The Past Is Prologue? Venture-Capital Syndicates' Collaborative Experience and Start-Up Exits

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The Past Is Prologue? Venture-Capital Syndicates' Collaborative Experience and Start-Up Exits

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THE PAST IS PROLOGUE? VENTURE-CAPITAL SYNDICATES' COLLABORATIVE EXPERIENCE AND START-UP EXITS

ABSTRACT

Past research has produced contradictory insights into how prior collaboration between organizations—their relational embeddedness—impacts collective collaborative performance. We theorize that the effect of relational embeddedness on collaborative success is contingent on the type of success under consideration, and we develop a typology of two kinds of success. We test our hypotheses using data from Crunchbase on a sample of almost 11,000 U.S. start-ups backed by venture-capital (VC) firms, using the VCs' previous collaborative experience to predict the type of success that the start-ups will experience. Our findings indicate that, as prior collaborative experience within a group of VCs increases, a jointly funded start-up is more likely to exit by acquisition (which we call a focused success); with less prior experience among the group of VCs, a jointly funded start-up is more likely to exit by IPO (a broadcast success). Our results deepen understanding of the connections between organizational performance and collaboration networks, contributing to entrepreneurship research on the role of investors in technology ventures.

INTRODUCTION

From development of life-extending drugs to production of hit Broadway musicals, collaborations between organizations often beget achievements that surpass what any single organization can accomplish (Powell, White, Koput, & Owen-Smith, 2005; Uzzi & Spiro, 2005). Succeeding at inter-organizational collaboration, however, means confronting the challenges of coordination and exchange among multiple parties (Gulati, Wohlgezogen, & Zhelyazkov, 2012; Kapoor & McGrath, 2014; Rosenkopf & Schilling, 2007; Ter Wal, Criscuolo, McEvily, & Salter, 2019). These challenges include miscommunication, disagreement, and conflict, all of which can undermine a collaborative effort and make collective success elusive (Gulati, Sytch, & Mehrotra, 2008; Kale, Dyer, & Singh, 2002; Kellogg, Orlikowski, & Yates, 2006; Zaheer, McEvily, & Perrone, 1998). The juxtaposition of these vexing challenges with the promise of greater success has motivated a long tradition of scholarship in organizational theory and strategy on the evolution and outcomes of inter-organizational collaboration.

Prior work on inter-organizational collaboration models how relationships form between organizations and why they persist or dissipate. Factors such as complementary capabilities, proximity, and similarity in domain specialization can incline two organizations to form a strategic alliance, investment syndicate, joint venture, or other form of collaboration (Ahuja, 2000; Khanna & Rivkin, 2006; Sorenson & Stuart, 2008; Mitsuhashi & Greve, 2009; Shipilov & Li, 2012; Whittington, Owen-Smith, & Powell, 2009). One prominent research stream looks at how prior relationships between organizations—the extent to which organizations are *relationally embedded*[1]—facilitate later partnerships between the same organizations (Gulati & Gargiulo, 1999; Powell, Koput, & Smith-Doerr, 1996; Zhang & Guler, 2019). This scholarship has enriched our understanding of how organizations take cues from the environment when selecting partners to forge a collaboration.

Yet, a puzzle emerges when we examine findings about how prior relationships between organizations affect their collective collaborative performance. Some research finds prior experiences of working together create embedded relationships that provide reliable information about partners' capabilities, engender trust, and produce coordination efficiencies and relationship stability, all of which can enhance performance (Granovetter, 1985; Polidoro, Ahuja, & Mitchell, 2011; Reagans & McEvily, 2003; Tortoriello & Krackhardt, 2010). Other research argues that, when collaborating organizations are "over-embedded" by virtue of long histories of working together, performance suffers: they become rigid and insensitive to novel information as well as vulnerable to competency traps, and partners may even begin to lose trust in each other (Rogan, 2014; Uzzi, 1997). At the interpersonal level, for example, repeat teams in creative industries and academia can fall victim to groupthink and ignore information from outside their network,

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[1]Consistent with prior research (Nahapiet & Ghoshal, 1998), we conceptualize *relational embeddedness* in terms of the existence of prior relationships (Zhelyazkov & Gulati, 2016); it arises from a history of interactions or repeated direct ties (Polidoro, Ahuja, & Mitchell, 2011). Relational embeddedness is a function of how often the various members of a group have previously collaborated.

diminishing performance over time (Janis, 1972; Uzzi, 1997). Further complicating the picture is evidence that whether or not prior relationships trigger collective success depends on overlap between organizations' capabilities and specializations (Rodan & Galunic, 2004; Ter Wal et al., 2016). Tensions among these various perspectives motivate our research question: *Under what conditions do prior collaborations between organizations breed collaborative success*?

Disentangling whether prior collaboration contributes to later collaborative success requires, we argue, a clear specification of the type of collaborative performance in question. We distinguish between two types of success outcomes—*focused* and *broadcast*—whose principal differences lie in their *appraisers*, *complexity*, and *prominence*. Focused successes are determined by domain-specific appraisers who possess the expertise to assess the value of a specialized enterprise; by contrast, broadcast successes are determined by appraisers across a range of domains. In addition, focused successes entail more straightforward, less complex processes involving fewer stakeholders than broadcast successes do (Gompers, Kovner, & Lerner, 2009). Finally, noteworthy broadcast successes tend to reverberate more prominently across society and across markets than do comparable focused successes.

We posit that collaborations characterized by higher levels of relational embeddedness among their members promote focused success; lower levels of relational embeddedness promote broadcast success. Our reasoning builds on prior work in organization theory, sociology, and social psychology that has pinpointed the tradeoffs associated with greater and lesser familiarity among members of a team. More collaborative experience among team members reduces coordination costs, builds greater trust, and generates greater knowledge overlaps, enabling them to accomplish routine, domain-specific tasks more effectively. Greater relational embeddedness derived from repeated collaborations facilitates the development of common shared interpretive schema that position a team to converge focused achievements (Simon 1966, Gulati 1995a). However, greater familiarity and attendant social obligations among team members can create "over-embeddedness" (Granovetter, 1985; Gulati & Gargiulo, 1999; Uzzi, 1997) that results in suboptimal performance outcomes by constraining members' access to diverse knowledge and pushing them into competency traps. By contrast, whereas lesser relational embeddedness might impede efficient coordination, teams that have not had prior experience tend to also bring more divergent viewpoints and introduce a greater breadth of knowledge that can benefit a joint effort toward broadcast successes.

We test our theory by examining venture-capital (VC) syndicates and the successful equity exit outcomes of the start-ups in which such syndicates invest. When a VC opts to invest in a start-up, it often does so as part of a group of VCs known as a syndicate. Syndicates represent collaborations among VCs, in which they typically share knowledge and resources in an effort to guide their collective investee start-up toward a successful exit outcome (Brander, Amit, & Antweiler, 2002; Nanda & Rhodes-Kropf, 2019; Zhelyazkov, 2018; Zhelyazkov & Tatarynowicz, 2020). In this context, relational embeddedness is a function of how often the various members of the VC syndicate have previously co-invested in start-ups. We distinguish between two types of exits that VC-backed start-ups can experience: an acquisition or an initial public offering (IPO). An acquisition exit corresponds to a *focused* success outcome, and an IPO exit to a *broadcast* success outcome.

We find that a start-up funded by a VC syndicate whose members share more prior co-investment experience is more likely to exit via acquisition than via IPO; by contrast, a start-up funded by a VC syndicate with less prior co-investment experience is more likely to exit via IPO. Our additional analyses reveal that funding by a VC syndicate with less prior co-investment experience is also associated with start-up failure. Our evidence comes from an analysis of longitudinal data on almost 11,000 U.S.-based start-ups that received first-round VC funding from multiple VCs between 1982 and 2011. Building on prior work, we address sample selection bias with a Heckman approach and rule out selection on observable variables via inverse probability treatment weighting to isolate the effects of a VC syndicate's relational embeddedness on a start-up's likelihood of exiting by acquisition or IPO.

Our study contributes to research on inter-organizational collaboration, networks, and entrepreneurship. First, we advance a theoretical understanding of differences between types of collective performance by developing a typology that distinguishes between broadcast and focused successes. Second, we provide some resolution to contradictions in the existing research on prior collaboration and subsequent collaborative success. Our results indicate that groups characterized by higher relational embeddedness are more strongly associated with focused successes; conversely, groups with lower relational embeddedness are more associated with broadcast successes. Finally, we shed light on the relationship between start-ups and their VC investors by emphasizing the nature of investors' prior collaborative experience as an underappreciated factor in start-ups' successes.

THEORETICAL BACKGROUND AND HYPOTHESES

Relational Embeddedness and Firm Advantage

Research on social capital has examined how inter-organizational relationships—alliances, board interlocks, and R&D collaboration—relate to firm performance (Beckman & Haunschild, 2002; Beckman, Haunschild, & Phillips, 2004; Dushnitsky & Lavie, 2010; Joshi & Nerkar, 2011; Powell, 1990; Powell et al., 1996; Uzzi, 1996; Shipilov & Li, 2008). One important research stream has established that the particular resource and information benefits that a firm gains from its network partners are often contingent on the structure of *existing* ties among those partners (Hoehn-Weiss et al., 2017; Powell et al., 1996; Reagans & McEvily, 2003; Zhang & Guler, 2019). This research builds on the insight that a firm's relationships embed it within a network, and thus enable it to access valuable information about future opportunities and partners (Granovetter, 1985; Gulati, 1995a; Uzzi, 1997).

Such *relational embeddedness*[2] (Granovetter, 1992; Gulati, 1995b; Gulati & Gargiulo, 1999)—the prior direct ties a firm has formed with other firms and the information that flows through them—can confer advantage in many ways. For example, firms relationally embedded in the better-dress sector of the New York fashion industry were privy to valuable fine-grained information about emerging trends and aesthetics, enabling them to engage in joint problem solving with partners that minimized costly errors with manufacturing (Uzzi, 1996; 1997). Another study found that small firms with embedded ties to their bankers were less likely to incur late-payment penalties on trade credit and more likely to receive discounts from their banks (Uzzi & Gillespie, 2002). Similarly, a study of hotel managers who were ostensibly competitors demonstrated that they benefitted from embedded friendship ties that facilitated sharing information and collectively improving yields at their hotels (Ingram & Roberts, 2000).

Although prior research has documented the benefits of relational embeddedness, it has also highlighted the so-called *paradox of embeddedness* whereby a certain degree of embeddedness confers informational and relational advantages, but being overly embedded can impede a firm from achieving its goals (Uzzi, 1997). For example, a study of mergers and acquisitions in the advertising industry found that, when competitors target many of the same clients, increased relational embeddedness led to the dissolution of relationships (Rogan, 2014).

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[2] Adopting a distinction made by Granovetter (1992) and Gulati (1998), we focus only on firms' direct ties (*relational embeddedness*), not on both direct and indirect ties (*structural embeddedness*). We thank an anonymous reviewer for helping us to clarify this distinction.

Related research suggests that both higher and lower levels of relational embeddedness within a network can enhance the likelihood that a firm will achieve its desired outcome, but that the two configurations' trade-offs result in different firm trajectories (Burt, 2005; Uzzi, 1997). Firms that are more embedded in a network tend to develop specialized products and technologies whereas firms that are less embedded develop assets and capabilities with broader applicability (Powell et al., 1996; Lazer & Friedman, 2007).

A key idea from this research is that repeated collaborative experiences result in *common interpretive schema*: shared frameworks, logics, and assumptions two or more firms use to reason through a problem or a decision (Sewell 1992, Simon 1966). Being highly relationally embedded in a network offers firms the advantage of operating with a common interpretive schema, which can create shared identities and solidarity (Granovetter, 1985; Uzzi, 1997). Prior experiences working together allow firms the opportunity to align on routines and perspectives (Gulati 1995a). In other words, the more frequently firms collaborate and learn together, the more likely they are to have constructed common repositories of knowledge and insights that can inform their future decisions.

Possessing a common interpretive schema aids partners in two ways. First, they increase the efficiency with which partners transfer and process knowledge (Hansen, 1999; McEvily & Reagans, 2003). Because they operate under shared logics, partners can more effectively anticipate each other's needs and approaches when it comes to solving a problem. Such prior relationships therefore enable a firm to develop specialized technologies or products effectively because its network partners have already established a shared understanding of its practices and routines. By contrast, having divergent interpretive schemas creates cognitive barriers between partners that may complicate or even preclude them from coming to agreement on the value of new information (Uzzi & Lancaster 2003).

Second, having a common schema allows for information and advice to be triangulated via partners' common experience (Tortoriello, McEvily, & Krackhardt, 2015; Gavetti & Warglien, 2015; Uzzi, 1996). Triangulation refers to the process by which one verifies the meaning and value of information by looking to the evaluation of others (Gavetti & Waglien, 2015; Hallen &Pahnke, 2016). Having a shared interpretive schema makes the perspectives of a firm's partners more reliable because their prior collaborative experiences create shared expectations (Gruenfeld et al., 1996). These shared expectations in turn compel partners to focus on elements of information that they both value because of their common understanding. Research on social cognition and groups has shown how repeated collaboration results in more efficient processing of information in group members' shared specialized domains (Gruenfeld et al., 1996). Thus, the convergence of interpretive schema, shared expectations about process, and enhanced information processing underpin the advantages of collaborating in networks with higher relational embeddedness.

Lower levels of relational embeddedness in a network confer a different set of advantages. First, the perspectives of partners without prior collaborative ties draw on a broader range of experiences (Beckman, Haunschild, & Phillips 2004). These dissimilar experiences in turn generate different approaches to problems and decisions, enabling a firm to pursue novel recombinations of its partners' ideas (Baum et al., 2000; Ruef et al., 2003). Thus, a firm is more likely to find solutions that appeal to diverse audiences if it is less embedded within a network and receives more varied guidance from unconnected partners (Burt, 2005; Pollock, Porac, & Wade, 2004; Beckman et al., 2004). In a similar vein, less relationally embedded partners can access a broader range of knowledge because their ties to other organizations are more diverse. According to Burt (2004), partners with prior direct relationships to one another are also more likely to share ties to other common organizations whereas firms without prior ties to one another are less likely to have common 'neighbors.' As a result, through their more diverse networks, less relationally embedded partners can access a broader array of knowledge. Being less embedded furthermore encourages a firm to engage in a broader search for knowledge by making it harder to fall back on existing models (Lazer & Friedman, 2007). Although partners less embedded in a network are less apt to acquire a deep shared understanding of a firm's specific needs, their attentiveness to "broader market issues" can also prompt them to find common ground and to argue for solutions that appeal to more diverse market segments (Beckman, 2006). At the same time, shared cognitive schema are unlikely to develop in less embedded networks, leading to more varied advice and directions for the firms they partner with.

Being more versus less relationally embedded within inter-organizational networks is thus associated with different sets of advantages aligned with different goals. Next, we distinguish between two types of success, and demonstrate how the distinct advantages conferred by more versus less relational embeddedness relate to these different collaborative outcomes.

Focused and broadcast successes. We build on research on valuation processes, audience recognition and collaborations to theorize that collaborative successes can be characterized as either *focused* or *broadcast*. Prior research in organization theory and strategy has characterized some successes in terms of their impact on subsequent organizational efforts, for example when discussing the "halo" (e.g. Sine et al., 2003) or "beacon" (e.g. Bermiss et al., 2017) effects. Such terms highlight the impact that certain successes have in increasing the salience or prestige of other actions; the terms also signify a positive spillover either on an organization's own future efforts, or on other organizations that are related to the focal success. Notably, these prior conceptualizations of successes do not account for the collaborative structures and processes required to develop and execute different kinds of collective performance. Therefore, we develop theoretical constructs that consider the type of success that an individual organization achieves, irrespective of its impact on other organizations in the field. Specifically, focused and broadcast successes differ in terms of the *appraisers* who determine them, the *complexity* of coordinating activities outside of the organization to achieve them, and the *prominence* with which each kind of success is recognized.

Appraisers act as third parties, who by virtue of their own expertise, determine whether or not a success is achieved by other organizations. Whether appraisers are specialized domain experts or are part of a broader and more diverse group can determine if a success is focused or broadcast. For example, novels vying for a National Book Award to gain standing within their genres are judged by a narrow set of appraisers, who have specialized expertise and experience with literary fiction (Kovács & Sharkey, 2014). By contrast, restaurants garner acclaim from ratings posted by broad swaths of diners who appraise the restaurants they visit on platforms such as Yelp.com (Luca, 2016). *Complexity* refers to the difficulty and variety of steps required to orchestrate a collaborative success, and the number of stakeholders involved (Van Knippenberg, et al., 2004). The types of coordination and teams that benefit a given outcome depend on its complexity. Prior work in social psychology and organizational behavior has found that the cognitive and demographic diversity of a group benefits its performance more when undertaking projects high in complexity (Van Knippenberg et al., 2004; Higgs et al., 2005, Wegge et al., 2008; Stahl, 2010). *Prominence* reflects how widely known and recognized an outcome is across different types of observers. Prior research on organizational status and reputation conceptualizes prominence as the “collective knowledge and recognition of a firm” (Rindova et al., 2005: 1035) or "large scale public attention" (Rindova, Pollock, & Hayward, 2006: 50). In other words, an organization's success is more prominent when it is widely acknowledged by a diverse set of observers outside of its immediate peers and experts in its field.

These dimensions, *appraisers*, *prominence*, and *complexity,* each vary between focused and broadcast successes. Focused successes tend to rely on information shared by firms embedded in the same network, and thus are likely to be evaluated and valued by members of the same network. Focused successes are also typically conferred or determined by expert specialists who belong to the same domain. These appraisers are equipped to assess knowledge, technologies, and artistry unlikely to be understood or appreciated by broader audiences. Although focused successes depend on such expert appraisal, they are *less complex* to transact—in terms of the number and variety of constituents in need of coordination and implementation—and thus more quickly executed than broadcast successes. This is the case because experts' knowledge positions them to confer approval, provide resources, and make deals on behalf of an organization or product they assess favorably, and to execute these transactions quickly. Focused successes are typically widely familiar to industry insiders, but *less prominent* in networks that lack the knowledge needed to understand and appreciate them.

In contrast, broadcast successes are typically determined by a broader set of appraisers who belong to different networks and thus do not possess the shared expertise and knowledge unique to a particular domain. As a result, those who confer broadcast successes are likely to value commercial applications produced collaboratively. The diversity of such appraisers makes orchestrating broadcast successes *complex*; doing so calls for reaching, appealing to, and coordinating assorted constituents. Importantly, appealing to such diverse audiences does not obligate a firm to be relationally embedded with them. However, the ability to appeal to a broad—

and typically larger—set of appraisers increases the potential *prominence* of broadcast successes once achieved.

Focused and broadcast successes for start-ups. We argue that, for VC-backed start-ups, acquisition exits are focused successes; IPO exits, by contrast, constitute broadcast successes. Although both are desirable outcomes for start-up founders and their VC investors (Beckman, Burton, & O'Reilly, 2007; Hoehn-Weiss & Karim, 2014; Pollock et al., 2015; Sørensen, 2007; Zarutskie, 2010), they differ in important ways[3]. In an acquisition, a start-up is purchased outright by another company that assumes a controlling ownership stake (Kapoor & Lim, 2007). The shares of the founders and investors thus become fully liquid, but they must sacrifice control over the start-up (Graebner & Eisenhardt, 2004). In an IPO, a large fraction of ownership is sold on public markets, enabling any investor to purchase shares. Founders and their investors can typically obtain partial liquidity for their shares, and the management team often remains in place.

Prior research on differences between start-ups that exit by acquisition and those that exit by IPO aligns with our distinction between focused and broadcast successes. For example, start-ups whose technologies and products have broad appeal are easier for a diverse market audience to value; thus an exit through an IPO is apt to generate higher returns than an acquisition (Beatty & Ritter, 1986; Ellingsen & Rydqvist, 1998; Poulsen & Stegemoller, 2008). Conversely, greater information asymmetry about its products between a start-up and potential purchasers of its stock in public markets increases the odds that it will exit via acquisition rather than IPO. Specialized products—technologies valued only by niche markets or a narrow swath of consumers—are more difficult for non-specialists to evaluate (Gompers, Kovner, & Lerner 2009); thus, a single buyer

[3] Our intent is not to explore the financial intricacies of each type of transaction; instead, we summarize their conceptual differences.

operating in a similar space is better equipped to value such a venture, making an acquisition exit more likely (Haleblian, Kim, & Rajagopalan, 2006; Poulsen & Stegemuller, 2008). Also, coordinating the multiple stakeholders in an IPO—investment banks, underwriters, auditors, and lawyers—is a complex challenge that not all start-ups are equipped to handle (Brau et al., 2003; Cumming & MacIntoch, 2003; Grégoire, de Koning, & Oviatt, 2008). Generally speaking, those with more diverse partners are better prepared to mobilize the variety of participants in an IPO.

Translated into our typology of focused and broadcast successes, prior research indicates that a start-up is likely to be acquired (a focused success) if it develops assets of a kind best valued by industry insiders (Lowry & Schwert, 2004). Furthermore, acquisition of a private company is a relatively straightforward financial transaction that can be accomplished rapidly. In contrast, a firm is more likely to exit via IPO (a broadcast success) if it shows the promise of serving multiple market segments, if its growth potential is high, and if it can mobilize a diverse set of partners. Like other broadcast successes, an IPO is a complex and time-consuming transaction that requires coordinating service providers, such as investment banks, with professional investors such as endowments; it also requires appealing to a broader set of potential investors. We broaden our inquiry into factors in a start-up's success by suggesting that prior collaboration among its VC investors influences the firm to develop in such a way as to promote either an IPO exit (a broadcast success) or an acquisition exit (a focused success).

Hypotheses: VCs' Past Collaboration and Start-ups' Exits

When VCs repeatedly collaborate with other VCs (that is, syndicate their investments), they minimize their exposure to the risk that a given investment will fail while increasing their chances of "home runs" that is, investing in firms that achieve high-valuation exits (Bygrave, 1987; Lerner, 1994). Having numerous collaborative partners also increases access to sources of human, social, and financial capital as executive-search firms, lawyers, and investment banks (Gorman &

Sahlman, 1989; Hochberg et al., 2007; Kaplan & Stromberg, 2003; Ferrary & Granovetter, 2009). Access to such resources tends to enhance VC syndicates' impact on a start-up's activities, from strategic planning to product development (Dencker, Gruber, & Shah, 2009). Our core argument is that the array of information advantages that VC partners bring to a start-up is attributable to their past experience collaborating with one another on other start-up investments.

Focused successes. Receiving funding from VCs that exhibit high relational embeddedness encourages start-ups to pursue specialized activities that build on existing capabilities, positioning them for a focused success via an acquisition. Greater shared collaborative experience among a start-up's VCs create shared interpretative schema that reinforce prevailing advice-giving norms and information processing among syndicate members in shared domains. In turn, these shared schemas facilitate the transfer of complex and tacit knowledge to the start-up, such as information about specific products and technologies (Levin & Cross, 2004; McEvily & Reagans, 2003). Shared expectations also reduce coordination costs among syndicate partners by enabling them to reach consensus more quickly and act more efficiently (Friedkin, 2004; Uzzi, 1996). Efficiency benefits start-ups whose unpredictable and time-sensitive challenges make them dependent on their VCs for timely advice and resources. Thus, VCs that have previously co-invested develop strong relationships characterized by shared beliefs and specialized knowledge that can generate targeted advice about firm-specific problems (Reagans & McEvily, 2003; Petkova et al., 2014; Ter Wal et al., 2016).

These arguments suggest that start-ups backed by VCs with more joint collaborative experience are better equipped to build on existing product-development routines, to make timely technical improvements, and to respond to the demands of a particular market. Because such syndicates acquire a deeper shared understanding of a portfolio firm's specific challenges, they are likely to encourage the firm to develop firm-specific assets that address those needs; possession of such assets, which are difficult for public markets to value, make start-ups more attractive candidates for an acquisition than for an IPO.

Hypothesis 1: A start-up is more likely to exit via acquisition if its VC investors have higher levels of relational embeddedness.

Broadcast successes. By contrast, less extensive shared collaborative experience—which implies a lower level of relational embeddedness—promotes development of technologies and products that appeal to multiple market categories, making such start-ups better suited to IPO exits than to acquisition. Shared learning among partners with greater collaborative experience could result in mere replication of prior practices, limiting experimentation to improve a start-up's outcomes. By contrast, VC syndicates with less collaborative experience tend to constitute a more heterogeneous set of organizational mentors—a configuration that can expose portfolio firms to diverse perspectives, knowledge, and mentorship styles. Such syndicates are less likely to share mental templates and more likely to contribute diverse knowledge, which can prompt portfolio firms to pursue strategies that create value in a range of market segments (Beckman, 2006; Fleming et al., 2007; Ter Wal et al., 2016). Thus, receiving guidance from VC partners with less collaborative experience sets the stage for a start-up to discover new high-growth opportunities.

Specifically, diverse perspectives can foster discovery of novel opportunities at the intersection of market categories (Fleming et al., 2007; Whittington et al., 2009). Such networks can promote a start-up's pursuit of innovations by situating it at the nexus of diverse viewpoints (Burt, 2005; Hargadon & Sutton, 1997; Ibarra et al., 2005; Lingo & O'Mahony, 2005). Access to an array of information domains creates recombinative potential by encouraging portfolio firms to generate products and technologies that result from diverse inputs (Burt, 2005; Padgett & McLean, 2006; Powell et al., 2005; Wang & Soule, 2016). Such start-ups are likely candidates for broadcast success because of the greater growth potential of firms whose products meet the unfulfilled needs of customers in different segments; such growth in turn requires subsequent financing, which is more readily generated by an IPO exit than an acquisition.

VC partners with less shared collaborative experience are also more likely to enjoy an array of affiliations, roles, and organizational connections, equipping them better to mobilize the resources necessary to handle the complexities of an IPO (Cumming, 2006; Gulati & Higgins, 2003). Thus the diverse relationships of VC partners without shared collaborative experience can more effectively mitigate the uncertainty associated with IPOs; by contrast, VCs with greater co-investment experience are apt to consult a narrow set of partners whose evaluation of a start-up's IPO prospects is apt to be less comprehensive. VCs with less co-investment experience draw on broader market knowledge, which enables them to better assess a portfolio firm's potential appeal in public markets (Beckman & Haunschild, 2002). In short, because it takes diverse information both to execute an IPO and to understand the market, VCs with less collaborative experience are better equipped to help a portfolio firm go public.

Hypothesis 2: A start-up is more likely to exit via IPO if its VC investors have lower levels of relational embeddedness.

DATA AND METHODS

We use data from Crunchbase (CB) to construct our sample of start-ups and VC investors. Affiliated with the technology-news website Techcrunch and marketed as "the world's most comprehensive dataset of start-up activity," Crunchbase was launched in 2007 as a publicly accessible and crowd-curated online database of information on investment in start-ups worldwide.[4] Crunchbase allows open editing, but contributors must verify their identities at multiple authentication portals before adding to or making changes in the database. We supplemented the Crunchbase data with more detailed hand-collected data on acquisitions and IPOs, and checked these exit data against other sources to verify their accuracy.[5] We identified 71,624 rounds of funding, involving 42,027 new ventures and 20,142 investors, between 1982 and July 2014.

Crunchbase utilizes multiple data-collection strategies to provide accurate and timely data on entrepreneurs, start-ups, VC and angel investors, their investments, and entrepreneurial exits such as IPOs and acquisitions. Unlike other crowd-sourced platforms, CB vets contributions to ensure the accuracy and quality of each data point. To triangulate CB's data, its staff also mines press releases, SEC filings, and other databases, such as VentureSource and CB Insights (unaffiliated with Crunchbase). A variety of external observers, and such recent scholarship as Ter Wal et al. (2016), have checked the accuracy of Crunchbase data and validated its use to study co-investment relationships among VC investors. Dalle, den Besten, and Menon (2017) and Koning, Hasan, and Chatterji (2019) also endorse the use of Crunchbase data for research on firm behavior.

Because the United States is the primary context of CB's data collection, we limit our analysis to U.S.-based start-ups. And because our focus is collaborative relationships among start-ups' first-round VC investors, we also limit our analysis to start-ups that received first-round funding from at least one VC firm. Finally, as part of a two-step estimation approach, inclusion in

[4] Crunchbase was established in 2007; thus casual observers might expect its data on the post-2007 period to be more reliable. We analyzed a subsample of firms that received their first round of VC funding prior to 2007 and found no major differences with our results.
[5] Analysis by others has shown that, for example, Crunchbase and VentureSource overlap by 85–95 percent in their coverage of investment rounds during our period of study. This finding implies that we would obtain similar results if we drew from those databases (last accessed on October 4, 2019: https://inn0vationmatt3rs.wordpress.com/2013/07/02/crunchbase-accuracy/).

our sample requires available information on the locations of the firm itself and of its VC investors; we use that information to account for initial-selection bias. After dropping cases with missing data in our explanatory variables, our final analyzable sample consists of 10,879 start-ups.

Variables

Dependent variables. We analyze the likelihood that a venture-backed start-up experiences either an IPO or an acquisition exit. In keeping with past research, we define a successful exit as either a focused success in the form of an acquisition[6] or a broadcast success in the form of an IPO. An exit can occur at any time after a start-up's first round of investment; thus we use Cox proportional hazards regression models, which allow for inclusion of time-varying covariates (Giot & Schwienbacher, 2007). Of the 10,879 U.S.-based VC-backed start-ups we analyze, 1,689 (15.5 percent) experienced an acquisition exit; 317 (2.9 percent) experienced an IPO exit. The mean time-to-exit for start-ups that went public was 1,658 days, or 4.5 years from the date of their first VC investment round (standard deviation = 1,409 days or 2.9 years); for start-ups that were acquired, mean time-to-exit was 1,237 days or 3.4 years (standard deviation = 827 days or 2.3 years). This empirical pattern is largely consistent with prior theoretical models of the speed of various exit events for venture-backed start-ups (Bayar & Chemmanur, 2011).

Independent variable: VC joint collaboration experience. Our principal explanatory variable operationalizes relational embeddedness among the VC partners in a syndicate by

[6] Acquisitions are not all considered successful. We scrutinized each of the initial 1,689 acquisition exits in our dataset by searching news reports and press releases to determine whether a given acquisition could be considered successful. We based our criteria for success on prior research. For example, Arora and Nandkumar (2011) evaluated press releases to determine whether an acquisition was called an asset sale (not successful) and whether the transaction value was greater than the amount the company had raised (successful). For Kerr et al. (2014), an acquisition was deemed a success if it had an exit value greater than a threshold amount ($5 million); failures were those described as asset sales in media reports. Using these criteria, we found that 8.5 percent of our events (144 out of 1,689) could be considered "masked failures" (Cochrane, 2005). We therefore estimated alternative versions of our main models that either eliminate these cases from our data or code them as closures rather than acquisitions. The results from these models do not differ substantially from those of our main models.

measuring the shared collaboration experience of a start-up's first-round VC funders. We focus exclusively on first-round VC investors because they shoulder the most risk when investing in young, unproven firms (Zhelyazkov & Gulati, 2016; Ter Wal et al., 2016); they are also much more likely to guide a start-up's trajectory via active monitoring and mentorship than are later-stage investors, who typically invest more money but exercise less control over a company (Huang & Knight, 2015; Zarutskie, 2010). Also, later-stage investors tend to be viewed as outsiders and to participate less in the group dynamics of the syndicate. In unreported analyses, we calculate VC collaborative experience including later-round VC investors; doing so does not meaningfully alter our results because a large proportion of such investors also invest in the first round.

We measure VC joint collaboration experience by first observing whether any VC partners co-invested in at least one other firm within the five years prior to a given date (Dahlander & McFarland, 2013; Fleming et al., 2007). In unreported analyses, we also used windows ranging from two to ten years, which did not substantially change our findings. For two reasons, simply counting the number of collaborative ties among a firm's investors is too imprecise for our purposes: first, two VCs might have co-invested in more than one firm; second, some co-investments entail more intense engagement than others.

To capture variation in the intensity of past collaborative ties, we develop a measure that weights such ties; we adopt Newman's (2001) method of weighting one-mode projections of two-mode networks, drawn from his work on scientific collaboration networks (see also Opsahl, 2013).[7] For each co-investment tie between a start-up's VCs, we first count the number of

[7] Newman (2001) examines the collaboration networks of authors of scientific papers. To weight a collaboration tie between two scientists, Newman first counts the number of papers they have co-authored. The weight of their collaborative tie for *a given paper* is inversely proportional to the number of its other co-authors. The assumption is that, on a paper with more co-authors, any two co-authors are less likely, on average, to have become well acquainted

companies in which VCs *A* and *B* invested prior to time *t*. For each such company, we then observe the number of investors other than *A* and *B*. The more investors, we assume, the weaker the average relationship between any two investors, because each must divide its attention among more co-investors. We then assign a tie-strength score to each co-investment experience of *A* and *B*. We designate the sum of these scores as the weight of the co-investment tie between *A* and *B*. Finally, the sum of the weights of all co-investment ties among a given firm's investors is our measure of VC joint collaboration experience.

[**Figure 1** – Drop.io Example]

Figure 1 illustrates how VC joint collaboration experience is calculated for Drop.io, a start-up (eventually acquired) whose service enabled users to create temporary file-sharing spaces anonymously. Prior to October 2010, Drop.io had three investors: DFJ Gotham Ventures, RRE Ventures, and Rose Tech Ventures. Two of these investors, DFJ Gotham and RRE, had previous collaborative experience. To calculate the strength of their collaborative relationship, we use the following formulas, adapted from Newman's method (2001: 5) for weighting scientific-collaboration networks:

$$S_{A,B} = \sum_{i \neq j}^{m} \frac{1}{N_i - 1} \qquad (1)$$

$$C_j = \sum_{A \neq B} S_{A,B} (2)$$

In formula 1, the strength $S_{A,B}$ of the collaborative relationship between *A* and *B* via past investee company *i* is inversely related to company *i*'s total number of investors, N_i. For example, if *i* had only two co-investors, *A* and *B* (if $N_i = 2$), the strength of their collaborative relationship would be equal to 1, given that 1/(2-1) = 1. If *i* had three investors, *A*, *B*, and *D*, the strength of *A*

because their attention is divided. The weight of the tie between two co-authors is the sum of the weights of each of their collaborations. Our measure substitutes VCs and portfolio firms for authors and scientific papers.

and B's collaborative relationship via i would be equal to 1/(3-1) = .50. The weight of A and B's overall collaborative relationship in company j, their current investee, is therefore the sum of all $1/(N_i - 1)$ values for the m companies in which they co-invested prior to company j. The value of VCs' prior collaboration C_j for company j is the sum of the weights of all of the co-investment dyads among j's investors.

Control variables. For start-up-level control variables, all of our models include dummy variables for the *year in which a start-up received its first round of funding*. We also control for location using the *state in which the start-up is headquartered*, and for the primary Crunchbase-assigned *market segment*, or sub-industry, to which the start-up belongs.[8] Because many of our start-ups are affiliated with multiple market segments, we include a count variable for the *number of market segments* to which a firm belongs. We control for a start-up's *total number of VC investors* to account for variation in the VC joint-collaboration-experience variable attributable to simply having more investors. Because we expect the likelihood of an exit to increase as a start-up ages, we include the *number of years since founding.* We also account for the *number of years between founding and first round of funding* because, arguably, start-ups that take longer to secure funding might exhibit less promise of a successful exit. Our models also include *a start-up's number of funding rounds*, which approximates its growth potential. Finally, we control for *total IPOs* and *total acquisitions* during the quarter of a given firm-day observation to account for whether a given period represents a "hot market" for IPOs or acquisitions (Ritter & Welch, 2002).

[8] We include dummy variables for California, New York, Massachusetts, Texas, Washington, Illinois, Pennsylvania, Colorado, Florida, and Virginia, which jointly account for 92 percent of the firms in our sample. Our database consists of 444 Crunchbase-created market segments, initially self-assigned by the firms in question and verified by Crunchbase staff. We include dummy variables for the twenty largest segments: software, curated web, advertising, enterprise software, analytics, e-commerce, mobile, clean technology, games, health care, finance, education, hardware & software, health and wellness, semiconductors, cloud computing, security, apps, web hosting, and the Android operating system.

At the VC-syndicate level, we control for features that could confound the relationship between prior collaboration and the likelihood of exit. We account for a VC investor's average number of co-investors (which we call *average VC centrality*) and for each investor's *average number of other portfolio firms*: VCs with more co-investors tend to enjoy higher status, and having numerous portfolio companies can signify greater experience. A similar approach would be to control for the time elapsed since the VCs' earliest investments, a variable that when included in our models did not affect our main results. We also control separately for the *proportion of other portfolio companies funded by a start-up's first-round VCs that eventually went public, were acquired, or closed*. If, for instance, a start-up's VCs had invested in many firms that eventually went public, their baseline preference might be to take the focal start-up public. We also include the *proportion of a start-up's investors who are angel investors*. Firms with many angel investors might be riskier investments: compared to VCs and private-equity firms, angel investors tend to lack formal processes for vetting deals, and tend to invest in start-ups based on "rough rules of thumb or their gut feeling" (Prowse, 1998: 789). Since we cannot observe the underlying quality of a start-up, counting angel investors is an indirect way to gauge its expected performance. Our models also include the *proportion of a start-up's first-round VCs that had previously invested in companies in the same market segment* to account for the possibility that VCs with experience in the firm's market segment might be better positioned to offer guidance.

Finally, we control for the *market-segment diversity of first-round VCs*. To construct this variable, we calculate a Herfindahl index based on the market categories represented by other start-ups funded by the firm's VCs with the formula $1 - \sum_{j=1}^{q} s_j^2$. Here, s_j is the proportion of investors' n other portfolio companies that belong to market segment j (out of q market segments represented). The scale ranges from 0 to 1; higher values indicate greater market-segment diversity. Controlling for VCs' segment diversity accounts for high levels of joint collaboration experience that might be attributable to similar market-segment expertise.

Table 1 presents summary statistics for our variables. Our data are longitudinal; for time-varying covariates, we present means and standard deviations on the date of the first round of funding and the last date of observation (either the date of exit from the risk set via an IPO, acquisition, or closure or the last date of observation due to right-censoring: July 1, 2014). Table 2 reports correlations for our variables on start-ups' dates of first funding.[9]

[**Table 1** – Summary Statistics]

[**Table 2** – Correlation Table]

Descriptive analysis. Figure 2 reports (1) the mean number of first-round VC investors in all start-ups, those that are acquired, those that go public, and those that fail; and (2) mean VC prior collaboration at first funding. Start-ups that eventually go public or are acquired tend to attract more first-round VC investors than average; this pattern suggests that, even at early stages in new ventures' life cycles, those that exhibit greater promise of a successful exit attract more attention from investors. The figure shows only slight differences in the average number of first-round investors between start-ups that are acquired (mean = 2.92 investors), those that go public (mean = 2.81 investors), and those that fail (mean = 2.67). However, the figure also reveals that acquired firms' first-round VCs have greater average joint collaborative experience (mean = 2.95) than do those of firms that go public (mean = 1.20) or fail (mean = 2.36). Consistent with our hypotheses,

[9] Of note is that VCs' prior collaborative experience and the Total Number of VCs is correlated at r = 0.61. Although we control for the Total number of VCs in our models, we conducted robustness checks by removing observations that had values of Total Number of VCs above the 90th percentile. Using this subsample did not meaningfully affect our results.

this comparison offers preliminary evidence of a correlation between the joint collaborative experience of a start-up's first-round VC funders and the start-up's expected exit outcome.

[**Figure 2** – VC joint collaboration experience by Exit Type]

Two examples from our data will help to contextualize the values in Figure 2. Gridiron Systems and Carbonite are both VC-backed companies whose products provide digital data storage. In its first funding round, Gridiron attracted investment from Foundation Capital, Mohr Davidow Ventures, and Trinity Ventures; Carbonite received funding from 3i Group, Converge Venture Partners, and the Kereitsu Forum. The prior collaboration of Gridiron Systems' VCs was high (our formula generated a value of 4.3): each pair of VCs had co-invested in at least two companies prior to investing in Gridiron. By contrast, the prior collaboration of Carbonite's VCs was equal to 0: none had previously jointly co-invested. Gridiron Systems, which continued to specialize in storage technology, was acquired in 2013. Carbonite, which extended its cloud-services technologies to other markets, went public in 2011.

Model Estimation

Competing-risks hazard models. Because we use time-varying data in our sample, we estimate proportional-hazards models to examine the instantaneous probability that a start-up will experience an exit event on a given date. Our start-ups all enter the risk set when they receive their first round of VC investment and leave when they go public, are acquired, or fail. Thus, we estimate competing-risks models rather than standard Cox proportional-hazards models because our start-ups can experience any of three exit events rather than one specific event (Fine & Gray, 1999). According to Fine and Gray (1999), failure to account for all events that can cause observations to leave a risk-set in a hazard model can result in biased estimates. Importantly, experiencing any of the three events causes a firm to leave the risk set by virtue of the firm either not existing (through failure) or no longer being defined as a VC-backed start-up (by being acquired, a VC-backed start-up becomes wholly owned by another company, and by going public, ownership is distributed among public shareholders). As such, even though a firm might potentially go public *and then* fail, going public first causes the firm to leave the risk set.

To estimate our competing-risks models, we adopt the procedure used by Katila and Shane (2005), who study the dynamic process underlying several possible innovation-related events: they estimate a hazard model for one event while treating observations of "competing" events as right-censored. This censoring approach is appropriate when the same underlying process can affect all exit events; simultaneously modeling an alternative risk event is only valid when exogenous factors cause it to occur (Cannella & Shen, 2001).

Therefore, we estimate one set of competing-risks models of IPO exit, treating acquisition exits and failure as right-censored; a second set of models of acquisition exit, treating IPO exits and failure as right-censored; and a third set of models of failure, treating IPO and acquisition exits as right-censored. To test the proportional-hazards assumption associated with these models, we plotted the Schoenfeld residuals for each of our independent variables (from each model) against their actual values (Allison, 1984). Because none of the best-fit lines for our plots have slopes significantly different from zero, we consider the proportional-hazards assumption to be reasonably satisfied.

Heckman correction: Initial VC matching. Because we cannot observe all the factors that prompted a VC syndicate to invest in the start-ups, our sample might suffer from selection bias. Some of these factors—such as VCs' perceptions of the quality of a given start-up—might be simultaneously correlated with the probability that the firm will exit successfully. A related possibility is that a VC syndicate with higher relational embeddedness might be more likely to invest in start-ups predisposed to exiting by acquisition; conversely, a VC syndicate with lower relational embeddedness might be more likely to fund start-ups predisposed to exiting by IPO. Therefore, any correlation between VC joint collaboration experience and a given exit outcome could be due to an initial selection stage that matches VCs to start-ups.

Because our sample consists of start-ups across a range of industries, we cannot use approaches to matching that rely on uniform sector-specific indicators of quality to rule out selection in VC funding (Fox et al., 2012). Thus, we adopt Hallen's (2008) method instead. For each start-up in our sample, we match the first-round VC syndicate to those of ten other randomly chosen start-ups not funded by the same syndicate. We then generate all of our independent and control variables for these "simulated" firm–syndicate pairs, and combine our "real" firm–syndicate pairs with our simulated pairs to produce a new dataset. Next, we estimate a first-stage probit model predicting whether a firm–syndicate pair is "real"—that is, whether it will be included in our analysis sample. From this probit model, we calculate an inverse Mills ratio for each start-up, which we include as a control variable in all of our proportional-hazards models to account for sample-selection bias.

As an instrumental variable in the first-stage probit model, we use the average geographic distance between a start-up and its VC investors (Sorenson & Stuart, 2001). Others have used distance as an instrument in similar analyses, arguing that closer distances make VCs more likely to invest in a start-up but does not meaningfully predict the start-up's performance (Hallen, 2008; Ter Wal et al., 2016). Table 3 reports the result of our probit model, which shows that a one-standard-deviation decrease in the average distance between a syndicate and a start-up increases the odds that the syndicate will invest in the start-up by 43 percent ($p < .001$, Table 3, Model 1).

Of course, we cannot explicitly test whether the average distance between a start-up and its VCs is related to our ultimate outcome variables of interest.[10] In our sample, however, similar proportions of firms being acquired appear above and below the median average distance (15.6% and 15.4%). We obtained similar results for the proportion of firms going public (3.1% and 2.7%) and failing (6.1% and 5.3%). Nevertheless, we encourage readers to interpret these results cautiously: some research suggests that less distance between VCs and portfolio firms lowers monitoring costs, which can increase the overall value generated by the start-up (Bernstein, Giroud, & Townsend, 2016; Cumming & Dai, 2010); other research suggests that improved virtual-communication technologies have rendered negligible the challenges associated with greater distance (Fritsch & Schilder, 2008). This work has yet to explicitly analyze the relationship between VC-to-firm distance and differences in start-ups' exit paths, which is the principal outcome that we study. Thus, we have no compelling reason to suspect that proximity would make a start-up more likely to pursue an IPO than an acquisition exit or vice-versa. As an alternative approach, rather than including the inverse Mills ratio as a control variable in our models, we include the average distance between a start-up and its VCs as control variable instead. This did not substantially alter our results.

[**Table 3** – First-Stage Probit Regression Model for Inverse Mills Ratio]

Inverse probability treatment weights (IPTW). Our principal endogeneity-related concern is that certain features of a start-up might simultaneously (1) predispose it to aim for a certain exit outcome and (2) predict its likelihood of attracting VC investors with more or less extensive prior

[10] Although the exclusion restriction cannot be explicitly tested, we can test the relevance assumption for our instrument. The F-statistic for the first-stage probit model is equal to 16.52, exceeding 10, which as a rule of thumb suggests that the relevance assumption is satisfied. Because we cannot identify another candidate instrumental variable in our dataset, we cannot also use a J-Test of overidentifying restrictions to rule out endogeneity.

shared co-investing experience. To address this concern, we adopt inverse-probability treatment weighted (IPTW) estimation for our models, an approach that has been previously deployed in similar empirical settings in which selection and treatment effects might be confounded (Azoulay et al., 2009; Rider & Negro, 2015; Wu, 2012). IPTW estimation assumes that we can observe a set of confounders that adequately predicts both the outcome of interest and selection into a treatment (Azoulay et al., 2009; Robins, 1997). The estimation procedure involves calculating a series of weights that, when applied to our observations, creates a "pseudo-population" whose set of confounders "no longer predicts selection into treatment," and in which "the causal association between the treatment and outcome is the same as in the original population" (Azoulay et al., 2009: 12). In our case, the treatment is VCs' prior collaboration; the outcome is the firm's IPO, acquisition, or failure.

IPTW estimation resembles a propensity-score matching approach in that both generate a quasi-experimental subsample of observations in which the likelihood of receiving a treatment is not contingent on other observable variables. We prefer IPTW estimation because propensity-score matching is only suitable for binary treatments; IPTW can be used for continuous treatments (Robins, 1997; van der Wal & Geskus, 2011). IPTW estimation can be applied to longitudinal data to create weights for individual spells, whereas matching spells by propensity scores across or within firms would create gaps in our longitudinal data structure. To create a weight SW_{it} for a start-up i at time t, we use the following equation (van der Wal & Geskus, 2011: 3):

$$SW_{it} = \prod_{k=0}^{t} \frac{f(C_{ik}|X_{ik})}{f(C_{ik}|X_{ik}, Z_{i,k-1})} \qquad (3)$$

In equation 3, $f(C_{ik} \mid X_{ik})$ gives the predicted value of VC prior collaboration C_{ik} for a start-up i given a set of independent variables, X_{ik}, at time k. $Z_{i,k-1}$ represents a set of lagged confounders.

To address the assumption that we measured all possible confounders, we categorized control variables as confounders based on a literature review of the factors that predict co-investment ties between VCs, which range from organizational distance (Stuart & Sorenson, 2001; Sorenson & Stuart, 2008) to network embeddedness (Uzzi, 1996) and status differences (Podolny, 2010). Those we designated as confounders are (1) *average number of other portfolio firms for each of a firm's VCs* (lagged one year), (2) *average VC centrality* (the number of other VCs with which a firm's VC has co-invested, lagged one year), (3) *proportion of a firm's investors who are angel investors* (lagged one year), (4) *proportion of the VCs' other portfolio companies that eventually went public/were acquired/closed* (lagged one year), (5) *density of the VCs' co-investment network* (lagged one year), (6) *number of years between a firm's founding and its first round of funding*, and (7) *a complete set of state and market-segment dummy variables*. We follow Azoulay et al. (2009) and Wu (2012), who recommend lagging time-varying confounders to avoid the possibility of reverse causality. To calculate our lagged variables, we take the set of firm *i*'s first-round VCs at time *t* and calculate, for example, its average number of co-investors one year before *t*. Because these confounders were already incorporated in our calculation of treatment weights, we omit them from the models we estimate with IPTW; including them would incur the risk of over-specification (Wu, 2012). The next section presents both weighted and unweighted (with and without confounder control variables) model estimates.

RESULTS

We use the GLM estimates from our numerator and denominator models to calculate our inverse probability treatment weights (see equation 1). Using the treatment weights calculated from these models (Table 4), we estimate hazard models for each exit type, reported in Table 5: Models 1–3 use acquisition exit as the dependent variable, Models 4–6 use IPO exit, and Models 7–9 use closure exit. For each dependent variable's set of models, we compare specifications for unweighted models (with and without confounders as control variables) to IPTW estimated models. In separate analyses, we also test our models' sensitivity to outliers by omitting firms whose VCs' shared collaborative values were above the 95th percentile; doing so does not substantively affect our results.

[**Table 4** – OLS Models Predicting Treatment Weights]

The models reported in Table 5 support Hypothesis 1, which posits that greater VC prior collaboration increases the likelihood that a start-up will be acquired. In Model 1, each standard-deviation increase in VCs' prior collaboration boosts the hazard ratio of a firm achieving an acquisition exit by 6 percent ($exp(0.054) = 1.055$, $\beta = 0.054$, 95% Confidence Interval = [0.028, 0.080], $p = 0.013$, Table 5). According to Table 5, when confounders are included, under the IPTW estimation, the effect of VCs' prior collaboration persists with a similar magnitude ($\beta = 0.050$, CI = [0.018, 0.082], $p = 0.016$, Model 2; $\beta = 0.042$, $p = 0.015$, Model 3).

[**Table 5** – Cox Hazard Models for Acquisition and IPO Exits]

Table 5, Model 4, shows that as VCs' joint collaboration experience decreases, the probability of a firm exiting by IPO increases, in keeping with Hypothesis 2. A one-standard-deviation *decrease* in VCs' joint collaboration experience leads to a 37 percent *increase* in the hazard ratio of a firm experiencing an IPO exit ($exp(-1 \times -0.317) = 1.373$, $\beta = -0.317$, CI = [-0.611, -0.023], $p = 0.016$, Table 5, Model 4). The effect of VCs' prior collaboration is robust to the inclusion of confounder variables ($\beta = -0.297$, $p = 0.012$, Model 5); however, the strength of the effect diminishes noticeably when subjected to our treatment weights ($\beta = -0.209$, CI = [-0.561, -0.033], $p = 0.018$, Model 6). Importantly, these results hold while controlling for the diversity of the VC syndicate's market-segment experience, suggesting that the non-redundant knowledge that VC investors without prior collaborative experience bring to a portfolio firm outweighs the knowledge diversity captured in segment-specific expertise.[11] Figure 3 illustrates the predicted hazard for each exit type over the range of values for VCs' prior collaboration in our data.

[**Figure 3** – Predicted Hazard-Ratio of Exit by VC Joint Collaborative Experience]

Additional Analysis

Failure Exits. In addition to modeling the successes in our data, we ran models to understand what collaborative structures and relationships might predict failure. To do so, we created a variable for whether a start-up in our sample fails, such as via bankruptcy, an outcome that 2,388 start-ups experienced (21.9 percent). Mean time-to-failure for this group of start-ups was 1,218 days, or 3.3 years from the date of first investment.[12]

Table 6 reports estimates of hazard models specified similarly to those in Table 5, with firm failure as the outcome variable. Here we find that less shared collaborative experience among a firm's VCs significantly increases the likelihood of failure (Table 5, Models 7–9). In the previous section we estimated that a one-standard-deviation reduction in VCs' prior collaboration increases the hazard ratio of an IPO exit by 37 percent (Table 5, Model 4); it also more than doubles the hazard ratio of a closure ($exp(-1 \times -0.763) = 2.144$, $\beta = -0.763$, CI = [-1.201, -0.325], $p = 0.000$, Table 5, Model 7). Thus, although VC syndicates with less shared collaborative experience seem better poised to take a start-up public (e.g., because they offer access to more diverse resources), the greater coordination challenges involved may also create complications for start-ups. This unexpected finding reinforces the observation that, though highly prized, VC investment may

[11] We also tested whether VCs' joint collaboration experience has curvilinear effects on acquisition and IPO exits. Including a quadratic term did not significantly improve model fit for either outcome.

[12] We conducted further sensitivity analyses by coding a start-up as having experienced a closure if it did not record any form of venture funding activity in the five years or more prior to the end of our study period (July 31, 2014). Here we draw on Ghosh (2011) and Bourgeois and Eisenhardt (1987), who regard a start-up as having essentially ceased operations if it does not report any funding or liquidity event for several years in a row. Coding closure events using this method did not generate substantially different results.

entail considerable risk even for generously-backed start-ups. We return to these findings in the discussion section below and explore their implications for emerging research on exceptions to the benefits that VCs bestow on start-ups (Kim & Park, 2017; Pahnke et al., 2015b; Ozmel & Guler, 2015).

[**Table 6** – Cox Hazard Models for Failure Exits]

The effect of VC joint collaboration on start-up strategy. Hypotheses 1 and 2 assume that VCs with less prior collaborative experience contribute more diverse knowledge, encouraging a start-up to develop products and assets that will appeal to multiple markets; VCs with more prior collaborative experience are more likely to guide a start-up to elaborate on its existing capabilities. We cannot observe the strategies that our 11,000 start-ups pursue—much less reliably measure and compare them—but we can observe whether their actions are indicative of extension into new market segments or of focus on their original target segments. Specifically, our data allow us to test whether start-ups whose VCs have less prior collaborative experience are themselves more likely to make acquisitions outside their original target market segments. To do so, we estimate a model whose primary independent variable is VC prior collaboration and whose dependent variable captures the extent of the focal start-up's market-segment diversification via acquisition.

[**Table 7** – Diversification through Acquisition Regression Analysis Results]

In Table 7, Model 1 analyzes a sample of 1,692 VC-backed start-ups that made acquisitions after their first round of VC funding. Here, the dependent variable is the Jaccard similarity between a focal start-up's set of market segments and the market segments associated with the firms it acquired. We find that greater VC prior collaboration has a positive association with market-segment similarity between a focal start-up and its acquisitions ($\beta = 0.023$, CI = [0.003, 0.043], $p = 0.009$, Table 6, Model 2). This result suggests that, conditional on making an acquisition, a start-up tends to target firms that operate in similar spaces if its VCs have more prior collaborative experience with each other. The results demonstrate that the magnitude of VCs' prior collaboration is associated with a start-up's acquisition strategy, which is in turn indicative of whether the start-up concentrates on its existing market segment or branches out into other market segments.

VC syndicates' prior history of exits. Another salient empirical issue is that our main results do not account for whether VCs and company founders have tendencies toward an IPO or acquisition exit prior to establishing an investment relationship—for which, as noted earlier, there are few systematically measurable indicators. It is plausible that past exposure to certain types of start-up success shapes the subsequent preferences of VCs in a syndicate. In particular, the benefits of VCs' collaborative experience may be conditional on the nature of that experience. For example, when VCs co-invest in a start-up that is eventually acquired, they develop a set of skills that is apt to be less applicable to taking a firm public, and vice-versa. Shared experiences in pursuit of a specific goal may predispose group members to resort to the same routines when performing subsequent collective tasks because they are biased toward "what works" (Woolley et al., 2010).

To address these questions, we calculate a syndicate's shared collaborative experience using only past co-investments in companies that eventually went public or were acquired. To measure the *acquisition-specific VC joint collaboration experience*, or $C_{j,ACQ}$, of investors in focal firm j, we adapt our method for operationalizing total joint co-investment experience (see formulas 1 and 2) using only the set of companies in which j's investors previously invested that were eventually acquired; we calculate acquisition-specific joint co-investment experience by dividing $C_{j,ACQ}$ by total joint co-investment experience, C_j. We measure *IPO-specific VC joint collaboration experience* similarly by calculating $C_{j,IPO}$ and dividing it by C_j. We divide by C_j for both measures to reduce artificial correlation and potential multicollinearity in our models. For example, if all of the past co-investments of the VCs in a syndicate were in start-ups that eventually exited via IPO, its IPO-specific joint experience would be equal to 1.

[**Table 8** – Cox Regression Models with Exit-Specific VC Joint Collaboration Experience]

The model estimates in Table 7, which include both $C_{j,ACQ}$ and $C_{j,IPO}$, suggest that the nature of its VCs' past collaborative experience strongly influences a start-up's exit outcome, above and beyond the VCs' total collaborative experience. As the proportion of acquisition-specific experience increases by a standard deviation, the hazard ratio of a firm being acquired increases by 4 percent ($exp(0.038) = 1.039$, $\beta = 0.038$, CI = [0.012, 0.064], $p = 0.001$, Table 7, Model 1). The effect is almost identical under the IPTW specification ($\beta = 0.038$, CI = [0.010, 0.066], $p = 0.003$, Table 7, Model 3), but weakens considerably when confounders are included without weighting ($\beta = 0.012$, CI = [-0.034, 0.058], $p = 0.298$, Table 7, Model 2). Similarly, as IPO-specific co-investment experience increases by a standard deviation, the hazard ratio of a firm exiting via IPO increases by 12 percent ($exp(0.110) = 1.116$, $\beta = 0.110$, CI = [0.022, 0.198], $p = 0.006$, Table 7, Model 4), an effect that largely holds in terms of magnitude when confounders are included and our treatment weights are applied ($\beta = 0.085$, CI = [0.011, 0.159], $p = 0.010$, Model 5; $\beta = 0.012$, CI = [0.021, 0.201], $p = 0.007$, Model 6).

Furthermore, Table 7, Models 1, 2, and 3, indicate that IPO-specific collaborative experience has a consistently negative relationship with the hazard of an acquisition exit. Likewise, Table 7, Models 4, 5, and 6, show that acquisition-specific collaborative experience has a consistently negative association with the hazard of an IPO exit. These results offer evidence of a boundary condition for our main findings: the beneficial effects of VCs' collaborative experience on a start-up's successful exit can be conditional on whether that experience matches the type of exit the start-up is seeking.

Ex-ante preferences might confound our findings by creating a selection problem in which a VC might select into a syndicate with high relational embeddedness precisely because that group of VCs have led acquisition exits in the past. Although we cannot measure what the idiosyncratic ex-ante exit preference a given VC firm, we can infer preferences by looking at their prior history of exits. To explore this possibility, we looked for meaningful variation in the types of exit outcomes among the portfolio firms for VCs that tended to co-invest in syndicates with low and high relational embeddedness. We found that even for VCs in the top quartile of syndicate relational embeddedness, 4.0% of their portfolio start-ups went public, and for VCs in the lowest quartile of syndicate relational embeddedness, 12.6% of their portfolio start-ups were acquired. This suggests whether a VC prefers investing in syndicates with high or low relational embeddedness does not necessarily reveal the VC's ex-ante preferences for a certain type of exit outcome.

Prior expertise of VC syndicates. Finally, a related question is whether prior expertise gained from the separate individual investment experiences of VCs in a syndicate might substitute for the benefits of their relational embeddedness. Although we find that greater VC joint experience reduces a start-up's likelihood of exiting by IPO, it is conceivable that this effect could be reversed if the syndicate's VCs possessed individual experience investing in a wide variety of domains. In other words, in keeping with Ter Wal et al.'s (2016) "best-of-both-worlds" argument, it is possible that the VC syndicates best poised to take their start-ups public are those with high levels of relational embeddedness *and* more diverse experience investing across market segments (see also Fleming et al., 2007).[13]

[13] We appreciate the thoughtful comment of a reviewer that prompted this analysis.

To test this possibility, in an unreported set of models we added an interaction between our VC joint-experience variable and our variable for the market-segment diversity of a start-up's VCs' other investments. For an IPO exit, we found evidence for the best-of-both-worlds effect described above; we found no evidence for an interaction effect when considering acquisition exits. To explain this difference, we speculate that, for a complex transaction like an IPO, VCs' market-segment diversity is necessary to extend the breadth of its impact, but that coordination is also important—and that coordination is lacking when VCs exhibit low levels of relational embeddedness. For an IPO exit, therefore, an ideal VC syndicate may have greater joint experience, allowing for more effective coordination, *and* can draw on a variety of domains thanks to diverse prior investment experience. By contrast, we argue that executing an acquisition exit does not require diverse market experience among VCs because it is a focused success, appraised mainly by industry insiders; thus VC syndicates need not have "the best of both worlds" in the form of strong prior relationships and market segment diversity.

DISCUSSION

We began by comparing contradictory findings on how prior relationships between organizations impact their collective collaborative performance: some studies emphasize the benefits of prior collaborations (Reagans & McEvily, 2003; Tortoriello & Krackhardt 2010); other research finds that shared experience may hinder performance (Rogan, 2014; Uzzi, 1997). Our theory and findings help resolve this tension by suggesting that the impact of prior collaboration depends on the type of success in question. Specifically, we differentiate between focused and broadcast successes, defined in terms of their appraisers, complexity, and prominence.

We find that different levels of relational embeddedness in VC syndicates, traceable to their prior collaborations with each other, are associated with different kinds of success for the start-ups they back. Higher levels of relational embeddedness are likely to support focused successes (acquisitions); lower levels of embeddedness are more frequently associated with broadcast success (IPOs). Our theory and findings thus refine and extend research on inter-organizational collaborations and entrepreneurship, and point to several promising directions for future theoretical and empirical explorations.

Contributions

We first contribute to research on inter-organizational collaborations and networks. Unlike past studies that have focused on a single performance outcome at a time, we explore whether two different types of success are driven by different patterns of collaboration. Our findings suggest that one resolution to "the paradox of embeddedness" is that differing levels of relational embeddedness promote different kinds of success. Networks with high embeddedness are associated with focused successes; repeated collaborations create shared identities, promote solidarity, and enhance organizations' ability to coordinate their activities efficiently. In our context, repeated collaboration among VCs creates common interpretative schema, through which specialized knowledge and expectations are triangulated about how to guide firms toward domain-specific outcomes – in particular, equity exits by acquisition.

In contrast, networks with lower levels of relational embeddedness expose organizations to more diverse ideas and social ties, resulting in an increased likelihood of a broadcast success. VCs with less collaborative experience may lack shared interpretive schema and be apt to provide start-ups a wider range of guidance and resources, increasing the likelihood that they will adopt strategies that create value across markets and thus pursue an IPO. We thus contribute to research on how network structure impacts organizational performance. The impact of a given type of network structure depends, we suggest, on the appraisers, complexity, and prominence of the outcome under consideration. Future work may explore how different types and features of network structures vary in their impact on focused and broadcast successes, in contexts ranging from academic publication to joint R&D ventures and artistic productions.

Our second contribution is to research on entrepreneurship. The practice of venture capitalists and the contribution they make to their portfolio companies has emerged as a key research domain within entrepreneurship (see Grégoire et al., 2006: 358; Lerner & Nanda, 2020). A significant stream of this research has connected VCs to start-ups' (largely positive) performance outcomes (e.g. Ferrary, & Granovetter, 2009; Pahnke, Katila & Eisenhardt, 2015). But unlike prior work that treats exits in a monolithic way by collapsing them into a single performance variable (e.g. Hall and Woodward 2010), we take a fine-grained approach by distinguishing between different exit pathways (McDonald & Eisenhardt, 2020). Importantly, we find that differences in VCs' past collaborative experience promote different exit pathways for the start-ups they support. More broadly, these findings indicate that understanding the dynamics and structural properties of existing collaborative networks may be of value to low-power players seeking to form ties and to embed themselves in such networks (Hallen & Eisenhardt, 2012; Ozcan & Eisenhardt, 2009; Pahnke et al, 2015a; Pahnke et al, 2015b).

Theoretical Implications and Extensions

Our main findings lend credence to the central idea of the paper: different levels of relational embeddedness prompt different kinds of collaborative success. However, the additional analyses we performed point to several opportunities for theoretical extensions. For example, our results highlight an underappreciated trade-off: lower levels of VC joint experience increase the likelihood of exit via IPO (a lucrative and enviable outcome for many parties involved) but also raise the chances of start-up failure before reaching *any* successful equity exit (see Eisenmann, 2021 for a comprehensive treatment of failure factors). This finding is consistent with recent work that has emphasized the performance trade-offs entailed in receiving venture capital funding. For example, Pahnke, et al. (2015b) showed that when a start-up's VCs back competitors in the same sector, the focal start-up's innovation performance diminished. Similarly, Ozmel and Guler (2014) showed that receiving funding from a VC can harm a start-up's chances of a successful exit if it has low relative standing in the VC's portfolio. Finally, Kim and Park (2017) demonstrated how start-ups that take corporate venture capital early on tend to produce more innovations, but are also less likely to exit by IPO. Our results extend these findings by introducing an additional risk-reward calculus: lower levels of relational embeddedness among VC backers might increase the potential of reaching a more prominent IPO exit, but it also comes with the higher risk of failure.

Why might less embedded syndicates *also* be associated with start-up failure? One reason, which resonates with our main argument, is an inability to coordinate efficiently (see Nanda & Rhodes-Kropf, 2019). Another possibility is that less-embedded syndicates bring in a wider variety of market information (Ter Wal et al., 2016), enabling them to detect flaws in a start-up's operations or strategy more effectively, and results in their encouraging those start-ups to shut down rapidly. Conversely, more embedded syndicates—falling prey to commitment traps—may support underperforming companies for longer (Guler, 2007). We conducted supplemental analysis, showing that time-to-failure is indeed shorter for start-ups funded by less embedded VCs than those funded by more embedded VCs. This finding highlights a novel mechanism that might explain failure rates among VC-backed start-ups that, although beyond the scope of our work, deserves further inquiry.

Another important theoretical implication of our analyses relates to how VCs' relational embeddedness affect strategic choices more broadly. Although we analyze how VCs' prior joint experiences shape a start-up's exit pathway, our models also reveal that relational embeddedness may influence VCs' *own* strategy of which start-ups to fund. A complementary explanation for our results is rooted in selection effects: more relationally embedded VC syndicates might fund start-ups they perceive as 'aiming to be acquired' whereas less embedded VC syndicates might back start-ups perceived as 'IPO candidates.' Such reasoning resonates with Gulati's (1995a: 624) suggestion that "networks of interorganizational relations are maps both *of* and *for* strategic action" (see also Barley, et al [1992]). Relational embeddedness among VCs may thus serve as a map—guiding the strategic choice of which start-ups to fund. This insight invites further investigation into how relational embeddedness can account for both VCs' selection of which start-ups to fund and their actions guiding the start-ups' subsequent behaviors.

Finally, our additional analyses also surface important boundary conditions that elaborate the precise theoretical mechanisms underlying the relationship between relational embeddedness and collective collaborative performance. In particular, we find that greater prior joint experience among VCs can lead to a *higher* likelihood of IPO when VCs themselves have accumulated investment experience across a broad range of market segments in their own prior experiences. The benefit of diverse expertise enjoyed by lower levels of relational embeddedness may therefore be redundant when organizations themselves possess diverse expertise. Under this scenario, lower levels of relational embeddedness and diverse expertise could be interpreted as substitutes. Our findings join a chorus of recent work on organizational networks (Kwon et al., 2020; Li & Piezunka, 2019; Ter Wal et al., 2016) that ask scholars to specify whether and how the effects of inter-organizational ties on organizational success might be conditional on certain environmental features and the content that flows through these ties. More broadly, our results point to the need for further investigation into the interplay between network structure and informational context to gain a comprehensive understanding of the relationship between embeddedness and collaborative performance.

Though we developed our distinction between focused success and broadcast success in the context of venture-capital firms' co-investments in start-ups, the idea that embeddedness in different network structures engenders different types of success is potentially generalizable to any domain where appraisal, prominence, and complexity shape the environment for rewards and recognition. As another example of a focused success, consider the annual Academy Award for Best Sound Editing of a feature film. Few outside of the professional sound-editing community will recall that the 2019 winner was Alan Robert Murray for *Ford v Ferrari*. Only members of the Sound Editing branch of the Academy of Motion Picture Arts and Sciences are eligible to cast votes in this category; thus interest in the award, and its impact, are restricted to a small and narrowly focused community of experts (appraisers). By contrast, the Academy Award for Best Picture is voted on by all Academy members, a much more diverse set of appraisers which amplifies overall prominence of the award with all of the attendant increases in complexity and coordination that the expanded process entails. Far more people, from industry insiders to casual film fans, will recall that 2019's Best Picture winner was *Parasite*.

Closer to home, an example of a focused success for management scholars is publication in a respected specialty journal like *The Journal of Technology Transfer (JTT)*. Reviewers (appraisers) for *JTT* possess specialized knowledge and evaluate papers based on their potential contribution to its subfield. *JTT* is likely to be read and cited by academics interested in technology transfer and adjacent fields but probably not by colleagues in other disciplines. Publication in a high-impact generalist management journal, by comparison, requires potential appeal to a broader audience (often by making a theoretical contribution that transcends a specific context), increasing both the complexity of the submission process and the likelihood of rejection but elevating the prominence of a successful submission.

Managerial Implications

Our findings may be useful to entrepreneurs, venture capitalists, and other participants in the start-up ecosystem, with the caveat that our aggregate findings describe a general pattern that may have limited pertinence to any particular situation or firm. For start-ups, the finding that investment by highly embedded VCs increases the likelihood of exit by acquisition is a useful, though neutral, insight that ultimately leads back to founder motivations. Founders with the luxury of choice may favor VCs whose network position and record of exit types match their own preferences. Start-ups in search of funding may want to investigate not only the track record of each firm that offers a term sheet (as is standard) but also its *relational embeddedness*, as revealed by its relevant history of co-investment partners. If founders learn that a venture firm is relatively highly embedded, has a record of pulling in peer firms from its network, and usually exits when its portfolio companies are sold to big-company acquirers (a focused success), they may have a better sense of the likely road ahead with this particular investor or set of investors. Some founders, weighing the costs and benefits of VC embeddedness in light of these findings, might actively seek out well-embedded VCs in order to benefit from their sector experience, proven network of partners, and collective eye for steering start-ups toward promising opportunities to be acquired.

Alternatively, founders intent on an IPO (a broadcast success) could view our findings as good reason to be wary of highly embedded VCs; instead, they might cultivate a more diverse set of investors that will push them to develop multiple interested audiences earlier and support multiple visions of success. This strategy could also provide founders more room to maneuver amid the influences of investors (Ewens & Marx, 2017; McDonald & Gao, 2019), if and when acquisition and exit conversations begin. Simultaneously, of course, such entrepreneurs should also glean from our findings that this network strategy entails a higher overall risk of failure.

For venture capitalists, our findings can be translated into several pieces of advice. More embedded VCs with consistent records of acquisition hits but fewer IPO home runs may want to strategically seek out more diverse co-investors in order to foster greater diversity of inputs while increasing the percentage of portfolio firms on the IPO track. Less-embedded VCs seeking more stable returns might pursue the opposite approach, becoming strategically embedded in a network of like-minded investors that regularly invest in each other's companies and thus achieving a steadier stream of successful acquisition exits each year. Early-stage VCs seeking different degrees of relative embeddedness could in turn calibrate their co-investment behavior to their long-term strategic goals.

Future Research Directions and Conclusion

We subjected our empirical analyses to a number of robustness checks. However, the limitations of our analysis highlight opportunities for future work. First, our measure of VCs' collaborative experience pertains only to first-round investors. Although these early investors tend to be the most active in shaping start-up trajectories, later-round investors matter, too (though in an unreported analysis, including VC investors from all rounds does not substantially alter our results). Second, our work also does not address how VC partners and entrepreneurs reach consensus on which exit pathway to pursue. Prior ties among network partners can affect the influence that a partner wields in such a collective decision, but our data restrict our ability to study this phenomenon (Thomas-Hunt et al., 2003). Finally, we did not scrutinize the value created by firms that went public or were acquired. Having gone to great lengths to verify that acquisition exits were indeed positive outcomes rather than fire sales or "masked failures," we lacked data on the premiums they generated. Future work could investigate the ultimate financial returns of VC syndicates' collaborative experience using acquisition premiums and IPO pricing as outcome variables.

Furthermore, we study a particular type of collaboration in which successful outcomes are mutually exclusive: VC-backed start-ups are *either* acquired *or* they go public. Future studies might explore collaborations in settings where different types of success are more tightly coupled or non-exclusive. For example, members of dissertation committees collaborate to help their students publish in academic journals *and* win placement at prestigious institutions, two outcomes that are often tightly coupled. In entertainment collaborations, critical acclaim and box-office success are not mutually exclusive outcomes; in fact, they may build on each other. Additionally, in some settings, focused and broadcast successes may not differ across all three of the dimensions that we consider in this study. Future research in other domains may explore interdependencies between focused and broadcast successes, the sequences in which they occur, and when some dimensions of distinct types of successes overlap.

Finally, one of the challenges of a macro level study like ours is that we theorize about mechanisms that we do not directly observe in our data. In particular, we theorize that factors such as identity, ease of coordination, and shared interpretive schema positively impact the likelihood of one kind of success or the other. However, we do not observe, nor measure how these kinds of cognitive factors may shape the ex-ante preferences of investors to favor one kind of success over the others. Future studies, particularly micro-level experimental research, may be able to better distinguish the role that such cognitive factors may play in driving different kinds of successes.

Connecting structural aspects of collaborative networks to performance continues to be a prominent focus of organizational scholarship. By theorizing about different kinds of success, we hope to inspire future work on how the dynamics of inter-organizational networks affect the performance of their members. Future appraisals of focused and broadcast success, drawing on increasingly rich and accessible data sources like Crunchbase, may yield additional insights into the relational dynamics of entrepreneurial firms and their partners and provide a more comprehensive understanding of the structural facets of success in different collaborative settings.

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Table 1. Summary statistics for entrepreneurial firms in sample (n = 10,879 entrepreneurial firms)

	At date of first funding round		At final date of observation	
Variable	Mean	SD	Mean	SD
Acquisition Exit	0.155			
IPO Exit	0.029		0.130	0.336
VC Joint Collaboration Experience	2.153	13.565	8.747	39.781
VC Joint Collaboration Experience, IPO-specific	0.011	0.081	0.011	0.081
VC Joint Collaboration Experience, acquisition-specific	0.046	0.166	0.049	0.169
VC Joint Collaboration Experience, failure-specific	0.013	0.084	0.015	0.089
Total quarterly acqusitions in U.S. market	15.536	5.772	18.783	4.584
Total quarterly IPOs in U.S. market	24.765	13.226	35.441	10.542
Years since firm founding	3.303	6.156	6.282	6.681
Number of rounds of funding	1.000	0.000	1.695	1.138
Total Number of VCs	2.253	2.242	3.443	3.523
Proportion of VCs with other portfolio firms in same segment as focal start-up	0.341	0.427	0.690	0.375
Segment diversity of VCs' other portfolio firms	0.163	0.179	0.124	0.152
Number of start-up's market segments	2.299	1.976	2.288	1.973
Years between start-up founding and first round of funding	3.303	6.156		
Average VC centrality (lagged)	37.658	78.284	90.241	127.458
Average number of VCs' other portfolio firms (lagged)	45.617	90.493	155.890	221.654
Proportion of Investors who are Angels (lagged)	0.147	0.317	0.146	0.293
Proportion of VCs' other portfolio firms that go IPO (lagged)	0.054	0.129	0.041	0.080
Proportion of VCs' other portfolio firms that are acquired (lagged)	0.170	0.202	0.148	0.131
Proportion of VCs' other portfolio firms that failed (lagged)	0.062	0.114	0.062	0.082

Table 2. Correlation Matrix of selected variables used in analysis

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Acquisition Exit																				
2	IPO Exit	0.00																			
3	VC Joint Collaboration Experience	-0.01	0.00																		
4	VC Joint Collaboration Experience, IPO-specific	0.00	0.01	-0.05																	
5	VC Joint Collaboration Experience, acquisition-specific	0.00	0.00	0.11	0.00																
6	VC Joint Collaboration Experience, failure-specific	0.00	0.00	0.03	0.01	0.04															
7	Total quarterly acquisitions in U.S. market	0.00	0.00	0.04	-0.02	-0.05	-0.03														
8	Total quarterly IPOs in U.S. market	0.00	0.01	0.11	-0.05	-0.12	-0.08	0.18													
9	Years since firm founding	0.01	0.01	-0.12	0.15	-0.01	0.00	-0.02	0.03												
10	Number of rounds of funding	-0.01	0.01	0.19	0.12	0.16	0.02	0.02	0.08	0.12											
11	Total Number of VCs	-0.01	0.00	0.61	0.05	0.25	0.09	0.02	0.09	-0.02	0.46										
12	Proportion of VCs with other portfolio firms in same segment as focal start-up	0.00	0.00	0.02	0.05	0.01	0.01	-0.01	0.00	0.02	-0.09	-0.24									
13	Segment diversity of VCs' other portfolio firms	0.02	0.02	-0.13	0.03	-0.13	-0.03	-0.03	-0.03	0.13	-0.17	-0.19	-0.04								
14	Number of start-up's market segments	0.00	0.00	0.06	-0.08	0.04	-0.03	0.00	0.01	-0.17	0.13	0.11	-0.10	-0.11							
15	Years between start-up founding and first round of funding	0.01	0.01	-0.13	0.10	-0.05	0.00	-0.01	-0.03	0.85	-0.16	-0.11	0.01	0.19	-0.17						
16	Average VC centrality (lagged)	-0.01	-0.01	0.18	0.01	-0.03	-0.02	0.09	0.26	0.00	0.02	-0.06	0.30	-0.29	0.00	-0.07					
17	Average number of VCs' other portfolio firms (lagged)	-0.01	0.00	0.66	0.04	0.12	0.03	0.10	0.28	0.02	0.41	0.57	0.09	-0.29	0.07	-0.13	0.52				
18	Proportion of Investors who are Angels (lagged)	0.00	-0.01	0.32	-0.12	0.12	0.03	0.01	0.06	-0.26	0.07	0.50	-0.31	-0.10	0.17	-0.22	-0.10	0.18			
19	Proportion of VCs' other portfolio firms that go IPO (lagged)	0.01	0.03	-0.12	0.20	0.02	0.02	-0.06	-0.09	0.26	0.02	-0.08	0.04	0.34	-0.10	0.23	-0.12	-0.10	-0.18		
20	Proportion of VCs' other portfolio firms that are acquired (lagged)	0.01	0.00	-0.02	0.04	0.23	0.07	-0.10	-0.27	0.06	0.02	0.05	-0.02	-0.06	0.00	0.06	-0.13	-0.13	0.03	0.11	
21	Proportion of VCs' other portfolio firms that failed (lagged)	0.00	-0.01	0.01	-0.02	0.03	0.08	-0.08	-0.14	-0.11	-0.03	0.00	0.02	-0.07	0.02	-0.10	-0.04	-0.01	0.03	-0.17	-0.03

Table 3. First-stage probit model of VC syndicate investing in a start-up in the first round

Variable	Model 1
Average Distance between VC Partners and start-up	-0.356***
	(0.009)
VC Joint Collaboration Experience	0.064***
	(0.006)
Total quarterly acquisitions in U.S. market	-0.004***
	(0.001)
Total quarterly IPOs in U.S. market	-0.005***
	(0.001)
Years since firm founding	0.001
	(0.001)
Total number of VCs	-0.087***
	(0.003)
Proportion of VCs with other portfolio firms in same segment as focal start-up	2.226***
	(0.023)
Segment diversity of VCs' other portfolio firms	-0.556***
	(0.032)
Number of start-up's market segments	0.027***
	(0.004)
Intercept	-1.057***
	(0.041)
Market segment dummies	Y
State dummies	Y
df	40
Log likelihood	-21516
n (Start-up syndicate pairs)	84027

* $p < 0.05$, ** $p < .01$, *** $p < .001$ (two-tailed test)
Note: Below each coefficient, stardard error appears in parentheses.

Table 4. GLM coefficients in numerator and denominator models for stabilized treatment weight calculation in IPTW estimation

	Dependent Variable: VC Joint Collaboration Experience	
Variable	Numerator	Denominator
Total quarterly acquisitions in U.S. market	0.021***	-0.009**
	(0.003)	(0.003)
Total quarterly IPOs in U.S. market	0.076***	0.032***
	(0.001)	(0.001)
Years since firm founding	-0.309***	-0.684***
	(0.003)	(0.007)
Number of rounds of funding	-4.462***	-4.123***
	(0.014)	(0.016)
Total Number of VCs	2.230***	2.202***
	(0.004)	(0.005)
Proportion of VCs with other portfolio firms in same segment as focal start-up	8.713***	3.765***
	(0.065)	(0.070)
Segment diversity of VCs' other portfolio firms	-6.238***	5.881***
	(0.173)	(0.188)
Number of start-up's market segments	-0.549***	-0.516***
	(0.009)	(0.009)
Years between start-up founding and first round of funding		0.489**
		(0.009)
Density of VCs' co-investment network (lagged)		7.885***
		(0.056)
Average VC centrality (lagged)		0.028***
		(0.000)
Average number of VCs' other portfolio firms (lagged)		-0.012***
		(0.000)
Proportion of Investors who are Angels (lagged)		1.033
		(0.083)
Proportion of VCs' other portfolio firms that go IPO (lagged)		-3.919
		(0.238)
Proportion of VCs' other portfolio firms that are acquired (lagged)		1.251***
		(0.152)
Proportion of VCs' other portfolio firms that failed (lagged)		-5.430***
		(0.266)
Intercept	-9.199***	-8.109***
	(0.105)	(0.121)
Year of First Funding Dummies	Y	Y
Market Segment Dummies	Y	Y
State Dummies	Y	Y
df	39	47
Log-likelihood	-6307229	-6278406
n	1460973	1460973

* p < 0.05, ** p < .01, *** p < .001 (two-tailed test)

Note: Below each coefficient, stardard error appears in parentheses. The following variables were standardized prior to estimation: average VC centrality (lagged), average number of VCs' other portfolio firms (lagged).

Table 5. Estimated coefficients from proportional hazards regression of exit by acquistion and IPO with and without treatment weight

s

	Hypothesis 1 (DV: Acquisition Exit)			Hypothesis 2 (DV: IPO Exit)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	Unweighted, no confounders	Unweighted, with confounders	IPTW estimation	Unweighted, no confounders	Unweighted, with confounders	IPTW estimation
VC Joint Collaboration Experience	0.054*** (0.013)	0.050*** (0.016)	0.042** (0.015)	-0.317* (0.147)	-0.297* (0.132)	-0.209* (0.099)
Total quarterly acquisitions in U.S. market	-0.004 (0.005)	0.003 (0.006)	-0.004 (0.004)	-0.032*** (0.007)	-0.018** (0.007)	-0.034*** (0.006)
Total quarterly IPOs in U.S. market	0.002 (0.002)	0.002 (0.003)	0.001 (0.002)	0.032*** (0.003)	0.027*** (0.003)	0.032*** (0.002)
Years since firm founding	0.024*** (0.003)	0.477*** (0.049)	0.026*** (0.003)	0.034*** (0.007)	0.682*** (0.074)	0.037*** (0.007)
Number of rounds of funding	0.075*** (0.022)	0.028 (0.025)	0.075*** (0.022)	0.351*** (0.021)	0.266*** (0.017)	0.358*** (0.023)
Total Number of VCs	0.040*** (0.006)	0.029*** (0.007)	0.040*** (0.006)	0.105*** (0.012)	0.139*** (0.016)	0.101*** (0.011)
Proportion of VCs with other portfolio firms in same segment as focal start-up	0.365*** (0.080)	0.229** (0.078)	0.349*** (0.079)	1.468*** (0.300)	1.286*** (0.219)	1.409*** (0.315)
Segment diversity of VCs' other portfolio firms	-0.798*** (0.265)	-0.440* (0.216)	-0.779** (0.268)	1.320 (0.235)	0.367 (0.262)	1.321*** (0.271)
Number of start-up's market segments	-0.017 (0.015)	-0.017 (0.016)	-0.016 (0.015)	0.009 (0.013)	0.065*** (0.017)	0.005 (0.011)
Years between start-up founding and first round of funding		-0.464*** (0.049)			-0.656*** (0.071)	
Average VC centrality (lagged)		0.068* (0.032)			0.616 (0.175)	
Average number of VCs' other portfolio firms (lagged)		0.078** (0.030)			-0.444** (0.170)	
Proportion of Investors who are Angels (lagged)		0.346*** (0.098)			-2.812*** (0.602)	
Proportion of VCs' other portfolio firms that go IPO (lagged)		0.505* (0.267)			4.833*** (0.337)	
Proportion of VCs' other portfolio firms that are		2.262*** (0.206)			0.955* (0.506)	

acquired (lagged)						
Proportion of VCs' other portfolio firms that failed (lagged)		0.373 (0.270)			-0.902 (0.915)	
Inverse Mills Ratio	0.015 (0.048)	0.044 (0.046)	0.010 (0.049)	-0.241 (0.113)	-0.194* (0.100)	-0.223* (0.103)
Year of First Funding Dummies	Y	Y	Y	Y	Y	Y
Market Segment Dummies	Y	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y	Y
df	40	47	40	40	47	40
Log-Likelihood	-13743	-13554	-14212	-2328	-2186	-2368
n	1377404	1377404	1453668	1377404	1377404	1453668

* p < 0.05, ** p < .01, *** p < .001 (two-tailed test)

Note: Below each coefficient, standard error appears in parentheses. The following variables were standardized prior to estimation: VC Joint Collaboration Experience, VC Joint Collaboration Experience (acquisition specific), VC Joint Collaboration Experience (IPO specific), VC Joint Collaboration Experience (failure specific), average VC centrality (lagged), average number of VCs' other portfolio firms (lagged). Confounder controls are not included in IPTW models because they were used to calculate treatment weights. Note that "Density of VCs' co-investment network" was dropped from the models above due to multi-collinearity as assessed by an abnormally high VIF (> 10).

Table 6. Estimated coefficients from proportional hazards regression of exit by closure

	Hypothesis 3 DV: Closure Exit		
	Model 1	Model 2	Model 3
Variable	Unweighted, no confounders	Unweighted, with confounders	IPTW estimation
VC Joint Collaboration Experience	-0.763***	-0.693***	-0.580***
	(0.168)	(0.168)	(0.161)
Total quarterly acqusitions in U.S. market	-0.017***	-0.016***	-0.033***
	(0.004)	(0.004)	(0.010)
Total quarterly IPOs in U.S. market	0.013***	0.014***	0.033***
	(0.002)	(0.002)	(0.004)
Years since firm founding	0.108***	-0.092***	0.037***
	(0.007)	(0.017)	(0.006)
Number of rounds of funding	-0.320***	-0.307***	0.361***
	(0.034)	(0.035)	(0.036)
Total Number of VCs	-0.034***	-0.057***	0.152***
	(0.013)	(0.014)	(0.019)
Proportion of VCs with other portfolio firms in same segment as focal EF	0.190***	0.301***	1.721***
	(0.079)	(0.082)	(0.303)
Segment diversity of VCs' other portfolio firms	-1.150***	-1.193***	1.350***
	(0.165)	(0.177)	(0.296)
Number of EF's market segments	0.003	-0.001	0.026
	(0.014)	(0.014)	(0.037)
Years between EF founding and first round of funding		-0.012	
		(0.019)	
Average VC centrality (lagged)		0.128***	
		(0.052)	
Average number of VCs' other portfolio firms (lagged)		-0.291***	
		(0.052)	
Proportion of Investors who are Angels (lagged)		0.347***	
		(0.093)	
Inverse Mills Ratio	-0.003	-0.068**	-0.259***
	(0.038)	(0.040)	(0.107)
Year of First Funding Dummies	Y	Y	Y
Market Segment Dummies	Y	Y	Y
State Dummies	Y	Y	Y
df	37	44	37
Log-Likelihood	-17147	-17113	-2273
n	1377404	1377404	1371658

* p < 0.05, ** p < .01, *** p < .001 (two-tailed test)
Note: Below each coefficient, stardard error appears in parentheses. The following variables were standardized prior to estimation: VC Joint Collaboration Experience. Confounder controls are not included in IPTW models because they were used to calculate treatment weights. 'Density of VCs' co-investment network' was dropped from the models above due to multi-collinearity as assessed by an abnormally high VIF (> 10).

Table 7. Estimated coefficients from linear regression, predicting the similarity between market segments of the start-up acquirer and acquisition target

Variable	Model 1 (Linear Regression) DV: Jaccard similarity between acquirer and target's self-reported market segments
VC Joint Collaboration Experience	0.023**
	(0.010)
Total quarterly acquisitions in U.S. market	0.001
	(0.001)
Total quarterly IPOs in U.S. market	<0.001
	(0.000)
Years since firm founding	0.002
	(0.001)
Total Number of VCs	-0.005
	(0.003)
Proportion of VCs with other portfolio firms in same segment as focal start-up	-0.066***
	(0.021)
Segment diversity of VCs' other portfolio firms	-0.108**
	(0.042)
Number of start-up's market segments	0.023***
	(0.003)
Intercept	0.780***
	(0.031)
Market Segment Dummies	Y
State Dummies	Y
df	41
R-squared	.206
n	1692

* $p < 0.05$, ** $p < .01$, *** $p < .001$ (two-tailed test)
Note: Below each coefficient, stardard error appears in parentheses. Model 1 uses all start-ups in our dataset that have made at least one acquisition of another firm.

Table 8. Estimated coefficients from proportional hazards regression of exit by acquistion and IPO on exit-specific VC Joint Collaborative Experience Variable

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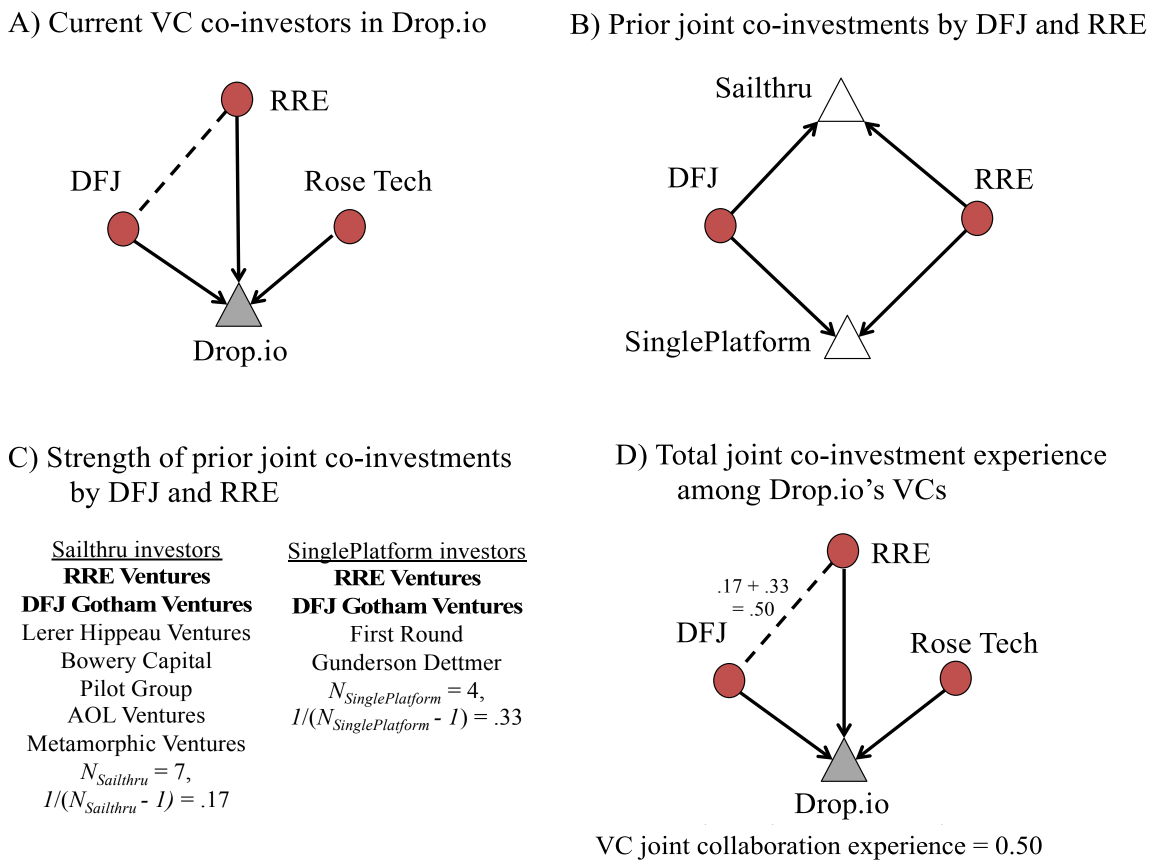
	Hypothesis 1 (DV: Acquisition Exit)			Hypothesis 2 (DV: IPO Exit)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	Unweighted, no confounders	Unweighted, with confounders	IPTW estimation	Unweighted, no confounders	Unweighted, with confounders	IPTW estimation
VC Joint Collaboration Experience	0.050***	0.048***	0.036*	-0.335	-0.326	-0.219
	(0.012)	(0.016)	(0.020)	(0.226)	(0.227)	(0.178)
VC Joint Collaboration Experience, IPO-specific	-0.029	-0.034	-0.031	0.110**	0.085**	0.111*
	(0.019)	(0.023)	(0.019)	(0.044)	(0.037)	(0.045)
VC Joint Collaboration Experience, acquisition-specific	0.038***	0.012	0.038**	-0.085	-0.078	-0.089
	(0.013)	(0.023)	(0.014)	(0.054)	(0.051)	(0.057)
Year of First Funding Dummies	Y	Y	Y	Y	Y	Y
Market Segment Dummies	Y	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y	Y
df	43	50	43	43	50	43
Log-Likelihood	-13741	-13554	-14210	-2321	-2181	-2359
n	1377404	1377404	1453668	1377404	1377404	1453668

* $p < 0.05$, ** $p < .01$, *** $p < .001$ (two-tailed test)

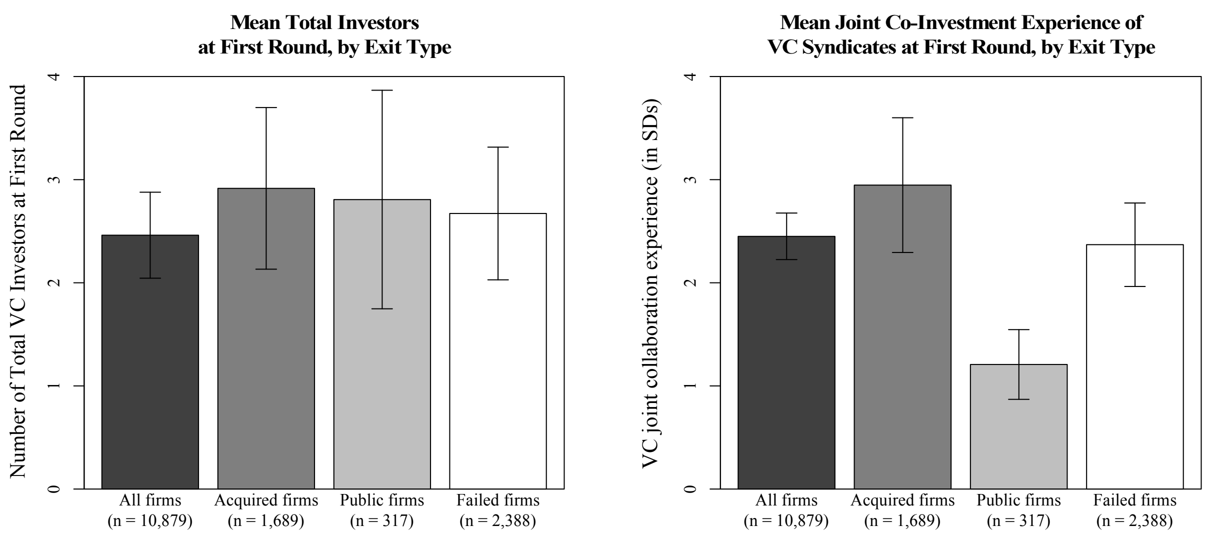
Note: Below each coefficient, standard error appears in parentheses. The following variables were standardized prior to estimation: VC Joint Collaboration Experience, VC Joint Collaboration Experience (acquisition specific), VC Joint Collaboration Experience (IPO specific), average VC centrality (lagged), average number of VCs' other portfolio firms (lagged). Confounder controls are not included in IPTW models because they were used to calculate treatment weights. Confounder controls are included in Models 2 and 5, but are not shown due to space constraints. 'Density of VCs' co-investment network' was dropped from the models above due to multi-collinearity as assessed by an abnormally high VIF (> 10).

Figure 1. Calculation of VC joint collaboration experience



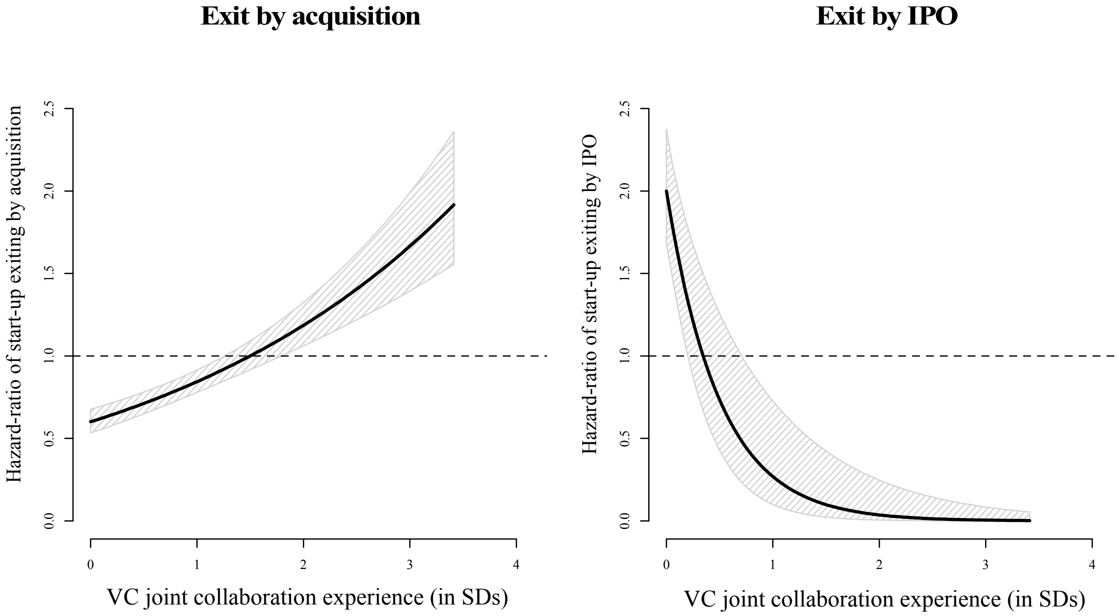
Note: See the Variables section of the text for more detail.

Figure 2. VC syndicates' joint collaborative experience, by exit type



Note: The right-hand graph standardizes VCs' joint collaboration experience by dividing the measure by its standard deviation; it is not mean-centered.

Figure 3. Predicted hazard-ratios of exit (via acquisition, IPO), by VCs' joint collaboration experience



Note: The hazard-ratio of exit via acquisition, for example, consists of the ratio between the hazard rate of a start-up exiting by acquisition and the baseline hazard rate estimated by the model. The predicted hazard ratio of exit by acquisition is calculated using estimates from Table 5, Model 1 and that of exit by IPO from Table 5, Model 4

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