firms jointly invested in their first round via a syndicate during the focal year (labeled *Coinvestment* in the data tables). We explicitly ignored continued coinvestment; if the two firms coinvested in a given company in 1990 and continued to do so in follow-up rounds in 1991 and 1992, we only counted 1990 as a "real" coinvestment. Our reasoning is that the crucial decision to collaborate is made at the outset, and because subsequent coinvestments are largely assumed and entail a high exit cost. We also decided to use a dichotomous indicator rather than a count variable due to the very small number of multiple joint investments in the same year.

Another overarching question was "the statute of limitations" on past behavior; that is, how soon do prior investments and connections lose their relevance to the present? We followed established practice in the study of VCs (e.g., Sorenson & Stuart, 2001; 2008) and used a 5-year sliding window for all network variables: connections, centrality, and withdrawals. This decision is justified by the typical 5-year lifespan of a venture capital transaction. The portfolio of deals over this timeframe defines the totality of active, ongoing connections. Because scholars have expressed concerns about the reliability of VentureXpert data prior to 1980 (e.g., Podolny, 2001), we used data from 1980 to 1984 to create the network for 1985 and excluded all earlier dyad-years.

Independent variables. The core independent variables focus on the withdrawal behavior of VC firms. To test Hypothesis 1, we created the variable *Direct Withdrawal*$_{ij}$, equal to the number of times firm *i* withdrew from syndicates in which firm *j* continued participating in the prior five years to that dyad-year, divided by the overall number of unique syndicates between the two. Because withdrawals are node-specific, we summed the two values of the variable associated with both firms (*Direct Withdrawal Rate*).

To test Hypothesis 2, we calculated each VC firm's overall number of withdrawals over the preceding five years and divided it by the total number of unique syndicates in which it had participated (*Overall Withdrawal Rate*). The mean for the variable is about 14%, but it hides a significant amount of dispersion. Slightly more than 30% of firms had never withdrawn from a syndicate in the preceding five years, and more than half had withdrawn from fewer than 10% of their syndicates. On the high end, about 10% of firms had withdrawn from one-third or more of their syndicates. Such variability means that withdrawal behavior can be used readily as a means to identify potentially unreliable partners. In our empirical analysis, we summed the overall withdrawal rate of the two firms in the dyad, as we did with the other node-specific variables.

For Hypothesis 3, we need to distinguish between the each firm's ties to the abandoned and non-abandoned partners of the alter. We first created an overall *Social Overlap* measure of the shared ties between the two firms by constructing a Jaccard index of their partner sets (Jaccard, 1901). Conceptually, this measure standardizes the number of shared partners of the two firms by the number of non-shared partners into an index ranging from zero (if they have no shared partners) to one (if all of their partners are shared). It is preferable to a straight count of shared partners, because the latter can be heavily correlated with the actors' overall degree of centrality (e.g., Srivastava, 2013).

$$Social\ Overlap_{ij} = \frac{Shared\ partner\ count_{ij}}{Degree\ Centrality_i + Degree\ Centrality_j - Shared\ partner\ count_{ij}}$$

We then separately calculate the social overlap of each of the firms with the abandoned and the non-abandoned partners of the alter. This measure differs across pairs (e.g., the one firm in the dyad may not have connections to any of the firms that the alter has abandoned, whereas the alter might have connections to multiple firms that the first firm has abandoned) and therefore has to be summed as any of the node-specific variables.

$$\mathit{Social\ Overlap\ to\ Abandoned}_{ij} = \frac{\begin{matrix}\mathit{Count\ of\ ties\ to}\\ \mathit{abandoned}\end{matrix}_{\ ij}}{\begin{matrix}\mathit{Degree}\\ \mathit{Centrality}_i\end{matrix} + \begin{matrix}\mathit{Degree}\\ \mathit{Centrality}_j\end{matrix} - \begin{matrix}\mathit{Count\ of\ ties\ to}\\ \mathit{abandoned}\end{matrix}_{\ ij}}$$

$$\mathit{Social\ Overlap\ to\ Non\ Abandoned}_{ij} = \frac{\begin{matrix}\mathit{Count\ of\ ties\ to}\\ \mathit{non\ abandoned}\end{matrix}_{\ ij}}{\begin{matrix}\mathit{Degree}\\ \mathit{Centrality}_i\end{matrix} + \begin{matrix}\mathit{Degree}\\ \mathit{Centrality}_j\end{matrix} - \begin{matrix}\mathit{Count\ of\ ties\ to}\\ \mathit{non\ abandoned}\end{matrix}_{\ ij}}$$

Control variables. In addition to the main effects of the variables described, we incorporated several additional controls to address alternative explanations and potential concerns of endogeneity. First, we wanted to include a measure of the historical investment activity of each firm in the dyad. We represented this by the summed number of investments each of the firms made over the preceding five years. Second, we incorporated the summed degree centrality of each of the firms in the interorganizational network, which in other settings has been found to strongly predict tie formation behavior (Gulati & Gargiulo, 1999). The two measures, however, were highly correlated (above 80% correlation); thus, we retained only the summed centrality measure within the analysis to alleviate any multicollinearity concerns within our models. Our substantive results are not sensitive to whether we use just the investment count or both variables together.

We were very mindful of possible endogeneity concerns posed by variables that may increase the probability of withdrawals and independently reduce the attractiveness of the focal VC firm. One set of such variables is the capital availability to the focal VC firm. Firms that are more capital-constrained are more likely to withdraw from syndicates, because they are running out of capital to contribute. They are similarly less attractive to exchange partners because they cannot guarantee follow-on financing (Piskorski & Anand, 2011; also per author interviews). We operationalized capital constraints with two variables, both summed across each firm in the dyad. We first measured the percentage of the most recent fund that each firm had already invested. If this ratio was high, this means that a firm is running out of capital to continue participating in existing syndicates or to commit to new ones. We also included the age of the most recent fund of each firm in the dyad (logged to reduce the influence of outliers) to represent its stage in the fund lifecycle. Successful VC firms typically raise a new fund every two to three years; failure to raise funds over a longer horizon may signal fundraising troubles (Kaplan & Schoar, 2005). Firms that have very mature funds may want to preserve capital by not committing additional funds to existing syndicates or to new ones. At the same time, they are less attractive because their syndication partners might doubt their fundraising and follow-on capability. Fund information was unavailable for some observations (~15% of the total). For these instances, we introduced a dummy variable and imputed sample average values for fund age and percentage invested. Both the present funding-constraint variables and the missing fund dummies were incorporated into the model as controls.

We also incorporated several dyadic controls that prior research has demonstrated to be highly predictive of dyadic matching. One major determinant of the likelihood of coinvestment is the similarity of investment specialization across industries and geographies; similarly specialized VCs are more likely to be interested in the same portfolio companies and thus more likely to encounter each other (cf. Trapido, 2007). We operationalized *Industry Specialization Distance* based on Sorenson and Stuart's (2008) Euclidean distance measure. Specifically, we used a 10-industry categorization scheme adapted from Gompers, Kovner, and Lerner (2009) that aggregates the more finely grained VentureXpert classification into 10 broad industry categories (e.g., Biotech and Healthcare, Electronics, Internet and Computers, Energy, etc.). For each firm, we then calculated a 5-year trailing percentage of deals made in each industrial category. We then calculated the Euclidean distance between two specialization vectors as follows (p_{jl} represents the proportion of VC firm j's investments into industry sector l):

$$Industry\ Specialization\ Distance_{ij} = \sum_{l=1}^{10} (p_{jl} - p_{il})^2$$

We similarly calculate a *State Specialization Distance* based on the geographic location of the portfolio companies of each VC in the dyad. Specifically, for each firm we construct a 52-dimensional vector containing the proportion of their investments in each state plus the District of Columbia and Puerto Rico. We then calculate the Euclidean distance between the two vectors per the same formula (p_{jl} represents the proportion of VC firm j's investments into state l):

$$State\ Specialization\ Distance_{ij} = \sum_{l=1}^{52} (p_{jl} - p_{il})^2$$

Our final dyadic control is geographic distance between the two VCs, because geographically proximate VCs are more likely to engage in syndication (cf. Sorenson & Stuart, 2008). We calculated *Geographic Distance* using average distance in miles between the geographic coordinates of the ZIP codes of the two firms' headquarters, and then logging it to reduce overdispersion using the same procedure as Sorenson and Stuart (2001).

2.5 Method

The core analyses were conducted using a logit model, where the probability of both members of the dyad coinvesting together is modeled as:

$$P(t) = \mathrm{L}(a + bX_{ij} + cY_{ij}(t))$$

where L is the logistic function; $\boldsymbol{a}$, $\boldsymbol{b}$, and $\boldsymbol{c}$ are vectors of parameters to be estimated; and X_{ij} and $Y_{ij}(t)$ are the dyad-specific vectors of time-invariant and time-variant variables, respectively.

To account for the rare events nature of syndication data, we used the rare events corrections implemented by King and Zeng (1999b; 2001) as the *relogit* command in STATA. This method alleviates the tendency of logistic models to underestimate the likelihood of very low-probability events and the bias arising from oversampling factual versus counterfactual observations. Many recent studies have used a similar approach in analyzing tie formation in a variety of settings, including venture capital syndication (Rider, 2012; Trapido, 2007), strategic alliances (Sytch & Tatarynowicz, 2014b), and investment bank advising relationships (Jensen, 2003).

A typical challenge with such models is that they do not necessarily account for dyadic dependence; that is, the influence of unobserved variables of the individual firms that carry over to all the observations in which they participate. We addressed this issue in two ways. First, we controlled for the *Lincoln Autoregressive Constant*, first proposed by Lincoln (1984) and frequently used to alleviate dyadic autocorrelation in tie formation studies (Rider, 2009; Stuart, 1998; Sytch & Tatarynowicz, 2014b). It is based on the mean value of the dependent variable across all dyads involving either of the VCs in the dyad for the focal year, but excluding the focal dyad. This variable captures the raw level of syndication activity of both sides of the dyad in a given year and purges our results of period-specific, unobserved heterogeneity in the syndication likelihood of the two firms in the dyad. Second, in the presence of dyadic dependence, clustering merely by dyad would underestimate the actual correlation structure of the error terms and lead to inconsistent standard error estimates. Several solutions exist; we adopted the multiple clustering algorithm proposed by Cameron, Gelsbach, and Miller (2011) and implemented in STATA by Kleinbaum, Stuart, and Tushman (2013) as the *clus_nway* package. We clustered by both members of the dyad and by year, resulting in seven discrete clusters: 1) Firm 1; 2) Firm 2; 3) year; 4) Firm 1 and year; 5) Firm 2 and year; 6) Firm 1 and Firm 2; and 7) Firm 1 and Firm 2 and year. The algorithm combines the results of each of the seven clusters into a single, robust estimate.

Finally, we addressed the issue of potential unobserved heterogeneity—specifically, the extent to which a track record of withdrawals is correlated with unobserved variables that may independently reduce the attractiveness of the VC firm. We included measures of the financial resources of the focal firm, because scarce resources can trigger withdrawals, while simultaneously reducing the attractiveness of the VC firm (Piskorski & Anand, 2011). We also included year fixed-effects in all models to account for the dramatic swings in VC activity across time, which has been documented in prior research (Gompers & Lerner, 2000; Gompers & Lerner, 1999). We also conducted robustness tests using fixed effects for each of the firms in the dyad to rule out time-invariant, unobserved heterogeneity.

Note as well that although the present paper is based primarily on quantitative data, during the course of the project, we conducted seven formal interviews with VC principals and multiple informal interviews with venture capitalists at varying levels of seniority. To a large extent, their comments about the importance of the perceived reliability of the exchange partner inspired our research question. These interviews were important for shedding light on some of the mechanisms at play such as the financial circumstances of the VC firms and for refining our measures and controls for our quantitative analyses.

2.6 Results

Main results. Table 2.1 presents the univariate descriptive statistics and the correlation matrix for the final dataset. Realized observations account for approximately 17% of the total due to random sampling of counterfactuals (one realized value for every five unrealized values). All variables with potential for highly skewed distributions (such as centrality and geographic distance) have been logged to yield better-behaved distributions. Note that the variables representing node characteristics (such as centrality, withdrawal rate, and the social overlap with the alters abandoned/non-abandoned partners) have been summed across both sides of the dyad; therefore, the sample averages for the individual firms are approximately half of the reported values. Also, we have reported the uncentered means of all the independent variables, even though we centered them before computing the interactions.

The correlations between the main independent variables (direct withdrawals and withdrawal rates) and the likelihood of syndication are positive, but part of this relationship is clearly driven by other variables. For example, the correlation of direct withdrawals with syndication probability is confounded by the high correlation of both variables with the total number of past syndication ties within the dyad. The control variables have the expected correlations with the probability of syndication. Prior syndication experience, a higher number of shared partners, and greater industry and state specialization overlap are all associated with the higher probability of syndication. This is consistent with past research (Sorenson & Stuart, 2001, 2008; Trapido, 2007). Some other independent variables also appear highly correlated in the direction that one might expect. For example, the direct withdrawal rate is significantly correlated with the number of prior ties (64%), because no direct withdrawals are possible if no prior tie between the two VC firms in the dyad existed. Similarly, degree centrality is 62%

Table 2.1: Summary statistics and correlations for all key variables

	Descriptive Statistics		Correlation table													
Variable	**Mean**	**Std. Dev.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1. Coinvestment	0.17	0.38	1.00													
2. Degree Centrality (Logged and Summed)	0.01	1.39	0.24	1.00												
3. Most Recent Fund Age (Logged and Summed)	2.84	0.74	-0.12	-0.22	1.00											
4. Percent of Capital Invested (Summed)	0.66	0.40	-0.06	-0.08	0.51	1.00										
5. Fund Missing (=1) (Summed)	0.26	0.48	-0.04	-0.27	0.12	0.20	1.00									
6. Industry Specialization Distance	0.28	0.25	-0.14	-0.40	0.08	-0.01	0.16	1.00								
7. State Specialization Distance	0.38	0.33	-0.16	-0.34	0.05	-0.01	0.07	0.15	1.00							
8. Geographic Distance (Logged)	6.23	1.84	-0.13	-0.06	0.01	-0.01	-0.01	0.04	0.35	1.00						
9. Number of Prior Ties (Logged)	0.08	0.29	0.27	0.34	-0.06	-0.04	-0.11	-0.18	-0.19	-0.13	1.00					
10. Social Overlap (SO) with Alter's Partners	0.07	0.08	0.37	0.62	-0.12	-0.03	-0.17	-0.33	-0.35	-0.16	0.55	1.00				
11. Direct Withdrawal Rate	0.04	0.19	0.15	0.22	-0.02	0.00	-0.07	-0.12	-0.13	-0.09	0.64	0.34	1.00			
12. Overall Withdrawal Rate	0.27	0.27	-0.01	0.05	0.27	0.18	-0.09	0.00	-0.06	-0.02	0.12	0.13	0.13	1.00		
13. SO - Alter's Abandoned Partners (Summed)	0.02	0.04	0.21	0.40	0.04	0.05	-0.15	-0.22	-0.25	-0.11	0.47	0.66	0.37	0.44	1.00	
14. SO - Alter's Non-Abandoned Partners (Summed)	0.14	0.14	0.33	0.63	-0.06	-0.03	-0.21	-0.33	-0.36	-0.16	0.52	0.91	0.32	0.19	0.62	1.00

correlated with the social overlap with alter's partners; that is, more central firms are more likely to have ties with any other VC firm. Not surprisingly, the two controls measuring the financial health of the firms—percentage of capital invested and age of the most recent fund—are also significantly correlated at about 50%. Finally, social overlap with the non-abandoned partners of the alter is more than 90% correlated with overall social overlap; however, those two variables never enter the same regression equation together. To ensure that multicollinearity is not an issue, we ran diagnostics on all models reported on Table 2.2. The maximum variance inflation factor (VIF) is around 3.1, which is significantly below the maximum suggested limit of 10 (Kutner et al., 2004). Also, omitting individual control variables does not substantively affect the results.

The main analyses are presented in Table 2.2. Model 1 presents the baseline model predicting tie formation, with results similar to other studies of syndication (Sorenson & Stuart, 2001, 2008; Trapido, 2007). Consistent with the expectations of network theorists, a firm's prior number of ties and larger social overlap with the alter's past partners are associated with a higher probability of syndication (Gulati, 1995b). Firms also tend to syndicate with those who are geographically close or share similar investment specialization (Sorenson & Stuart, 2001; Trapido, 2007). Finally, a firm's financial resources—measured by having recently raised a fund—increase its attractiveness to coinvestors.

Models 2 through 4 test the relational and reputational consequences of withdrawals. Model 2 shows that a firm is less likely to syndicate with alters who have previously abandoned it, thus providing support for Hypothesis 1.[29] Model 3 adds the overall proportion of withdrawals

[29] The results are consistent whether we use the proportion or the count of the pair's syndicates that have resulted in a withdrawal.

Table 2.2: Rare event logit model predicting the likelihood of syndication

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Degree Centrality (Logged and Summed)	0.042+	0.043+	0.049*	0.055*	0.047+
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Most Recent Fund Age (Logged and Summed)	-0.195**	-0.194**	-0.166**	-0.175**	-0.171**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Percent of Capital Invested (Summed)	-0.07	-0.066	-0.051	-0.042	-0.048
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Fund Missing (=1) (Summed)	0.143**	0.142**	0.127**	0.145**	0.147**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Industry Specialization Distance	-0.667**	-0.668**	-0.661**	-0.675**	-0.664**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
State Specialization Distance	-0.495**	-0.497**	-0.507**	-0.519**	-0.497**
	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)
Geographic Distance (Logged)	-0.088**	-0.088**	-0.089**	-0.088**	-0.088**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lincoln Autoregressive Constant	3.045**	3.044**	3.018**	3.098**	3.058**
	(0.15)	(0.15)	(0.15)	(0.15)	(0.16)
Number of Prior Ties (Logged)	0.546**	0.635**	0.646**	0.689**	0.715**
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Social Overlap (SO) with Alter's Partners	3.318**	3.293**	3.341**		
	(0.42)	(0.43)	(0.42)		
Direct Withdrawal Rate (Summed)		-0.216**	-0.183**	-0.151**	-0.146**
		(0.05)	(0.04)	(0.04)	(0.04)
Overall Withdrawal Rate (Summed) - A			-0.504**	-0.398**	-0.431**
			(0.07)	(0.06)	(0.07)
SO - Alter's Abandoned Partners (Summed)				-1.036**	-0.64*
				(0.33)	(0.33)
SO - Alter's Non-Abandoned Partners (Summed)				1.934**	1.954**
				(0.23)	(0.19)
A * SO - Alter's Abandoned Partners (Summed)					4.938**
					(0.74)
A * SO - Alter's Non-Abandoned Partners (Summed)					-5.665**
					(0.63)
Constant	-3.872**	-3.871**	-3.857**	-3.874**	-3.907**
	(0.23)	(0.23)	(0.23)	(0.21)	(0.23)
Observation Count	250,730	250,730	250,730	250,730	250,730
Pseudo-R sq.	0.2152	0.2154	0.2157	0.2162	0.2177

Robust standard errors clustered by both firm identifiers and year in parentheses. Year fixed effects.

+ $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed tests) and shows that firms are less likely to enter in syndicates with alters that have withdrawn from a higher proportion of their syndicates, a finding consistent with Hypothesis 2. In Model 4, we disaggregate the overall social overlap with the alter's past coinvestors into social overlap with the abandoned coinvestors and social overlap with the non-abandoned coinvestors. Connections to non-abandoned coinvestors of the alter increase the likelihood of syndication, which is consistent with much of existing network research. However, connections to abandoned coinvestors of the alter—who are likely to be passing on negative private information—inhibit syndication. Those findings provide support for Hypothesis 3 and our argument for the local reputational consequences of withdrawal.[30]

Finally, Model 5 examines the interaction between the local and global reputational consequences of withdrawal. It shows that connections to the abandoned coinvestors of the alter attenuate the negative effect of the alter's overall history of withdrawals on the likelihood of syndication. This result provides support to Hypothesis 4b and the argument that the combination of negative public and private information about an actor has diminishing marginal effects on behavior. At the same time, it rejects Hypothesis 4a and the idea that negative private information can focus attention on, and increase the credibility of, negative public information. We also demonstrate that ties to non-abandoned coinvestors of the alter magnify the negative effects of the alter's history of withdrawal on the likelihood of syndication. In other words, firms do not take advantage of the syndication opportunities created by shared partners when they are concerned about the reliability of the prospective alter based on the public information about them. We elaborate on the implications of this finding in the Discussion.

[30] The results are robust whether we use the social overlap measures (which implicitly standardize for the centrality of the two VCs in the dyad) or simpler measures, such as logged count of ties to abandoned/non-abandoned syndication partners of the alter.

Thus far, we have focused on the statistical significance of the findings; we now focus on their substantive interpretations. For a pair with one prior deal from which one of the partners withdrew, the probability of syndication between them falls by approximately 17%. At average values across the sample, an increase of one standard deviation on the overall withdrawal variable yields a reduction of the likelihood of syndication from approximately 2.3% to 2.1%, or about 10% of the base rate.

Figure 2.2 illustrates the effects of the focal firm's social overlap with the abandoned and the non-abandoned partners of the alter.[31] Assuming there are no ties to non-abandoned syndication partners of the alter, an increase of the social overlap with abandoned partners of the alter by one standard deviation from zero reduces the likelihood of syndication from a baseline of 1.8% to 1.7%, for a change of approximately 6%. Although this decrease is substantively small, it should be considered in the context of the small variance of this variable due to the rarity of withdrawals, as well as the strong null established by prior research that connections to shared partners should increase the likelihood of syndication. Conversely, an increase of the social overlap with the alter's non-abandoned coinvestors by one standard deviation from zero increases the likelihood of syndication from 1.8% to 2.3%, for an increase of approximately 27%. The results make clear that ties to abandoned coinvestors have dramatically different effects than ties to non-abandoned coinvestors, presumably because of the different valence of the information they are passing along.

[31] All the charts are produced based on the rare event logit reported in Model 6, Table 2.2, and using the *relogitq* STATA package developed by King and Zeng (1999a, b). It simulates the rare event logit parameters based on the point estimates and the covariance matrix and uses those values to estimate the predicted probabilities under various scenarios.

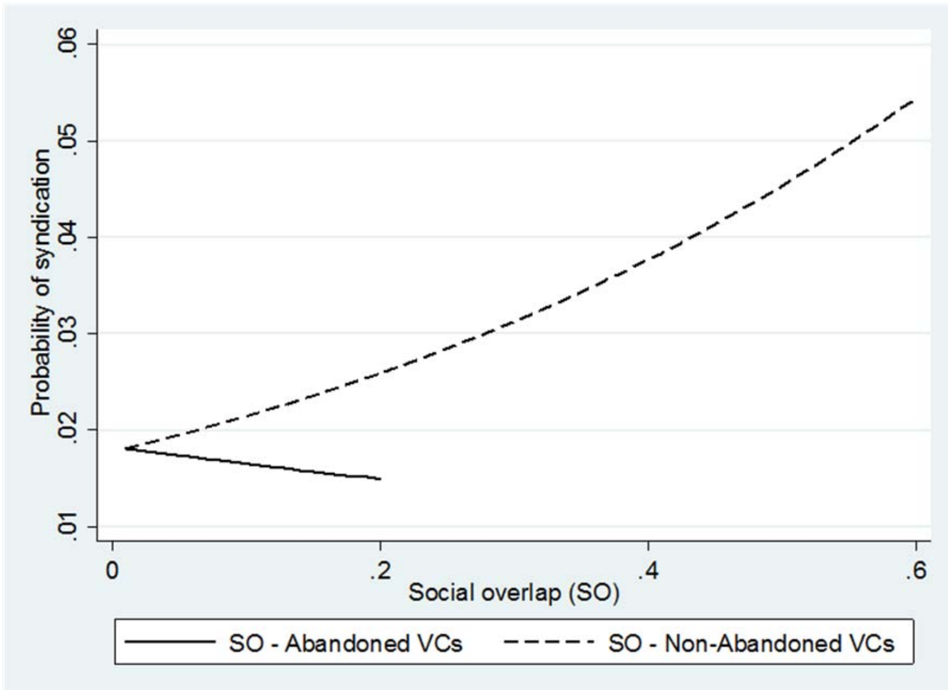

Figure 2.2: Predicted probability of syndication over different values of the social overlap with abandoned and non-abandoned partners of the alter (sets the other value at zero).

All other variables held at mean values (based on Model 4, Table 2.2).

Figure 2.3 examines how a focal firm's social overlap with abandoned coinvestors of the alter moderate the effects of the alter's overall history of withdrawals.[32] If the focal firm has no social overlap with prior coinvestors of the alter, a one standard deviation increase in the alter's withdrawal rate decreases the likelihood of syndication from 2.4% to 2.2%, for a decrease of approximately 8%. In contrast, at a higher level of overlap with the abandoned investors of the alter (mean plus one standard deviation), a one standard deviation change in the alter's withdrawal rate decreases the likelihood of syndication from 2.3% to 2.2%, for a decrease of

[32] Note that we vary only the alter's withdrawal rate and the focal firm's social overlap with its partners; the focal firm's own withdrawal rate, and the alter's social overlap to the focal firm's abandoned or non-abandoned partners are kept at mean values. The mean withdrawal rate on only one side of the dyad is 0.13, and the standard deviation is 0.17. Similarly, the mean social overlap with the abandoned coinvestors of the alter is 0.01 (standard deviation of 0.03) and the mean social overlap with the non-abandoned coinvestors of the alter is .07 (standard deviation of .08).

approximately 4%. The two curves cross at an alter withdrawal rate of approximately.27, which is within the observed range (approximately the 85% percentile).

We also present on Figure 2.4 the extent to which the effects of the alter's prior history of withdrawals are moderated by the focal firm's social overlap with its nonabandoned partners. When the focal firm has no connections to the alter's nonabandoned coinvestors, the alter's withdrawal rate has virtually no effect on the likelihood of coinvestment. In contrast, at a high level of overlap (mean plus one standard deviation), one standard deviation increase in the alter's withdrawal rate diminishes the likelihood of syndication from 3% to 2.6%, that is, a 14% decrease.

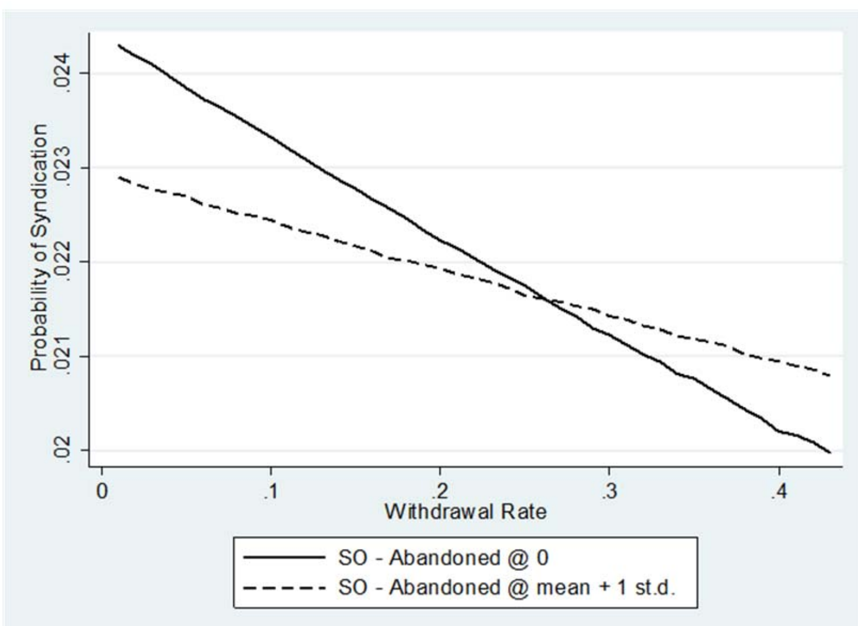

Figure 2.3: Predicted probability of syndication over different values of focal VC firm's overall withdrawal rate. Sets the other VC firm's social overlap with the abandoned coinvestors of the focal firm at either zero or one standard deviation above mean.

All other variables held at mean values (based on Model 5, Table 2.2).

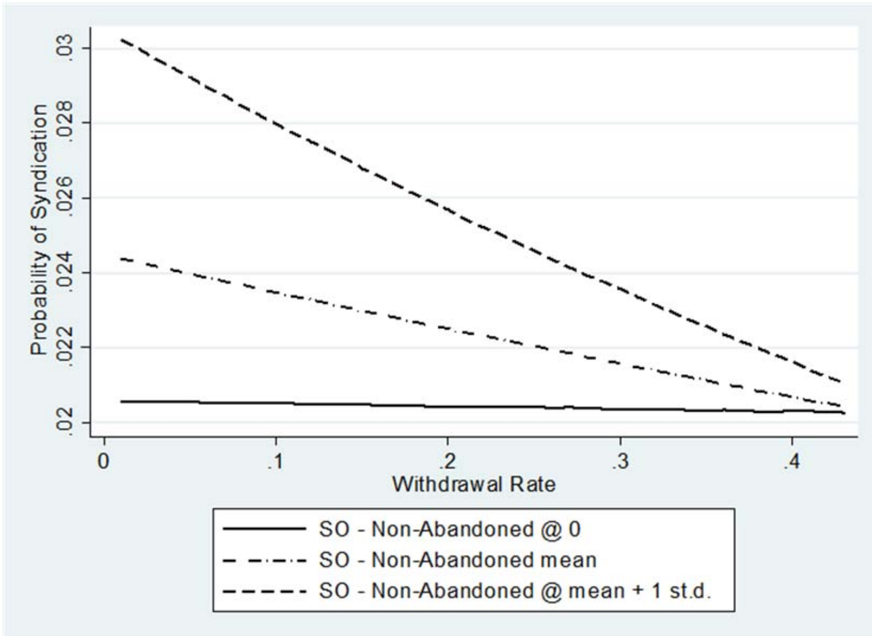

Figure 2.4: Predicted probability of syndication over different values of the focal VC firm's overall withdrawal rate. Sets the other VC firm's social overlap with the non-abandoned coinvestors of the focal firm at either zero or one standard deviation above mean.

All other variables held at mean values (based on Model 5, Table 2.2).

Robustness tests. We conducted several analyses to verify the robustness of these findings. The results are stable if we exclude serial withdrawers (the top 10%), who may have anticipated and prenegotiated their withdrawals. We also verified the robustness of the models with respect to alternative measures, such as logged count of shared partners in place of the Jaccard index to measure the social overlap or logged Bonacich centrality in place of degree centrality. We also tested the robustness of the results to alternative measures of the dependent variable, by only considering syndications in which one of the members of the dyad was a lead investor.[33] In addition, we verified the robustness of our results to different draws of the counterfactuals and to different ratios between factual and counterfactual observations; that is, in addition to the default 1:5 ratio, we also tested a 1:3 and 1:10 ratio (Jensen, 2003).

Studies of dyadic tie formation based on the rare event logit framework do not typically employ node-level fixed effects, relying instead on the autoregressive constant to absorb the unobserved heterogeneity in tie formation proclivities of each side of the dyad (Rider, 2012; Sytch & Tatarynowicz, 2014b; Trapido, 2007). Because the overall track record of withdrawal—a key explanatory variable in our model—is a monadic variable, however, we wanted to ensure that our results are not biased by unobservables that simultaneously drive the likelihood of withdrawal and the overall proclivity for syndication. We have already included the financial situation of the two VCs, a key time-varying driver of both withdrawals and syndication activity, as a control. To rule out the effects of time invariant-heterogeneity (e.g., long-term firm strategy to both withdraw often and be more selective about syndications), we incorporated firm-level fixed effects for all 1,812 firms in our model. The rare event logit could not handle this many additional covariates; therefore, we used a normal logit—reweighted to reflect the undersampling of control cases—to conduct the fixed-effect analyses. The effects were similar to those reported; the only substantive difference was that the social overlap with abandoned syndication partners of the alter lost its statistical significance. Even though it is not distinguishable from zero, it remains statistically different from the social overlap with non-abandoned syndication partners of the alter.

[33] We define lead investor based on the highest cumulative investment in the portfolio company, which is consistent with Sorenson and Stuart's (2008) definition. We allowed ties if two VCs have equal shares in the portfolio company.

Post-hoc analyses: Alternative channels of information diffusion. We considered alternative channels through which negative, private information from the abandoned coinvestors of the alter can reach the focal firm even in the absence of formal syndication ties. It is likely that venture capitalists are more likely to maintain informal connections to other firms that are 1) similar to them in terms of investment specialization or 2) geographically proximate to them. In unreported analyses, we constructed alternative proxies of the focal firm's access to the alter's abandoned coinvestors. These included 1) the number of abandoned coinvestors of the alter that have a high degree of industry specialization overlap with the focal firm (90th percentile or better); and 2) the number of abandoned coinvestors of the alter that are within close geographical proximity to the focal firm (50 miles or less). We used these two proxies in replacement of the social overlap with abandoned syndication partners of the alter to retest Hypotheses 3 and 4b. As expected, both proxies reduce the likelihood of syndication and attenuate the negative effects of overall withdrawals on the likelihood of syndication.

Post-hoc analyses: Circumstances of the withdrawal. In another set of post hoc analyses, we investigated whether the circumstances of the withdrawal might affect our results. In particular, we investigated whether the consequences of withdrawals differed depending on whether the syndicate from which the focal VC withdrew was successful (i.e., the portfolio company the syndicate supported went public or was acquired by a strategic investor) or unsuccessful (i.e., the portfolio company went bankrupt). Theoretically, we expected that the failure of the abandoned syndicate may soften reputational damage, because it would provide an ex post justification for the withdrawal decision. However, we did not see any moderating effect of the syndicate's outcome on either the relational or the reputational consequences of withdrawal. There are several explanations for this finding. First, the outcome of the portfolio company can manifest itself after several years. The outcome is thus uncertain in the immediate years following the withdrawal, when the relational and reputational consequences are likely to be the strongest. Second, the ex post outcome is subject to different interpretations that cannot be fully disentangled here and are beyond the scope of the present study. For example, a portfolio company failure could be interpreted as *validation* of the withdrawal decision or could be interpreted as *a result of* the withdrawal.

We also found that the reputational consequences of withdrawal diminished if the withdrawing VC firm was suffering liquidity issues, evidenced by a high percentage of invested capital or a very old most-recent fund. External audiences may attribute such withdrawals to the unfortunate circumstances in which the VC firm might find itself rather than to its underlying character (Thibaut & Riecken, 1955; Weiner, 1985).

2.7 Discussion and conclusion

In the present study, we explore the reputational impact to firms that are exiting business ties. In doing so, we also unpack a commonly held assumption that all business ties between firms cast a positive halo on their future interactions. We explore the relational and reputational consequences that ensue as a result of a firm terminating a collaborative tie. Specifically, we proposed that tie terminations have relational consequences, which disrupt the relationships with the abandoned collaborators and reduce the likelihood of future relationships. Going beyond the impact on existing relationships, we also assess the reputational costs to firms based on withdrawing from previous ties. We assess the flow of such reputational information at both the local and global levels. We show that withdrawals can have global reputational consequences for the withdrawing actor by undermining its reputation for reliability. Such actions also cause parties not involved in the collaboration to be less willing to form future relationships. However, even though the acts of tie terminations are observable globally, we show that there can also be local reputational consequences, driven by the negative, private information that abandoned coinvestors spread to their immediate network contacts. We also explored how the local and global reputational consequences interactively shape tie formation outcomes, adjudicating between the competing views that negative, private information would either magnify or attenuate the effects of negative, public information. We tested these dynamics in the VC setting, focusing on how a VC firms' decisions to withdraw from syndicates affect their likelihood of subsequent syndication with a particular alter.

Our results suggest that withdrawals from syndicates have both relational and reputational consequences. V firms are less likely to form ties with alters who have previously abandoned them or their syndication partners. Furthermore, the overall proportion of withdrawals in a VC firm's track record reduces the likelihood that any VC firm will select it as a syndication partner. This finding implies a real cost to the withdrawal decisions, because syndication is a crucial way for venture capitalists to secure deal flows to quality ventures, to diversify their investments, and to access the complementary expertise and networks that a syndication partner can provide (Lerner, 1994). Such costs could explain the unwillingness of venture capitalists to cut ties even with underperforming investments, which prior research has suggested (Guler, 2007). In view of our findings, such behavior may be interpreted not necessarily as wrongheaded ("throwing good money after bad") but a deliberate tradeoff between the financial costs of continuing to invest in failing investments with the reputational costs of withdrawing and potentially limiting future collaboration opportunities.

Of particular interest to network scholars is our finding that a focal firm's connections to VCs that a prospective alter has previously abandoned can hinder syndication between the firm and the alter. Existing network theory virtually takes for granted that indirect connections via shared partners increase the likelihood of direct tie formation between two actors. Our findings add an important caveat to this stylized fact: depending on the experiences the shared partner has had interacting with each of the actors, an indirect tie can carry either positive or negative private information, with corresponding effects on future tie formation behavior.

We also show that a VC firm's connections to abandoned syndication partners of the alter reduces its sensitivity to the alter's overall past history of withdrawals. This finding supports a perspective rooted in the idea that redundant information has diminishing marginal effects on behavior. To the extent that the public information is consistent with, and thus does not modify, the priors established by the presence of private information, it has little effect on behavior. The findings may also be driven in part by the unique features of the due diligence process, in which actors are focusing on finding disqualifying information about the prospective partner. If a sufficient threshold of negative information is reached, they are likely to terminate the search for additional information.

Based on the coefficients in our empirical analyses, alters that have very high proportion of past withdrawals (above the 85^{th} percentile) have a higher estimated likelihood of syndicating with firms that are connected to their abandoned coinvestors than those who are not. One possible interpretation is that firms that have withdrawn so frequently might have done so under extenuating circumstances, such as a temporary liquidity crisis. Such circumstances cannot be known without a rich understanding of the reasons for the withdrawals that only firsthand observers can provide; without such private information, other VC firms can assume the worst about such multitude of withdrawals.

Although a VC firm's connections to abandoned syndication partners of the alter attenuate its sensitivity to the alter's past history of withdrawals, connections to non-abandoned syndication partners of the alter magnify the sensitivity to the alter's history of withdrawals. In fact, if the focal firm has no ties to non-abandoned syndication partners of the alter, the alter's withdrawal rate has virtually no effect on the probability of syndication. Our explanation for this counterintuitive finding draws on Wang's (2010) idea that referrals can attract attention to a prospective alter, but have little effect on the detailed evaluation process. Similarly, the positive private information received from non-abandoned syndication partners of the alter can trigger the focal firm to begin due diligence on that alter, but if that investigation reveals an extended history of withdrawals, the syndication is less likely to happen.

This study contributes to the research on network evolution by demonstrating the effect of tie dissolutions on subsequent tie formation within the network. Network scholars have long been aware that the prior patterns of tie formation have a strong influence on future tie formation. Several studies have shown that actors are likely to form new collaborative ties with their past collaboration partners and those connected to their past collaboration partners (Baum et al., 2003; Chung et al., 2000; Gulati, 1995b). We extend these ideas by showing that the shadow of past ties is not always positive and that withdrawal events like the ones we examine here can disrupt the relationships with the abandoned coinvestors and reduce the likelihood of future syndication with their network contacts. As such, withdrawals can break the inertial preference for such repeat and structurally proximate ties and thus play an important role in the network churn often observed (Rowley et al., 2005; Sytch & Tatarynowicz, 2014a).

The present study also highlights the role of social structures in moderating the global reputational consequences of withdrawals. Prior research on reputation has largely assumed a direct link between reputation-relevant actions and reputation-related outcomes. For example, a reputation built on victories in certification contests increases a firm's odds of survival (Rao, 1994); unethical actions that sully an organization's reputation reduce its attractiveness to partners (Sullivan et al., 2007); and a track record of prior success increases the likelihood of successful fundraising (Hillmann & Aven, 2011). Global reputation is an attribute of the actor, and, in fact, much of the management research on reputation has treated it as an intangible property of the firm, almost inseparable from its name (Fombrun, 1996; Fombrun & Shanley, 1990). Only recently have scholars started recognizing that reputation varies across different audiences (e.g., D'Aveni, 1996; Jensen, Kim, & Kim, 2012; Lamin & Zaheer, 2012). Our results contribute to the growing interest in the heterogeneity of reputational effects by suggesting that social ties play a powerful role in shaping how different actors react to the same alter's track record of behavior. Direct exposure to those likely to pass negative information about an alter desensitizes a focal firm to the alter's history of withdrawals; in contrast, direct ties to those most expected to pass positive information about the alter increase the attention that the focal firms pay to the alter's past behaviors. We hope the present study encourages future research to shift from studying general reputation to a more nuanced investigation of the antecedents and consequences of reputation with individual exchange partners—in effect developing a dyadic theory of reputation.

Future research can address several limitations of this research that were largely unavoidable given the nature of our data. Our first challenge was that the decision to withdraw is non-randomly assigned and could be driven by unobservable factors that affect future syndication. We have addressed some obvious sources of endogeneity within the constraints of our data. Our controls for the capital availability of the firm (percentage of capital invested, age of most recent fund) address the most obvious source of time-variant heterogeneity; that is, capital constraint can simultaneously force premature withdrawals and make the VC firm a less attractive exchange partner. Our robustness tests using firm-fixed effects are intended to address any time-invariant unobserved heterogeneity, for example, some elements of a firm's investment strategy that simultaneously make it more likely to withdraw and also less likely to choose to engage in syndicates. Our data does not allow us to rule out other sources of endogeneity. For example, a firm may be more willing to withdraw from a syndicate if it no longer values the relationships with its syndication partners and does not plan future syndication with them. Such a scenario is especially likely if during syndication the firm had a relationship breakdown with its coinvestors or became disillusioned of their capabilities. In this alternative account, the withdrawing firm may, in fact, be the one avoiding the former coinvestors with whom it did not go along so well.[34] We see the promise of future qualitative research taking a deep look at the dynamics of the relationship between syndicating VCs both before and after the withdrawal. Such research could examine the role of factors such as future expectations of the collaboration ("the shadow of the future" as per Heide & Miner, 1992; Poppo, Zhou, & Ryu, 2008) play into the decision.

[34] This alternative explanation is especially important for interpreting the relational consequences of withdrawals but is less relevant to the relational consequences of withdrawals. It is not clear why a withdrawing firm might avoid not only the coinvestors that it no longer likes or respects, but every VC connected to them—or even every VC in general.

Another challenge that we hope future research will examine is digging deeper into understanding the heterogeneity of withdrawal types and their implications.[35] Our archival data does not allow us to look into the circumstances of each withdrawal and how these shape the attributions and interpretations that observers draw from the withdrawing firm's behavior. Some of our post-hoc findings illustrate the promise of such an approach. For example, we find that withdrawals by financially constrained firms prompt less severe reputational consequences than withdrawals by firms that do not suffer such constraints. These results are consistent with an attribution process in which observers discount the informational value of an action if it is considered unavoidable rather than a deliberate choice (Weiner, 1985). However, the data did not support other predictions of attribution-based models—for example, a subsequent failure of the abandoned syndicate would serve as an ex post justification for withdrawal and also reduce reputational consequences. Such conflicting results make it important to develop a deeper understanding of the heterogeneity of withdrawals, going beyond archival data and including more qualitative or survey evidence.

Future research can also examine the generalizability of our theory to other settings. Although our analyses are set in the VC industry, we believe that the underlying mechanisms behind this dynamic are likely to generalize across a broad spectrum of interorganizational collaborations such as strategic alliances and investment banking syndication. In all of these settings, the reliability of partner contributions is considered important (Li & Rowley, 2002;

[35] The importance of the withdrawal's context is a key reason we would be skeptical of using natural experiment or instrumental variable analysis to try to obtain a precisely identified estimation of the relational and reputational consequences of withdrawal. Scholars can potentially identify an exogenous shock that is likely to increase the likelihood of withdrawals, such as an industry-wide liquidity shock (cf. Townsend, 2011); however, external audiences may interpret withdrawals prompted by such exogenous constraints differently than unforced withdrawals. Therefore, it may be more important to explore the variations of the effects of withdrawals depending on their type than trying to identify precisely the effects of the "average" withdrawal.

Ring & Van de Ven, 1994), and reputational considerations play an important role in selecting partners (e.g., Sullivan et al., 2007). Different settings, however, can exhibit variations in the local institutional context regarding expectations of the partners (e.g., Vasudeva, Spencer, & Teegen, 2013), the reasons behind the tie dissolutions, as well as the interpretations that audiences attach to tie dissolutions. For example, in the North American VC industry, withdrawals are easily attributable to a decision of the withdrawing firm due to investor protections enshrined in syndication contracts. In other settings, investor protections may be weaker and organizations can be ousted from collaborations by more powerful or politically connected partners. Audiences are likely to draw different inferences if an actor chose to withdraw from a collaboration than if it was forcibly removed.

Another limit to the generalizability of our results comes from unique features of the VC industry, which may strengthen the importance of private information exchange for future tie formation. Venture capital firms are small and cohesive (rarely exceeding a dozen principals) and can be conceptualized easily as unitary actors that form positive or negative impressions from interacting with other VC firms. They can thus pass on such private information to other actors. In contrast, some large organizations (e.g., IT or pharmaceutical companies) have multiple highly autonomous divisions that would not necessarily share much information with each other regarding all their collaborations.[36] If a division is disappointed in its dealings with a particular partner, other divisions may not necessarily pass on this experience to their partners. Thus, the internal cohesion within an organizational actor can play a key role in its effectiveness as a conduit of reputational information (cf. Vissa & Chacar, 2009).

[36] This is a key reason that a centralized alliance management function is important for the performance of strategic alliances—it can act as an aggregator of the alliance experience of the various units that would rarely communicate directly with one another (Kale et al., 2002).

In summary, this research is an early step in building our understanding of how relationship disruptions, in this case, withdrawal from VC syndicates, can have not only dyadic implications, but also broader reputational consequences that affect relationships with third parties, both proximate and distant. We hope that future research will build on the present work and develop a better understanding of the underlying mechanisms, boundary conditions, and generalizability of our findings.

Chapter 3

When Does the Glue of Social Ties Dissolve? Collaboration Embeddedness and Performance Signals in Withdrawals from Venture Capital Syndicates

3.1 Introduction

Research in interorganizational network dynamics over the past 20 years has focused largely on the antecedents of collaborative ties and partner selection. Little research has focused on the stability of the collaboration itself, a lacuna noted by many prominent researchers (e.g., Greve et al., 2010). Only a handful of studies have examined the antecedents of dissolving interorganizational ties; for example, the unplanned termination of strategic alliances (Chung & Beamish, 2010; Park & Ungson, 1997; Polidoro et al., 2011); withdrawal of partners from ongoing alliances (Greve et al., 2010; Greve et al., 2013); and the failure of venture capital (VC) firms to provide continued support for a given portfolio company (Guler, 2007).

Two major explanations of tie stability have emerged from the aforementioned research. First, some scholars have focused on the social context in which the relationship has been established (e.g., Greve et al., 2010; Polidoro et al., 2011). Grounded in embeddedness theory within sociology (Granovetter, 1985), this perspective has maintained that the same structural factors that increase the probability of tie creation are also associated with its duration. For example, a history of extensive prior collaboration between actors not only makes them more likely to enter into repeat relationships, but also increases their aversion to terminating ties due to the mutual dependence, trust, and emotional attachment developing between collaborating partners (Deeds & Hill, 1999; Park & Russo, 1996; Uzzi, 1997). Similarly, a large number of shared partners between two firms can increase the odds of tie formation due to referral processes, but can also play a stabilizing role in ongoing collaborations due to the partners' reputational concerns (Polidoro et al., 2011).

A second perspective focuses on the performance signals an organization receives after embarking on a collaboration. The basic theoretical proposition is that partners in instrumental collaborations make withdrawal or retention decisions based on expected pay-offs relative to alternatives (cf. Dixit & Pindyck, 1994; Vroom, 1964). Because the pay-offs are uncertain, however, actors focus on performance signals, which I define as any information that predicts the eventual success of the collaboration. Negative performance signals can weaken performance expectations and trigger a search for alternative behaviors, including abandoning the effort (Cyert & March, 1963; Greve, 2003). Not surprisingly, significant quantitative and field evidence exists that signs that an interorganizational collaboration is performing poorly can hasten its demise (e.g., Arino & de la Torre, 1998; Chung & Beamish, 2010; Doz, 1996; Ring & Van de Ven, 1994).

Despite the plausibility and the evidence in favor of each perspective, our understanding is limited regarding how the effects of social embeddedness might be shaped by performance signals. Organizational theory makes conflicting predictions. On the one hand, good reasons exist to believe that the holding power of social ties is greatest exactly when the economic pressures are pointing toward an exit.[37] For example, the greater uncertainty triggered by negative performance signals stimulates a preference for familiar others (Beckman, Haunschild, & Phillips, 2004; Mizruchi & Stearns, 2001; Podolny, 1994), thus reinforcing the stickiness

[37] This spirit is well captured by the title of a recent article – "When the social structure overshadows competitive incentives: The effects of network embeddedness on joint venture dissolution" (Polidoro et al., 2011).

induced by prior ties. Second, weaker performance can trigger pressures from collaborators not to break ranks (Guler, 2007), which would be more effective if prior ties have built mutual dependence and increased the potency of retaliation threats (Heide & Miner, 1992). Finally, emotional commitments can make exit impossible even if a firm recognizes that it is against its economic interest (Sgourev & Zuckerman, 2011).

Equally compelling arguments can be made for the opposite perspective: that poor performance signals might undermine the holding power of social ties. Decisions to withdraw might be triggered either by relationship conflicts or by unsatisfactory performance. Social embeddedness might reduce the incidence of relational conflicts and thus be highly predictive of withdrawal when performance is good. In contrast, it may be a less important driver when times are bad and exits are driven primarily by economic factors. Furthermore, relational cohesion is threatened when the relationship does not deliver the expected economic value (Li & Rowley, 2002; Ring & Van de Ven, 1994; Rowley et al., 2005). Even embeddedness theorists such as Granovetter acknowledge that social ties have less of an effect when the economic pressures are high enough (1985: 492).

The key to resolving this tension is recognizing that the attachments embeddedness creates can differentially affect the processing of different performance signals. A long-established tenet of social psychological research holds that ambiguous signals are more susceptible than unambiguous signals to misinterpretations by individuals who have conscious or unconscious preferences about the final conclusions (Dunning, Meyerowitz, & Holzberg, 1989; Hsee, 1996; Kunda, 1990). To the extent that extended prior collaboration is associated with growing emotional attachment and greater mutual dependence among the collaborators (Lawler, 2001; Lawler et al., 2000; Uzzi, 1997) actors will be motivated to maintain a positive expectation of collaborations with long-term prior partners. Therefore, actors would be particularly inclined to discount negative performance signals that are of ambiguous relevance to the focal collaboration, but would be less willing and able to ignore negative performance signals that are unambiguously connected to the collaboration.

In the present study, I test these predictions in the context of the VC industry from 1985 to 2009 by studying what determines VC withdrawals from ongoing syndicates. For the purpose of the present paper, I define withdrawals as the failure to contribute additional financial capital in subsequent rounds of investment. The staged nature of the investments and the strong expectations of continuous participation until the end of the syndicate (Guler, 2007) make this an ideal setting to examine withdrawal behavior. Although withdrawals from VC syndicates are relatively rare,[38] they are significant in that they often involve breaking ranks with—and potentially damaging the relationship with—one's coinvestors. Furthermore, withdrawals can have devastating consequences for the portfolio companies, disrupting critically needed financing, while leaving a strongly negative signal in the marketplace (Townsend, 2011).

The present study makes two major contributions. First, it deepens our understanding of the conditional nature of embeddedness (Mizruchi, Stearns, & Marquis, 2006) in the context of dissolving collaborative relationships (Greve et al., 2010; Polidoro et al., 2011). It does so by highlighting the limits of the power of prior social ties in holding together interorganizational collaborations. Second, it contributes to the literature of learning from performance feedback (Greve, 2003) by showing how different classes of performance signals—general versus collaboration-specific—are processed differentially due to motivated cognition processes.

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[38] Withdrawals from VC syndicates are approximately 15%, as opposed to more than a 50% dissolution rate for alliances and joint ventures (Kale & Singh, 2009)

3.2 Theory and hypotheses

Embeddedness, expectations and attachments. A significant body of research has focused on the positive influence of embeddedness between actors – that is, the presence of long history of collaboration between them – on the stability of their present collaborations (Greve et al., 2010; Park & Russo, 1996; Park & Ungson, 1997; Polidoro et al., 2011). There are two major logics that are consistent with why actors are less likely to terminate embedded collaborations. Expectational logic maintains that actors are more willing to remain in embedded relationships because of the higher anticipated performance from those collaborations. Attachment logic, in contrast, focuses on considerations that go beyond the expected pay-off from the focal collaboration. For example, actors may expect future benefits for preserving the broader relationship with the collaborator or the emotional attachment to the relationship is an end in itself.

Expectational logic maintains that actors have higher anticipated pay-off from embedded collaborations than non-embedded ones. They are more likely to trust the partners, whether due to greater familiarity with their integrity and motivations (Gulati, 1995a; Gulati & Sytch, 2008), mutual dependence that makes misbehavior damaging to the long-term interests of the offender (Axelrod, 1984; Heide & Miner, 1992; Poppo et al., 2008), or emotional attachments (Lawler et al., 2000; Uzzi, 1997). This trust reinforces expectations that alters will do their part to ensure the success of the relationship and will not engage in activities that might be detrimental to the ego's pay-offs from the collaboration. Furthermore, actors can be more confident that embedded relationships will create value because they have first-hand knowledge of the alters' capabilities and the collaboration is benefitting from partner-specific routines and cospecialized assets from past collaborations (Dyer & Singh, 1998; Mayer & Argyres, 2004; Zollo et al., 2002). All in all, actors may be more likely to stay in embedded relationships because they expect an equitable piece of a larger pie (cf. Gulati, Wohlgezogen, & Zhelyazkov, 2012). Hereafter, I refer to this phenomenon as the expectational gap between embedded and non-embedded collaborations.

In contrast, the attachment logic argues that the relationship itself can be a source of attachment that transcends pay-off considerations from any single collaboration (Uzzi, 1997). For example, the mutual dependence fostered by long-standing ties creates a "shadow of the future" that increases the long-term cost of terminating the relationship and discourages relationship-damaging exits that would be rational if actors only cared about the probability of success of the focal collaboration (Guler, 2007). In such case, actors may be trading off reduced pay-offs from the present collaboration for expected benefits from future collaborations. Furthermore, actors can develop emotional connections that can sometimes cause them to stay in relationships even if they realize it is not in their best monetary interest in both the short and the long term (Gompers, Xuan, & Mukharlyamov, 2012b; Sgourev & Zuckerman, 2011). In this case, it is no longer the parties controlling the relationship but "parties being controlled by the relation itself" (Emerson, 1962: 34; cf. Uzzi, 1996).

Both the expectational and the attachment logics point in the same direction, even if they disagree with the particular mechanisms. In both logics, actors are less likely to exit embedded relationships, whether this arises from performance expectations or non-performance related attachments. However, the two perspectives disagree on how performance signals moderate the effects of embeddedness. If the expectational mechanism dominates, then the performance signals will rapidly override the initial expectations of high pay-offs shaped by embeddedness; thus negative performance signals can quickly eliminate the stability advantage of embedded ties (cf. Greve et al., 2010). Conversely, if attachment mechanisms dominate, then performance signals will have little effect on heavily embedded collaborations (Sgourev & Zuckerman, 2011). In the next section, I will propose a third possibility: that is, although performance expectations are important for remaining in the collaboration, the attachments created by embeddedness can bias the interpretation of some performance signals.

Performance signals and embeddedness. Abundant research on the stability of exchange relationships focuses on the role of performance signals in the decisions to terminate a collaboration. In particular, a wide range of theoretical perspectives assume that negative performance signals undermine actors' willingness to continue investing in the collaboration. In psychology, reduced expectancy of a positive outcome is typically associated with lower commitment and effort (Vroom, 1964). According to the Carnegie School, negative feedback can trigger problemistic search, which can result in abandoning the current course of action (Cyert & March, 1963). Finally, expectations of the ultimate valuation is the primary determinant of reinvesting in the real options approach in economics (Dixit & Pindyck, 1994). The idea that negative performance signals tend to undermine the stability of collaborations has also been supported by empirical research in a variety of settings—from investment banking syndicates (Li & Rowley, 2002; Rowley et al., 2005) to joint ventures and alliances (Arino & de la Torre, 1998; Chung & Beamish, 2010).

Theorists have examined two types of signals: general (e.g., Tong & Li, 2011) versus specific (e.g., Chung & Beamish, 2010). General performance signals affect the anticipated probabilities of success for all collaborations in a certain domain. For example, certain industries may go out of fashion on the financial markets, reducing the chances of a successful initial public offering (IPO); certain academic topics may go out of fashion, reducing the chances of publication in high-status journals; and technological advances can obsolete the R&D efforts in other domains. In contrast, specific performance signals only relate to the focal collaboration. For example, a molecule championed by a biotech startup may not pass the regulatory process or a large survey in which two collaborating scholars have invested significant time does not yield meaningful results. The main effect of both general and specific performance signals can be presumed to be in the same direction; that is, negative signals of either type can downgrade the expectation of the venture's performance and thus increase the probability that at least some of the collaborators will withdraw (Chung & Beamish, 2010; Cui, Calantone, & Griffith, 2011; Greve et al., 2013).

Theory is silent, however, regarding how signals relate to the presence of prior ties between the partners. Here, I argue that the expectational and attachment mechanisms yield discrete predictions about how embedded actors react to negative performance signals of any type. If the attachment mechanism dominates completely, then actors in embedded relationships may be willing to even go against their perceived economic interest to preserve a relationship that has taken on a value for its own sake (cf. Uzzi, 1997). The clearest example is provided by Zuckerman and Sgourev (2011), who documented how loyalty and psychological attachments can lead business owners to continue participating in an industry peer network, despite acknowledging that the costs of such actions far outweighed the benefits. As a result, embeddedness may not matter when the performance signals are positive, because few collaborations would break up in such cases anyway. It would be extremely important, however, when the performance signals are negative and when only the embedded parties continue the relationship.

The expectational mechanism gives completely opposite predictions. It depends entirely on the difference in expectations between embedded and nonembedded collaborations. Although the expectational advantage of embedded collaborations is likely ex ante due to the partners' familiarity and the existing stock of partner-specific routines and cospecialized assets, such expectations can be overridden by ex post performance signals (cf. Greve et al., 2010: 309). If the performance signals are consistent with positive expectations, then we expect limited change in the anticipated pay-off from the collaboration due to information redundancy (Haunschild & Beckman, 1998; Schwab, 2007). In other words, new information is anticipated to have a greater marginal effect if it conflicts with pre-existing expectations. Therefore, to the extent that negative performance signals suggest that the initial optimism is not warranted and actors adjust their expectations accordingly, we expect that the expectational gap between embedded and nonembedded collaborations will shrink and the relationship between embeddedness and withdrawal from the interorganizational collaboration will decline.

In summary, the attachment perspective assumes that embedded actors are largely oblivious to performance signals; in contrast, the expectational mechanism assumes that they react dispassionately to performance signals. We can reconcile those two perspectives by arguing that the attachments shape the way that actors interpret performance signals. Within organizations, accountability pressures mean that actors cannot be fully oblivious to performance signals and, at minimum, need a rational veneer to justify their actions (Tetlock, 1985). However, attachments can play an important role by shaping the perceptions and interpretations of the performance signals. Actors tend to overemphasize the signals that conform to their prior expectations and preferences and discount contradictory evidence (Nickerson, 1998; Snyder, 1992). For example, people have been shown to explain away the losses of their favored team as a fluke, but not its victories (Gilovich, 1983). Such logic suggests that we expect embeddedness will have the greatest effect on tie stability when it helps discount otherwise troubling negative performance signals.

Not all signals are created equal, however. Specifically, the ambiguity of the signal dramatically increases the role that self-serving biases play in its interpretation (Hsee, 1996; Kunda, 1990). For example, people tend to dramatically overestimate their worth along ambiguous dimensions, such as leadership, but are remarkably precise in their self-assessment along unambiguous dimensions such as height (Dunning et al., 1989). This behavior extends beyond mere self-delusions; indeed, people are more willing to stretch the truth when communicating ambiguous as opposed to unambiguous information, even though there is no likelihood of being caught in either case (Schweitzer, 2002).

Crucially, we contend that general performance signals present greater ambiguity than specific signals.[39] Other firms may be struggling with a certain strategy or similar collaborations may be facing distressed fortunes. However, firms can always discount how much such cases are similar to the collaborations that they favor, in the same way that one might estimate their odds of having a disease as being lower than the overall population that shares the same risk factor (Jemmott, Ditto, & Croyle, 1986). Thus, actors will be more likely to give the benefit of the doubt to the embedded collaboration that they already favor than to nonembedded collaborations about which they are more neutral. If the negative performance signals are discounted for the embedded collaborations but not discounted for the nonembedded ones, I predict the expectational gap will grow, and actors will abandon the latter while doubling down on the

[39] Real options scholars have argued that ambiguity should lessen the potency of a signal. In the face of a negative signal, actors will be averse in making irreversible actions, such as terminating their participation, in order to preserve the project's option value (Bragger, Bragger, Hantula, & Kirnan, 1998; Dixit, 1992; Dixit & Pindyck, 1994). However, note that this applies to the main effect only and not to its interaction with embeddedness, which is the core interest of the present investigation; no one in that tradition has suggested the possibility of differential treatment of different types of investments.

former. Namely, I argue that the in the face of general negative performance signals, the attachment logic will dominate, and the effect of embeddedness on tie stability will increase. Against this background, I present my first hypothesis:

> ***Hypothesis 1:*** *Negative general performance signals will strengthen the effect of collaboration embeddedness on the probability of continued participation.*

Conversely, specific signals are proximate to the collaboration and less likely to be discounted as irrelevant, even by motivated parties (Kunda, 1990). Actors process unambiguous feedback much more objectively than ambiguous feedback (Dunning et al., 1989). As such, I argue that specific negative signals will be tempered by attachments to a lesser extent. As a result, I expect the reasoning underlying the expectational logic to hold: the higher the ex ante expectation is, the lower it is likely to fall as actors incorporate discordant information from other sources (cf. Rhee & Haunschild, 2006; Schwab, 2007). Specific negative evaluations will therefore downgrade assessments of embedded collaborations more than they do for nonembedded collaborations. This, in effect, shrinks the expectational gap between the two and reduces the effect of embeddedness on continuing to participate in the collaboration. I thus present my second hypothesis.

> ***Hypothesis 2:*** *Negative collaboration-specific performance signals will weaken the effect of collaboration embeddedness on the probability of continued participation.*

Figure 3.1 summarizes the theoretical framework. My baseline expectation is that embeddedness between the collaborating parties will reduce the likelihood of withdrawal, while negative performance signals will increase the likelihood of withdrawal. My core hypotheses are that negative general performance signals will strengthen the negative effect of embeddedness on the likelihood of VC firm withdrawal (Hypothesis 1), while negative specific performance signals will attenuate the negative effect of embeddedness on the likelihood of VC firm withdrawal (Hypothesis 2).

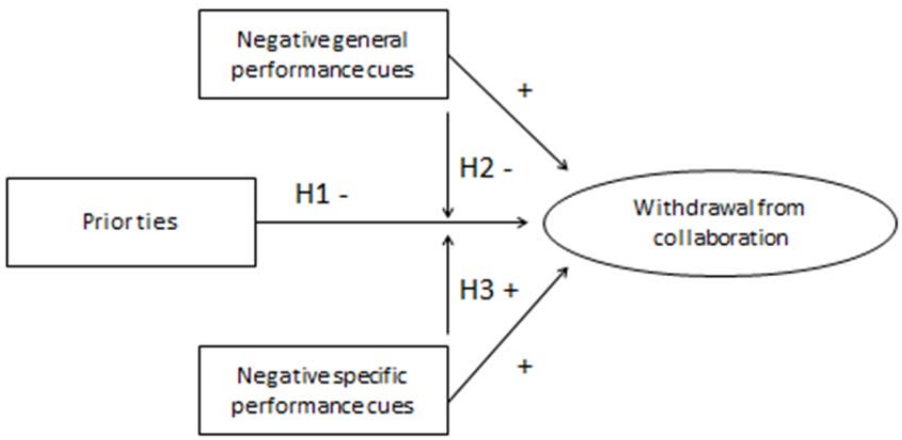

Figure 3.1: Theoretical framework

3.3 Research context

The syndication process in venture capital has long fascinated both finance (Gompers & Lerner, 1999) and organizational scholars (e.g., Podolny, 2001; Sorenson & Stuart, 2001). Borne out of the need for both risk sharing and tapping the complementary expertise critical for the early life of new ventures, syndication requires significant commitments in both financial capital and managerial attention from all major participants in the syndicate. Beyond contributing capital, most coinvestors are expected to sit on the board of the company and contribute management advice and coaching, as well as connect the company with their own networks (Gorman & Sahlman, 1989). To the extent that any member does not pull its weight in terms of financial or nonfinancial contributions, the performance of the venture—and the returns of all coinvestors—are likely to suffer. This makes trust a question of significant importance; as such, the role of prior relationships in selecting partners has been documented amply in the literature (Sorenson & Stuart, 2001, 2008). At the same time, VC managers are also acutely aware of their bottom line: there is a great dispersion of profits within the industry, and new funds flow consistently to the top performers (Kaplan & Schoar, 2005).

The staged nature of VC investments makes the industry an especially appealing setting to test my theory of withdrawing from interorganizational collaboration. Disbursing the investment in rounds, with each round conditional on the venture achieving pre-specified milestones, was devised as a solution to the dual problem of high uncertainty of picking ex ante winners and the agency costs of decreasing the stakes of managing the business. Staging the investment limits the investors' commitments in the earliest phases of the investment, when the uncertainty is the highest, all while keeping a tight leash on the entrepreneur who depends on the subsequent cash infusions (e.g., Gompers, 1995b).

The critical objectives of the VC firms participating in the syndicate is a successful exit, defined as either an acquisition by another company or preferably, an IPO within a reasonable time horizon of perhaps three to five years. To the extent that companies make acceptable progress towards the exit, VC firms steadily increase their valuations at each successive round, which reflects the increased expected payoff of a reward to the entrepreneur (Gompers & Lerner, 1999). A complete loss of confidence in the company, on the other hand, will most likely mean dissolving the syndicate and terminating future financing. There is a gray zone, however, where the portfolio company may be experiencing difficulties, but at least some of the coinvestors believe it still has a chance of success. Such situations are called down-rounds—additional financing is offered at lower valuation than previously. Down-rounds indicate a significant increase in the collaboration-specific risk as perceived by the funding syndicate.

At the same time, the potential exit valuation—and the probability of an exit—is affected not only by the health of the company but also the state of the financial markets. One popular type of market signal is the valuation of already public companies in the same industry as the focal portfolio company. A particularly well-suited measure is the book-to-market ratio, reflecting the ratio of the book shareholder's equity versus the market valuation; indeed, this reflects the value of the assets the VCs have poured into the company and is likely to be relevant for both the value of an IPO and a potential acquisition. More generally, the measure has been used throughout both the finance and the management literature as a proxy for the market's expectations of future growth of companies in the sector; this is a question of particular importance for VC firms (Fama & French, 1992; Tong & Li, 2011). Another very popular measure, the price-to-earnings ratio (the price per share divided by the earnings per share) is less appropriate in the context of this study, because it is meaningless for companies with negative earnings. Filtering out unprofitable companies can introduce severe biases. This is a particularly serious issue with some of the most popular sectors for VC activity, such as the internet and biotechnology, which feature both enormously profitable companies and many unprofitable ones.

VC firms withdraw from a syndicate for several reasons. Arguably the most common reason—and the primary theoretical engine behind my hypotheses—is disagreement among the coinvestors or the management team about the direction or prospects for the venture's success. All of my reasoning is based on discretionary withdrawals; however, I address other possible reasons with my analyses. The most common alternative reason for withdrawal is that a venture capital firm may be running out of money, either because it has spent most of its funds on other firms, or because it has set aside large reserves to support other ventures. A related concern, especially for smaller funds, is that they may be reaching the upper limits of their contributions if their charter mandates maximum concentration limits; for example, that no more than 5% of a fund be invested in a single company. Because such decisions are arguably made under duress, they have very different antecedents and therefore require a set of controls such as age of the investing fund, percent of the fund already invested in the company, the proportion of uncommitted capital, and the favorability of the funding environment. Finally, some of the withdrawals may have been prenegotiated, in the sense that a VC firm may have agreed or been asked to participate only in the early rounds. Some smaller VC firms will not have the financial firepower to participate in later rounds and target only the early segment of the market. I address this problem in the robustness tests.

3.4 Data and variables

Data. My core data source came from Thompson Reuter's VentureXpert database. This database has been tracking venture capital fundraising, investments, and exits since the 1970s and is used for research in both finance and economic sociology (Podolny, 2001; Sorenson & Stuart, 2001, 2008). To clean the data, I progressed through several steps. First, I excluded all non-US VC firms and all non-US investments. My intent was to focus on the dynamics specifically within the US venture capital market. Second, I eliminated entities not identified by VentureXpert as dedicated venture firms. Many of these entities are corporations making one-off investments in technologically related startups, and thus are not core participants to the industry. Third, I eliminated all firms that have made less than five investments over any five-year period. I excluded these inactive firms for two reasons: 1) I wanted to restrict my analyses to active participants in the industry, and my threshold (one investment per year) is a rather nonstringent criterion relative to other scholars (e.g., Podolny, 2001); 2) any network measurements will be meaningless if based on only a handful of ties. Fourth, researchers have expressed concern about the quality of the data from the 1970s (e.g., Podolny, 2001); for this reason, I dropped all data prior to 1980, and used the 1980 to 1985 period to create the initial network for 1985. The analysis itself was conducted on all investment rounds between 1985 and the end of the data series in 2009.

A critical part of my data cleaning was identifying withdrawals. Following Townsend (2011), I identify a withdrawal as the permanent disappearance of a VC firm from the ranks of the coinvestors, conditional on at least one of the coinvestors still continuing to support the portfolio company. Therefore, similarly to Greve and colleagues (2010) I modelled unilateral exit behavior from ongoing collaborations, as opposed to a collective decision by the entire syndicate to terminate the financing of the company. If a firm skipped a round, I still counted it as a participant in the syndicate for several reasons: 1) what the database may be recording as distinct rounds may be several disbursements by different groups of investors as a part of the same round; 2) many of the omissions are likely due to data errors; and 3) even if the firm did not participate in the investment (i.e., due to liquidity issues) the fact that it was admitted back suggests that it had a temporary reprieve from the other coinvestors. I also ensured that when none of the existing members of a syndicate participated in a follow-up round (e.g., if they were bought out by another syndicate) they were not counted as withdrawing. In fact, I stop tracking certain companies in the case of a complete change in syndicates, given the different dynamics of buyouts versus traditional VC investments. Finally, I did not consider withdrawals after a successful exit, such as an IPO or an acquisition, because it is customary for firms to terminate their stake shortly afterward.

Dependent variable. Following these procedures, the unit of analysis was the investment round × VC firm combination. Because a firm cannot withdraw before it has really entered, I dropped the first round in which the firm entered the syndicate. Participation in each subsequent round was included with the dependent variable *Withdrawal* coded as 0; if a firm withdrew from the alliance at round R, its entry was included for a final time at round R+1, with the dependent variable coded as 1. As a result, within each syndicate, each firm can have at most one withdrawal before disappearing in subsequent rounds.

Independent variables. The critical independent variable is the embeddedness of the firm within the syndicate, which I operationalize as the number of syndication ties the firm had to the other members of the syndicate in the prior 5 years. Five years is the standard horizon for recording network ties in prior studies in both finance and economic sociology (Hochberg et al., 2007, 2010a; Sorenson & Stuart, 2001, 2008; Trapido, 2007). Because some VCs play a larger role in the syndicate than others, I weighted the number of ties to the other coinvestors by the cumulative amount of capital each put up in the previous round. Therefore, ties to a leading member of the syndicate would weigh more than ties to a peripheral member, with little power or stake in the portfolio company. The results are similar, though, if an unweighted average of tie count to all syndicate members as of the previous round was used. In my analyses I logged this variable because it was highly skewed.

There are three other independent variables, whose interaction with the tie count form the basis for the present study's hypotheses. The *general performance cues* were determined by the valuation that public companies of the same industry as the portfolio company received on the financial markets (see for example Tong & Li, 2011). I used Compustat to calculate the industry market capitalization-weighted measures on book-to-market ratios for the month preceding the focal round, matching by four-digit NAICS. NAICS codes were available for more than 85% of the portfolio companies; for the remaining firms, I matched based on the NAICS code most representative of their VentureXpert third-level industrial classification (the most granular level, with more than 500 separate categories).[40] To account for inherent differences of valuations between industries, I subtracted the sample average for each industry, again at the four-digit NAICS level, so this variable represents the deviation from the long-term industry average. The *specific performance cues* were proxied by a dummy equal to 1 if an entity underwent a down-round, and 0 otherwise. One of the challenges is that a valuation trend—or the underlying information necessary to compute one—was only reported for about 10,000 of 40,000 observations; because disclosure is voluntary, there are likely to be significant selective reporting biases. As discussed in the *Methodology*, I followed prior literature in finance in using a Heckman correction to control for the probability of nonreporting when analyzing valuation trend data (Hochberg et al., 2010a). Finally, I measured *industry specialization* as the percentage of investments of the firm in the industry of the focal portfolio company within the past 5 years.

Control variables. I also used a large number of control variables to capture other potential drivers of withdrawal. I controlled for the *stage of the round* to proxy the uncertainty of the investment (Podolny, 2001; Sorenson & Stuart, 2008). I included three dummies representing early, expansion, and late-stage investments, with the seed stage as the omitted category. I also control for the number of coinvestors in the syndicate. On the one hand, they may represent collectively a greater amount of pressure against withdrawal (Guler, 2007), but at the same time, a large number of coinvestors can reduce the consequences of any single withdrawal (Sorenson & Stuart, 2008). I also included a dummy on whether the VC firm was *the lead investor of the*

[40] The results are robust to excluding the firms for which NAICS data is unavailable.

syndicate. Consistent with prior literature in finance (Hochberg et al., 2007), I defined the leader as the VC that has invested the most into the round, with ties broken by the total amount of cumulative investment. In rare cases where two or more firms were still tied, I classify them both as co-leads. A leader may be less likely to withdraw, because the pressure from any remaining coinvestors would be particularly high (withdrawal by the lead VC is a particularly devastating strike), but also because a withdrawal by the lead investor can mean the end of the syndicate and the financing of the company.

I used several controls to capture the effects of the general market environment. A common measure of the funding environment is *flow of institutional funds* to different subindustries for the previous quarter, weighted by the cumulative amount of the focal firm's investment in each industry.[41] In addition, I controlled for *logged number of IPOs in the company's industry* of the year prior to the round.

I was particularly careful to account for the possible funding-related reasons a particular firm may withdraw from the syndicate. First, I controlled directly for *the percentage of the most recent fund already invested*, to represent the most obvious source of funding constraint for the VC firm. Second, I controlled for *the age of the most recent fund* (capped at six years to reduce the influence of outliers) to represent its stage in the fund life cycle. Indeed, more mature funds may have already precommitted all of their reserves and thus may be less capable of supporting all of the portfolio companies, even if on paper they still have significant amounts of capital.[42] Third, I controlled for *the proportion of the most recent fund that had already been invested into*

[41] VentureXpert tracks amount raised by industry-dedicated funds in 10 global categories: biotechnology, communications and media, computer hardware, computer software and services, consumer related, industrial/energy, Internet specific, medical-related, semiconductors and electronics.

[42] Successful VC firms typically fundraise every two to three years, and funds more than six years of age represent less than 10% of the sample.

the focal portfolio company. This captured the diversification constraint; naturally, some funds cannot invest a fraction of their fund greater than a given threshold.

I incorporated several variables representing the stature of the focal firm and its relationship with the portfolio company. I measured its *overall degree centrality* within the investment network (Hochberg et al., 2007) as the logged count of the number of firms with which it has co-invested in the past five years. Finally, I included *the geographic distance from the headquarters of the VC firm to the headquarters of the portfolio company*, based on the assumption that VCs exercise more effective control overand thus may be more attached to, more proximate investments. I calculated the distance in miles using spherical coordinates and logged it due to overdispersion (Sorenson & Stuart, 2001).

I also controlled for the ties between the focal firms and the other firms in the syndicate; in all cases, the individual variables were weighted based on the cumulative contributions of each co-investor. I included the average number of shared partners with the co-investors (logged) to capture the possibility of indirect reputation effects serving as a constraint on withdrawal (Burt & Knez, 1995; Polidoro et al., 2011). I also controlled for the weighted distance between the focal firm and each of its co-investors in terms of geographic and industry specialization (Sorenson & Stuart, 2008). For the industry space, I calculated the Euclidean distance between the 10-dimensional vectors representing the percentage of investments by each firm in each of the 10 global industries (see footnote 5) of VentureXpert:

$$Ind.Distance_{lm=}\sum_{i=1}^{10}(p_{il}-p_{im})^2$$

I averaged the distances to each of its syndicate membersweighted by the co-investors' cumulative contributions. I followed the same procedure for distance in terms of geographic niches, but this time I used a 51-dimensional vector representing all states plus the District of Columbia.

3.5 Method

The modeling choices were driven by considering the potential issues that may face a normal binary response model, whether probit or logit. One issue is that we could expect a significant amount of unobserved heterogeneity in the sample. Some factors driving withdrawals could be firm-specific, for example, a strategic focus on early-stage investments. Industry may also play a role to the degree that there could be heterogeneity in local norms regarding persistence or withdrawal behavior. This could be driven in part by structural conditions within the industry. For example, in some industries the investment thesis can be tested relatively quickly (e.g., consumer Internet), whereas in others (e.g., biotechnology or clean technologies) the true potential would be unlikely to be known until after many years of investigations and significant outlays. Finally, time can independently exercise some influence, given that the nature of interorganizational embeddedness is fundamentally historically contingent (Mizruchi et al., 2006). To the extent that the variables are correlated in any way with the independent variables, estimates might be biased and inconsistent. For this reason, my model of choice was a conditional logit model grouped on the firm level and with fixed effects for both industry and year.

I also needed to account for selection at three levels. First, the probability of withdrawing from a syndicate is contingent on a firm actually joining the syndicate. To the extent that creating a syndicate is not randomized, this can create unobserved heterogeneity that biases the results (Robinson & Stuart, 2007). For example, if prior contacts between VCs are a major facilitating factor in the firms syndicating (Gulati, 1995b; Sorenson & Stuart, 2001, 2008), then those who have no other contacts and do syndicate may be high on some unobservable characteristic that facilitates syndication, such as the partners having attended the same university. If this same unobservable characteristic also reduces the future probability of withdrawal, then the impact of the prior ties variable will be attenuated; if the same characteristic increases the probability of withdrawal, then the impact of prior ties on withdrawal would be overestimated. To deal with this issue, I followed a procedure similar to Sorensen and Stuart (2001) in which I matched each VC firm's initial investment in a given portfolio company with 10 other potential investments that other firms made in the same quarter. I then used a probit to estimate the probability of a realized tie (as opposed to a counterfactual tie) based on the following independent variables: 1) the number of investments the focal firm made in the previous year and the previous five years; 2) the percentage of the firm's investments over the past five years in the same industry (based on the 10-industry VentureXpert classification); 3) state and investment stage (based on a 4-stage classification: seed, early, expansion, and later stage); 4) its geographic distance to the target; 5) the number of ties to the current investors in the target; and 5) the number of shared partners to the current investors in the target. The estimates were consistent with the normal expectations based on the literature (Sorenson & Stuart, 2001) and are available from the author. Using these coefficients, I predicted the probability of a match and calculated an inverse Mills ratio.

Second, I needed to account for the fact that I observed withdrawals only for syndicates that had subsequent rounds of funding; I did not observe the withdrawals from rounds that failed to ever materialize. To deal with this issue, I followed the approach outlined by Greve and his colleagues (2010; Greve et al., 2013) by constructing a probit model of the likelihood of syndicate dissolution, that is, failure to have a subsequent round. Broadly, there are two reasons a firm may not have subsequent rounds of funding: 1) failure of the portfolio company (such that the syndicate members collectively give up) or 2) its successful exit (such that no further funds are required). Empirically, the age of the company and the stage of its previous financing are powerful drivers that increase the probability of non-follow-up. Companies sponsored by larger, more experienced firms are more likely to have a subsequent round, as are those that are closer (geographically or via industry specialization) to the syndicate's VC members. In addition, I included dummies for the major industries and their interaction with company age to capture industry-specific norms of how long a venture is financeable (e.g., funders of Internet startups are significantly more impatient than those of biotech companies). Those analyses predicted the likelihood of overall syndicate dissolution that I used to generate the second inverse Mills ratio.

The third selection problem concerns the valuations variable. Valuations are self-reported and may be withheld for strategic purposes (Hochberg et al., 2010a). Furthermore, the coverage of the valuation variable in VentureXpert is rather low: only around 10,000 observations out of 41,000 include the valuation trend. To correct for this problem I followed a precedent in the finance literature (Hochberg et al., 2010a; Hwang, Quingley, & Woodward, 2005) and constructed a selection equation to predict the likelihood of disclosure based on the stage of the investment, days elapsed since the previous round (allowed to vary by different stages), industry, and geographic cluster. These estimations were used to construct a third inverse Mills ratio variable that was included in the analyses of the valuation trend.

The three inverse Mills ratios should not be included directly as regressors in the conditional fixed effects model, because the conditional logit model violates the assumption of normally distributed error term (Greve et al., 2010). Although the probit model satisfies this requirement, incorporating fixed effects could lead to biased and inconsistent estimates. As a result, I report both conditional logit and probit estimates to provide convergent evidence for the hypotheses (in the case of the conditional model, I use the probabilities instead of the inverse Mills ratios, as suggested by Greve et al., 2010). In both cases, I use robust standard errors clustered by VC firm.

3.6 Results

Main results. Table 3.1 reports the means, standard deviations, and correlations among all variables. The bivariate relationships have the expected direction: having a prior tie to co-investors is negatively associated, and all the risk variables are at least weakly positively correlated with the probability of withdrawals. The correlations are typically low; the most problematic variable is the logged number of shared partners, which is 55% correlated with the logged count of prior ties. This is unlikely to be a significant problem, however, because excluding it from the analyses does not significantly change the reported results. Thus, I preserved it in the model to present a conservative reading. The fact that it either loses significance or in some cases flips sign suggests that the primary constraint on withdrawals comes from direct as opposed to indirect connections.

Table 3.1: Summary statistics and correlations for all key variables

Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11
1. Withdrawals	0.169	0.375	1.000										
2. Rounds elapsed	2.344	1.607	-0.009	1.000									
3. Total # coinvestors	4.813	2.935	0.140	0.207	1.000								
4. Early stage investment	0.120	0.324	-0.052	-0.155	-0.108	1.000							
5. Expansion stage investment	0.434	0.496	-0.001	-0.032	-0.024	-0.318	1.000						
6. Later stage investment	0.409	0.492	0.047	0.175	0.126	-0.305	-0.733	1.000					
7. Age of most recent fund (years)	2.070	2.025	0.122	0.043	0.043	-0.030	-0.084	0.113	1.000				
8. Percent of most recent fund invested overall	0.272	0.278	0.047	0.055	0.037	-0.015	-0.015	0.020	0.205	1.000			
9. Percent of most recent fund invested in company	0.064	0.154	0.049	0.123	0.054	-0.036	0.000	0.035	0.070	0.316	1.000		
10. Book to market ratio deviation	0.000	0.152	0.032	0.045	0.089	-0.003	-0.002	-0.007	0.030	0.003	0.006	1.000	
11. Weighted flows (logged million $)	6.267	1.506	-0.057	-0.088	-0.235	-0.050	0.002	0.077	-0.105	-0.120	-0.032	-0.209	1.000
12. IPOs in the industry (logged)	3.080	0.799	-0.044	-0.087	-0.169	-0.043	0.037	0.018	-0.080	-0.051	-0.021	-0.283	0.564
13. Lead investor in syndicate	0.401	0.490	-0.113	-0.028	-0.307	0.072	0.024	-0.084	-0.071	-0.059	0.010	-0.032	0.082
14. Specialization in industry	0.273	0.208	0.041	-0.078	-0.050	0.021	-0.004	-0.005	0.109	-0.034	0.026	0.002	0.131
15. Distance from the portfolio company (logged)	5.206	2.489	0.044	-0.017	0.060	-0.023	0.003	0.018	-0.003	-0.009	-0.017	0.012	-0.016
16. Centrality of the focal firm (logged)	4.668	1.297	-0.116	0.167	0.146	-0.019	0.031	-0.026	-0.273	-0.019	-0.058	0.049	-0.132
17. Average number of shared partners (logged)	3.031	1.181	-0.045	0.198	0.293	-0.044	0.021	0.003	-0.192	0.014	-0.019	0.081	-0.251
18. Industry specialization distance from coinvestors	0.453	0.184	0.095	-0.071	-0.026	0.024	-0.036	0.015	0.166	0.006	0.028	-0.046	0.048
19. Geograpic specialization distance from coinvestors	0.457	0.215	0.060	-0.048	-0.026	0.012	-0.016	0.018	0.091	0.001	0.014	-0.016	0.055
20. Number of ties to coinvestors (logged)	1.151	0.586	-0.072	0.154	0.076	0.004	0.041	-0.061	-0.160	0.003	-0.014	0.057	-0.195
21. Down-round*	0.144	0.351	0.056	0.060	0.090	-0.050	-0.006	0.041	0.006	0.005	0.027	0.063	-0.083

Variable	Mean	Std. Dev.	12	13	15	16	17	18	19	20	21	21
12. IPOs in the industry (logged)	3.080	0.799	1.000									
13. Lead investor in syndicate	0.401	0.490	0.067	1.000								
14. Specialization in industry	0.273	0.208	0.128	0.014	1.000							
15. Distance from the portfolio company (logged)	5.206	2.489	-0.005	-0.031	0.014	1.000						
16. Centrality of the focal firm (logged)	4.668	1.297	-0.133	0.006	-0.400	0.008	1.000					
17. Average number of shared partners (logged)	3.031	1.181	-0.209	-0.122	-0.279	-0.011	0.817	1.000				
18. Industry specialization distance from coinvestors	0.453	0.184	0.051	0.004	0.180	0.042	-0.475	-0.539	1.000			
19. Geograpic specialization distance from coinvestors	0.457	0.215	0.071	-0.009	0.099	0.149	-0.361	-0.443	0.345	1.000		
20. Number of ties to coinvestors (logged)	1.151	0.586	-0.151	-0.021	-0.148	-0.069	0.547	0.657	-0.421	-0.353	1.000	
21. Down-round*	0.144	0.351	-0.151	-0.035	0.010	0.051	0.060	0.081	-0.085	0.012	0.026	1.000

* Correlation coefficients for the down-round valuation variable computed based on 9,722 observations for which a valuation trend was available. All of the other coefficients were computed on the 40,936 observations on which data for the remaining variables was available.

The analyses using the conditional logit with fixed firm, industry, and year effects are reported in Table 3.2. Model 1 reports the baseline model, including all the control variables and the prior social ties variable. As predicted by the baseline proposition, prior syndication ties to co-investors significantly reduce the probability of future withdrawals. Higher book-to-market ratio – indicative of depressed industry valuations – increases the likelihood of withdrawal. The directions of the control variables are largely as theory has predicted. The probability of withdrawal is lowest in the earliest stages of a portfolio company; the opportunity cost is lower due to the lower capital commitments; at the same time, the pressure from co-investors may be at its most intense early in a portfolio company's life, as a negative signal combined with the uncertainty around young ventures can doom a company (Stuart et al., 1999). The probability of withdrawal increases when the financing constraint is greater. This is due to the greater age of the fund, the smaller remaining amount of capital, or the reduced flows to the industry. Firms are also more willing to pull out from syndicates supporting geographically distant companies, just as they are less likely to participate in such syndicates initially (Sorenson & Stuart, 2001). Finally, VC firms are dramatically less likely to withdraw from syndicates when they are specialized in the same geographic and industry niches as the other co-investors. This likely reflects the greater reputational concerns.

Model 2 presents the interaction between the industry-adjusted book-to-market ratio and the logged count of prior ties to co-investors. As predicted by Hypothesis 1, the interaction is statistically significantly negative, indicating that the effect of prior syndication is greater during times of depressed industry valuations (higher book-to-market ratio). Models 4 and 5 introduce my proxy for specific negative cues—the down-round indicator—as well as its interaction with the embeddedness variable.[43] Not only is the interaction statistically significantly positive, as Hypothesis 2 predicted, but it is almost as large in magnitude as the coefficient of prior ties. In other words, during down-rounds, the effect of prior ties to the co-investors on the probability of withdrawal becomes virtually nil. Finally, Model 6 incorporates all interactions.

[43] Note that the number of observations drops due to the limited coverage of the valuation trend variable; for those equations, I have added the estimated probability of having the valuation trend available (for the conditional logit specification) or the inverse Mills ratio (in the probit specification).

Table 3.2: Conditional logit model (firm, industry, year fixed-effects) predicting probability of withdrawals from syndicates.

	Model 1	Model 2	Model 3	Model 4	Model 5
Rounds elapsed	0.0438***	0.0440***	-0.00424	-0.00528	-0.00304
	(3.54)	(3.57)	(-0.11)	(-0.14)	(-0.08)
Total # coinvestors	0.0663***	0.0667***	0.130***	0.132***	0.131***
	(10.38)	(10.47)	(7.60)	(7.65)	(7.62)
Early stage investment	-0.0122	-0.0160	0.711	0.697	0.695
	(-0.11)	(-0.15)	(1.23)	(1.22)	(1.21)
Expansion stage investment	0.139	0.134	1.067	1.058	1.046
	(1.35)	(1.29)	(1.91)	(1.91)	(1.89)
Later stage investment	0.129	0.123	1.174*	1.172*	1.154*
	(1.22)	(1.16)	(2.02)	(2.04)	(2.01)
Age of most recent fund (years)	0.0572***	0.0567***	0.0701*	0.0695*	0.0692*
	(4.20)	(4.16)	(2.53)	(2.51)	(2.49)
Percent of most recent fund invested overall	0.275**	0.273**	0.295	0.308	0.321
	(2.70)	(2.68)	(1.52)	(1.60)	(1.66)
Percent of most recent fund invested in company	0.149	0.148	0.207	0.176	0.183
	(1.04)	(1.03)	(0.61)	(0.52)	(0.54)
Weighted flows (logged million $)	-0.0888*	-0.0902*	-0.113	-0.105	-0.100
	(-2.35)	(-2.37)	(-1.18)	(-1.09)	(-1.03)
IPOs in the industry (logged)	0.102*	0.101*	0.0609	0.0662	0.0638
	(2.28)	(2.26)	(0.58)	(0.63)	(0.61)
Lead investor in syndicate	-0.390***	-0.388***	-0.450***	-0.445***	-0.445***
	(-10.08)	(-10.06)	(-4.77)	(-4.73)	(-4.72)
Specialization in industry	-0.174	-0.183	-0.423	-0.437	-0.448
	(-1.51)	(-1.58)	(-1.38)	(-1.43)	(-1.45)
Distance from the portfolio company (logged miles)	0.0186*	0.0182*	-0.0151	-0.0155	-0.0155
	(2.04)	(1.99)	(-0.66)	(-0.67)	(-0.67)
Centrality of the focal firm (logged)	-0.167**	-0.168**	-0.0951	-0.0910	-0.0954
	(-3.13)	(-3.15)	(-0.83)	(-0.80)	(-0.83)
Average number of shared partners (logged)	0.419***	0.417***	0.510***	0.513***	0.508***
	(9.88)	(9.83)	(4.40)	(4.44)	(4.41)
Industry specialization distance from coinvestors	0.706***	0.710***	0.922**	0.895*	0.892*
	(5.14)	(5.17)	(2.60)	(2.52)	(2.50)
Geograpic specialization distance from coinvestors	0.498***	0.499***	0.319	0.311	0.294
	(4.44)	(4.45)	(1.10)	(1.07)	(1.01)
Probability - Selection into Syndicate	-0.0797	-0.0868	-0.923*	-0.926*	-0.926*
	(-0.54)	(-0.59)	(-2.55)	(-2.56)	(-2.54)
Probability - Syndicate End	3.217***	3.230***	3.301***	3.290***	3.311***
	(9.82)	(9.82)	(4.33)	(4.32)	(4.34)
Probability - Valuation Trend			-1.006*	-1.045*	-1.010*
			(-2.26)	(-2.36)	(-2.29)
Number of ties to coinvestors (logged) - A	-0.232***	-0.223***	-0.225+	-0.310*	-0.358**
	(-4.38)	(-4.19)	(-1.83)	(-2.48)	(-2.87)
Book-to-Market Ratio Deviation - B	0.394***	0.419***	0.536*	0.561*	0.406+
	(3.83)	(4.18)	(2.37)	(2.47)	(1.68)
A × B		-0.567***			-1.312**
		(-3.39)			(-2.94)
Down-round - C			0.146	0.146	0.144
			(1.24)	(1.26)	(1.25)
A × C				0.443*	0.494*
				(2.23)	(2.48)
N	39504	39504	8197	8197	8197
Pseudo R-square	0.0523	0.0528	0.0904	0.0916	0.093

T-stats in parentheses (clustered by firm). * *p*<.05, ** *p*<.01, *** p<.001

Table 3.3 shows the identical specifications for a probit model, which may be better able to capture some of the selection effects at the cost of losing the benefit of firm fixed-effects. All three selection coefficients are highly significant (as opposed to just two in the case of the conditional logit) in the predicted direction. A better fit to the syndicate reduces the probability of withdrawal, whereas a greater probability of syndicate dissolution increases the probability of withdrawal. Otherwise, the directions and the significance of the effects are consistent in the probit and the conditional logit specifications, reinforcing my confidence in the findings.

The economic significance of the interactions are pronounced. In the conditional logit model, a single standard deviation increase in the negative general signals increases the coefficient for embeddedness from approximately .22 to approximately .28, a more than 25% increase. The specific negative signal variable has even stronger moderating effect; it is strong enough to virtually obliterate the effects of embeddedness on withdrawals, and in fact, it reverses its sign (though the positive slope for down-round observations is not significantly different from 0). Figure 3.2 and Figure 3.3 present both major moderating effects, taken from the probit specifications.[44] Figure 3.2 shows that the increase from an average of zero to an average of three ties to coinvestors reduces the likelihood of withdrawal from 12% to 10% when the conditions are relatively favorable (i.e., industry-adjusted book-to-market ratio one standard deviation below mean); the same change of embeddedness changes the likelihood of withdrawal from 16% to 9% when the industry conditions are poor (i.e., industry-adjusted book-to-market ratio one standard deviation above mean). Figure 3.3 shows that a downround not only increases the probability of withdrawal, but also completely removes the effects of embeddedness on withdrawal.

[44] To estimate predicted probabilities I used the “Clarify” package for STATA developed by Gary King and colleagues (Tomz, Wittenberg, & King, 2003).

Table 3.3: Probit model (industry and year fixed effects) predicting probability of withdrawal from syndicates.

	Model 1	Model 2	Model 3	Model 4	Model 5
Rounds elapsed	-0.0317***	-0.0318***	-0.0645***	-0.0646***	-0.0648***
	(-3.82)	(-3.83)	(-3.50)	(-3.52)	(-3.53)
Total # coinvestors	0.0451***	0.0454***	0.0754***	0.0755***	0.0757***
	(12.80)	(12.93)	(10.25)	(10.25)	(10.28)
Early stage investment	-0.0175	-0.0186	0.0925	0.0874	0.0913
	(-0.33)	(-0.35)	(0.45)	(0.42)	(0.44)
Expansion stage investment	0.157**	0.156**	0.299	0.295	0.300
	(2.99)	(2.96)	(1.54)	(1.52)	(1.55)
Later stage investment	0.162**	0.161**	0.215	0.211	0.215
	(3.06)	(3.04)	(1.09)	(1.07)	(1.10)
Age of most recent fund (years)	0.0476***	0.0476***	0.0897***	0.0895***	0.0894***
	(7.37)	(7.37)	(6.90)	(6.89)	(6.88)
Percent of most recent fund invested overall	0.0697	0.0691	0.173	0.177	0.176
	(1.33)	(1.32)	(1.78)	(1.80)	(1.80)
Percent of most recent fund invested in company	0.223**	0.222**	0.187	0.181	0.182
	(2.78)	(2.76)	(1.36)	(1.31)	(1.32)
Weighted flows (logged million $)	-0.0210*	-0.0211*	-0.0234	-0.0236	-0.0240
	(-2.22)	(-2.23)	(-1.12)	(-1.13)	(-1.15)
IPOs in the industry (logged)	-0.00747	-0.00764	0.0425	0.0445	0.0434
	(-0.58)	(-0.60)	(1.43)	(1.50)	(1.46)
Lead investor in syndicate	-0.210***	-0.209***	-0.264***	-0.264***	-0.262***
	(-11.07)	(-11.04)	(-6.08)	(-6.08)	(-6.05)
Specialization in industry	-0.0592	-0.0629	-0.196*	-0.197*	-0.198*
	(-1.22)	(-1.29)	(-2.04)	(-2.05)	(-2.06)
Distance from the portfolio company (logged miles)	0.0134**	0.0135**	0.0105	0.0104	0.0109
	(3.22)	(3.24)	(1.25)	(1.24)	(1.28)
Centrality of the focal firm (logged)	-0.193***	-0.193***	-0.199***	-0.201***	-0.202***
	(-10.53)	(-10.50)	(-5.35)	(-5.43)	(-5.45)
Average number of shared partners (logged)	0.181***	0.180***	0.187***	0.188***	0.188***
	(9.21)	(9.17)	(4.25)	(4.29)	(4.28)
Industry specialization distance from coinvestors	0.418***	0.421***	0.425**	0.418**	0.423**
	(6.71)	(6.74)	(3.08)	(3.03)	(3.07)
Geograpic specialization distance from coinvestors	0.0733	0.0731	-0.0961	-0.0980	-0.101
	(1.44)	(1.43)	(-0.92)	(-0.94)	(-0.97)
Inverse Mills Ratio - Selection into Syndicate	-0.380***	-0.378***	-0.423**	-0.423**	-0.414**
	(-5.62)	(-5.58)	(-2.85)	(-2.85)	(-2.78)
Inverse Mills Ratio - Syndicate End	1.851***	1.847***	2.689***	2.681***	2.678***
	(7.48)	(7.46)	(5.46)	(5.43)	(5.42)
Inverse Mills Ratio - Valuation Trend			-0.311***	-0.310***	-0.304***
			(-4.69)	(-4.67)	(-4.56)
Number of ties to coinvestors (logged) - A	-0.0753**	-0.0719**	-0.129*	-0.160**	-0.179***
	(-2.91)	(-2.77)	(-2.44)	(-3.06)	(-3.34)
Book-to-Market Ratio Deviation - B	0.191***	0.199***	0.184	0.191	0.130
	(3.50)	(3.72)	(1.51)	(1.56)	(1.07)
A × B		-0.237**			-0.488*
		(-2.68)			(-2.37)
Down-round - C			0.167***	0.170***	0.169***
			(3.39)	(3.46)	(3.44)
A × C				0.184*	0.196*
				(1.99)	(2.10)
Constant	-1.947***	-1.946***	-2.436***	-2.392***	-2.378***
	(-10.80)	(-10.78)	(-6.23)	(-6.12)	(-6.08)
N	40936	40936	9722	9722	9722
Pseudo R-square	0.071	0.0713	0.1194	0.1199	0.1205

T-stats in parentheses (clustered by firm). * *p*<.05, ** *p*<.01, *** p<.001

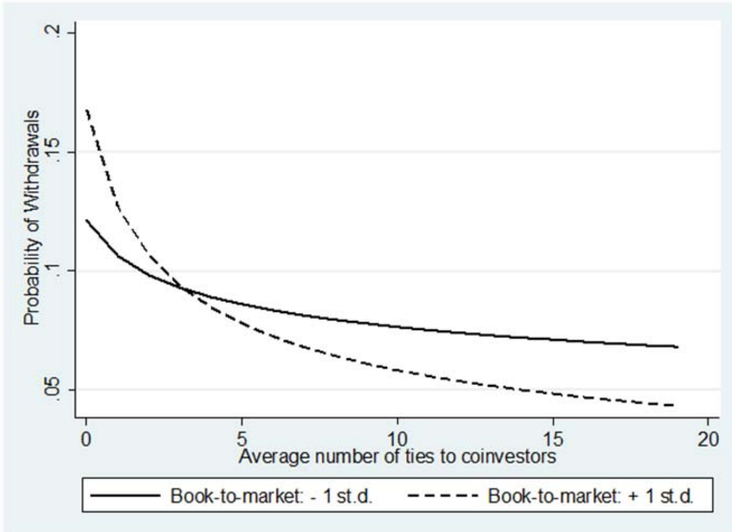

Figure 3.2: Interaction between embeddedness in the syndicate and book-to-market ratio deviation from the industry mean in predicting withdrawals from syndicates

Based on Model 5, Table 3.3; assumes up-round; all other variables held at means

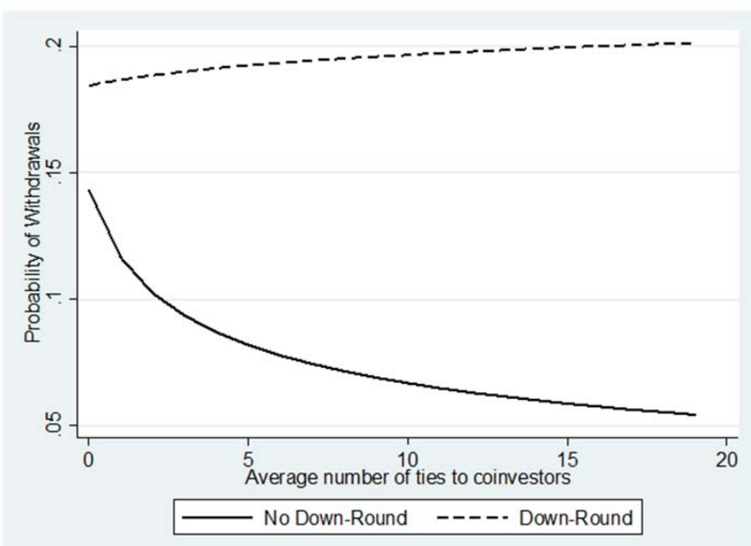

Figure 3.3: Interaction between embeddedness in the syndicate and down-round valuation in predicting withdrawals from syndicates

Based on Model 5, Table 3.3; assumes book-to-market ratios at industry mean; all other variables held at means

Robustness tests. I conducted several robustness tests to confirm the stability of the proposed results. As discussed, I tried several specifications, including conditional fixed-effect and probit specifications. Therefore, selection either into the syndicate or into the subset with reported valuation trend does not seem to explain the observed patterns. In unreported analyses, I also verified the robustness of the findings to a fixed-effect OLS regression (firm, industry, and year fixed-effects). In both analyses, I have been clustering the error terms at the firm level, arguing that this is a major source of autocorrelation of outcomes. However, at least two other major sources of unobserved shocks exist—industry and year. To confirm the appropriate nature of the standard errors, I reran the analyses using the multiple clustering algorithm proposed by Cameron, Gelsbach, and Miller (2011) and implemented by Kleinbaum, Stuart, and Tushman (2013) to simultaneously cluster by firm, industry, and year. The results were substantively unchanged. Combined, these findings increase my confidence that they are not driven by the choice of the specific functional form or standard error clustering.

I also conducted separate analyses in which I excluded serial withdrawers, defined as firms that have withdrawn from more than 31% of their syndicates (the top decile of the sample). My goal was to ensure that the results are not driven by firms that are known for not participating in later stages and may have made it a part of their investment strategy. Also, following the example of past studies (Guler, 2007; Sorenson & Stuart, 2008) I verified the findings excluding Internet-focused syndicates. In both cases the results were similar to the findings reported.

I also explored additional operationalizations of general performance signals. For example, the results remain robust if I use the change in industry valuation relative to the time of the previous financing round for the focal company, as opposed to the deviation relative to the historical average for the industry that I used in the main analyses.

Finally, I conducted instrumental variable analysis to assess the possibility of endogeneity of one of my performance signal measures—the valuation of the portfolio company. In particular, because this variable is simultaneously determined by withdrawals, it is possible that the exogenous willingness of actors to withdraw can cause a down-round, as opposed to the negative signal of a down-round prompting actors to withdraw. To investigate the possibility of such simultaneous causation, I estimated the influence of withdrawals on the probability of a down-round via an ordinary and instrumental variable probit estimation (see Table 3.4). The ordinary probit shows a powerful relationship between down-rounds and withdrawal, as could be expected from the preceding analyses. For the IV probit, I used the age of the most recent fund and the percent of the most recent fund invested under the assumptions that 1) these are strong predictors of withdrawals and 2) their only effect on valuation is through the withdrawal of syndicate participants, because it is implausible that these variables can affect the valuation of a portfolio company by themselves. Using these instruments, I found that the causal relationship from withdrawals to down-rounds to become negative and statistically insignificant. As a result, I conclude that the only causal relationship flows in the opposite direction, from down-rounds to withdrawals.

3.7 Discussion and conclusion

The present study had two major objectives. First, it elaborated on the mechanisms underlying the effects of embeddedness, distinguishing between expectational versus attachment mechanisms and arguing how the latter can lead to a biased interpretation of ambiguous performance signals. Second, this theory set the stage to investigate how different types of performance signals associated with the collaboration affect the pay-off expectations of embedded and non-embedded collaborations and thus the relationship between embeddedness

Table 3.4: Predicting down-rounds using an ordinary and instrumental variable probit.

Model	Probit	IV Probit Stage II	IV Probit Stage I
Dependent Variable	**Down-round**	**Down-round**	**Withdrawal**
Rounds Elapsed	0.0385**	0.0310*	-0.0238***
	(2.91)	(1.97)	(-7.00)
Total Number of Coinvestors	0.0360***	0.0436***	0.0244***
	(5.67)	(4.37)	(13.22)
Early Stage Dummy	-0.120	-0.119	0.00345
	(-0.95)	(-0.94)	(0.20)
Expansion Stage Dummy	0.0834	0.104	0.0735***
	(0.69)	(0.85)	(4.59)
Later Stage Dummy	0.132	0.151	0.0595***
	(1.11)	(1.26)	(3.57)
Book-to-Market Deviation	0.656***	0.657***	0.00199
	(6.57)	(6.61)	(0.09)
Constant	-1.425***	-1.418***	-0.0551**
	(-11.71)	(-11.65)	(-3.18)
Fund age (instrument for withdrawal)			0.0282***
			(10.62)
Percent of Fund Invested (instrument for withdrawal)			0.0530*
			(2.57)
Withdrawal	0.173***	-0.128	N/A
	(3.97)	(-0.45)	N/A

Instruments used: age of most recent fund, percent of capital invested. T-stats in parenthesis (clustered on firm). * $p<.05$, ** $p<.01$, *** $p<.001$

and withdrawal behavior. Negative general performance signals—stemming from macro-shocks that affect all the collaborations within a given domain—are less directly connected to the focal collaboration and are thus of ambiguous relevance. Embedded collaborations, therefore, get the benefit of the doubt relative to non-embedded collaborations. In contrast, negative specific performance cues can directly strike at the expectation of superior performance in repeat collaborations; therefore it can break the link between embeddedness and withdrawal behavior.

Analyzing withdrawal behavior of venture capital funds between 1985 and 2009 yields consistent support for the hypotheses. Prior syndication ties to co-investors reduced the likelihood of withdrawal from the ongoing syndicate. Poorer financial market valuations of the industry of the focal portfolio company, which raised doubts on the possibility of a successful exit and the potential payoff from exiting any venture in that area, increased the stability of syndicates with denser ties between the actors relative to sparser ones. However, a down-round of the portfolio company, an acknowledgement of the funding syndicate of a significant increase of the risks associated with the investment, caused the impact of preexisting ties to virtually disappear.

The present study has two limitations that can be examined in future research. First, I made the broad assumption that general performance signals are ambiguous, whereas collaboration-specific signals are unambiguous. Although I believe this is a justifiable assumption within my context, I recognize that even some collaboration-specific performance signals can vary significantly in their ambiguity. Further research with more fine-grained data can make more nuanced distinctions. Second, future research should examine the generalizability of these findings outside of the context of the US venture capital industry. In particular, the importance of performance expectations and the weakness of embeddedness considerations in the face of unambiguously negative signals may be due to the clear measurability of results and the intense focus on the bottom line within this particular setting. The role of the attachment mechanism may be more prominent in settings that are less subject to performance pressures, and such collaborations may exhibit less sensitivity to unambiguous performance signals.

The contributions of the present paper are twofold. First, I help integrate two important streams of the still relatively underdeveloped literature on dissolution of interorganizational relationships; that is, the embeddedness versus the performance expectations explanations. Existing theory has either treated these effects as orthogonal (often implicitly by examining the effect of embeddedness without attention to performance signals) or offered conflicting predictions regarding the nature of their interactions. These conflicting predictions posit that negative performance cues could lead to tightening the ranks and greater importance of embeddedness (Guler, 2007; Sgourev & Zuckerman, 2011) or attenuation of the role of prior ties as they are trumped by economic interest and even the fraying of the relationship (Chung & Beamish, 2010; Ring & Van de Ven, 1994). My findings add nuance to this debate, highlighting how some performance signals can strengthen the power of embeddedness, whereas others dampen it. In this way, I help advance the understanding of the conditional nature of embeddedness (Mizruchi et al., 2006). Like Granovetter (1985), I recognized the powerful role of social ties in shaping attitudes and behaviors; however, these effects are not immune to feedback and economic motivations.

I also contribute to the literature on learning from performance feedback (Greve, 2003). Much prior research has analyzed firms' reactions to disappointing performance signals, from abandoning strategies (Greve, 1995) to divesting subsidiaries (Duhaime & Grant, 1984) to terminating interorganizational collaborations (Doz, 1996). Limited attention, however, has been paid to how motivated cognition can affect actors' interpretation of similar signals across their portfolio of investments. In particular, VCs may be willing to give some of their investments the benefit of the doubt, while exiting others at the first sight of trouble. More broadly, I have argued that while the organizational learning research has made great progress incorporating insights from psychology, there is much room for understanding the role of motivated cognition and the distortions it can introduce in managerial decision-making.

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