Network Imprinting and the Variability of Venture Capital Firm Performance

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Abstract

This paper develops and tests a theory of firm entry and network imprinting. Sociological theory of networks indicates that firms positioned in the center of a market’s social network are more capable and have better access to resources. What results is a Matthew effect where the more central firms have access to better resources and can thus sustain outstanding performance for new firms entering a network. The closer to the center firms enter, the better they should perform. In this paper, I posit that new firms entering at the center of a pre-existing network are not necessarily better off, nor are the firms that enter at the periphery strictly worse off. Instead, firms that enter into the center are subject to both middle status conformity and learning myopia that leads to exploitation. On the other hand, firms that enter into the periphery develop an orientation toward external search that motivates them to be explorers. I test this theory using data on the co-investment networks of venture capital firms collected from 1981 to 2014. My results indicate that venture capital firms that enter into the center of the network experience are less likely to die, but also less likely to have extreme success. The converse is true for firms that enter into the periphery. I supplement my empirical analysis with qualitative interviews with venture capitalists to better understand the micro mechanisms at work.
Does occupying the center of the interfirm network result in better firm outcomes? Research on interfirm networks has suggested that there are benefits associated with the core of the network (Podolny, 1993). The center affords firms more status and influence (Brass & Burkhardt, 1993; Ibarra, 1993), more positive perceptions about the rest of the network (Ibarra & Andrews, 1993), and access to better resources (Tsai & Ghoshal, 1998). The center affords access to higher quality resources and exchange partners and is the most desired location in the network (Tsai, 2001).

The main findings of this work have stood up to a variety of empirical specifications and tests. However, one characteristic of this research is that it often treats the pool of network actors as static over time (for a review, see Hoang and Antoncic (2003)). This research follows a selected group of actors and observes how they perform. This analytic approach is useful for thinking about how current network positions impact firm outcomes. However, the static assumption treats the network growth of all firms the same (Hite & Hesterly, 2001). Thus, even when the complete network is used, it is only possible to draw inferences about outcomes insofar as they relate to the actors included in the initial survey at the time of observation. In actuality, most new entrants in the network emerge and form ties to existing players in the market. When a new firm enters the network, it inherits the social surroundings of the firms it first forms ties to.

Excluding a time dimension from network analysis can obscure important patterns of social influence. For example, a firm that has just entered the network might have the same pattern of ties as a firm whose tenure in that position is longer. Under the static approach, collapsing across the whole network implies structural equivalence between the two firms. However, the newer firm has not yet established the performance record to yield status and resources of its own. Instead, it is likely to be more dependent on its ties than the established firm with the same set of ties. This illustrates that considering the dynamic aspect of the network is critical for thinking about the effect of network positions at various stages of firm life. As an artifact of collapsing, the static perspective suggests that occupying the center of the
network should result in uniformly better outcomes for firms that reside there, all else equal. But, thinking dynamically reframes the opening question: does entering into the center of the network result in better firm outcomes?

In this paper, I argue that the social surroundings a new firm is initially exposed to form the basis of a social-structural imprint for the newly entered firm. I theorize that the same characteristics of the center that prevent bad outcomes for firms also demotivate external search for new firms. For firms entering into the center, the modest status boost afforded by association with existing firms benefits initial operations but also induces constraint through middle status conformity (Phillips & Zuckerman, 2001). Because early success is more likely in the center, firms that enter here encounter a kind of competency trap that demotivates additional search (Levinthal & March, 1993; Levitt & March, 1988). On the other hand, the periphery is not necessarily a good place to be, because it cannot confer status as easily, but it is freeing. Like Simmel’s “strangers,” firms in the outside of the network are not subject to the social constraints of the center and are free to pursue the opportunities they wish (1950). Search under adverse conditions can lead to failure, but it may also bring success from far afield (Fleming, 2001). Firms that find success this way escape the competency trap by learning that they must be more resourceful, more creative, and more pioneering or else they will fail. These social and cognitive processes influence firms towards a tradeoff between core and periphery that corresponds with the tradeoff between exploitation and exploration (March, 1991). I build these arguments into a theory of firm entry and network imprinting. I argue that the exploitative tendencies of the center that protect firms entering here from very bad outcomes also demotivate behaviors that lead to very good ones. In the periphery, firms are more likely to fail, but are free to carry out innovative search that leads to unforeseen success.

I test this theory in the context of venture capital co-investment networks. There are many industries where strategic collaboration between firms is just as important as interfirm competition. Firms often pool together resources to embark on joint endeavors in biotechnology, manufacturing, and investing (Faems, Van
Similarly, venture capital firms share information, trade complementary skills, and depend on each other for financial support (Bygrave, 1987). The network determinant of performance for venture capital firms is important (Hochberg, Ljungqvist, & Lu, 2007). A venture capital firm forms a tie with another when they jointly invest in a portfolio company as a part of a syndicate group. A focal firm enters into the center of the network by making its first investment with existing firms that are more centrally connected. The firm enters into the periphery of the network by making its first investment with existing firms that occupy sparse regions of the network. I propose that entering into the center promotes a set of strategies and behaviors that shrink the variance of performance outcomes. Firms that enter into the center are less likely to experience left-tail outcomes, which I define as becoming defunct. However, they are also less likely to experience right-tail outcomes, which I define as a notable acquisition or IPO. Conversely, firms that enter into the periphery will be more likely to fail, but also consistently more likely to experience notable acquisitions and IPOs. I analyze approximately 54,000 funding events over almost thirty-five years of data to build a venture capital investment network. As the network evolves over time, new firms enter and attach themselves to existing firms by engaging in investments with them. I find that the firms that enter into more central locations remain in operation longer. However, they are also less likely to experience extremely positive success in the investments they make. The opposite is true of firms whose first investment places them in the periphery. At face value, a review of the current research suggests that entering into different parts of the network might suggest only a divergence in mean outcomes. But, the results indicate that a critical shift in performance trajectory occurs in the variance of outcomes.

Firm Entry and Network Imprinting

Firms that enter an existing network inherit most of their position from the extant ties of the firms to which they attach. Many of the conditions that firms face at birth are imprinted on them for life (Stinchcombe 1965). I argue that the initial
network position is one such imprint. The prevailing social structure a firm enters into influences the opportunities, resources, and strategies it has access to (Carroll & Hannan, 2000). An important way of conceiving of this social structure is the interfirm network. Network theory is a useful lens for thinking about how social positions affect performance in many domains. These include learning, innovation, and other strategic behaviors (Ahuja, 2000; Powell et al., 1996; Uzzi, 1996). Networks provide an opportunity structure of social, financial, and technical resources that are particularly useful for facilitating entrepreneurial behavior (Aldrich & Zimmer, 1986). At the individual level, entrepreneurs rely on contacts in their network to discuss how to plan their business and implement these plans (Greve & Salaff, 2003). At the firm level, interfirm networks help a burgeoning firm to uncover new strategic opportunities, provide a stream of resources, and confer reputation and status (Hoang & Antoncic, 2003).

The key claim of much of this research is that the center of the network contains the richest clusters of exchange partners, strategic opportunities, and resources. At the individual level, employees located closer to the center of the network are treated as if they have more power (Brass & Burkhardt, 1993; Ibarra, 1993). At the firm level, occupying the center of the network builds access to social capital and a consistent stream of resources (Tsai & Ghoshal, 1998). Organizational units located closer to the center of the network have greater access to informational spillovers from other units, and are able to leverage these into generating more innovations of their own and improving their own performance (Tsai, 2001). The ties a firm maintains not only provide it with resources and information, but also signal its merit (Podolny, 2001). Firms that are located in the center signal that they are higher status and more legitimate, and thus are more attractive exchange partners (Podolny, 1993).

By contrast, peripheral actors are usually relatively unknown, have less status, and also have lower access to potential exchange partners and resources (Borgatti and Foster, 2003). The films of movie producers in the Hollywood film industry who are more peripheral in their network of earn less money in the box office (Ferriani, Cattani, & Baden-Fuller, 2009). Similarly, joining a less accomplished filmmak-
ing group confers a cumulative disadvantage that persists over time for receiving Academy Award nominations (Rossman, Esparza, & Bonacich, 2010). Individuals who were less central the advice network of a firm suffer in job evaluations from their group leaders (Sparrowe, Liden, Wayne, & Krainer, 2001). At the organizational level, service organizations who were more peripheral in inter-organizational flows of communication and joint activities are granted less influence in inter-organizational meetings and transactions (Boje & Whetten, 1981). Firms that are located in the periphery have a more difficult time perceiving the network and trusting potential exchange partners (Krackhardt, 1990). Their resulting exchange relationships are less reliable (Powell et al., 1996). These results suggest that for a group of potential entrants who are otherwise equal, entering into the center should produce better outcomes. Similarly, firms that enter into the periphery should perform worse.

Up to this point, firms are treated as having equal propensities to enter the network at any location. This is unlikely to be the case. There may be entrants with pre-existing connections or prior stocks of capital that exert greater influence on their starting location. However, this variability actually suggests another reason that better outcomes should be observed for firms in the center: a disproportionate share of better-endowed firms are granted entry here. When firms enter the network, they jostle to obtain the positions that are most advantageous. The center of the network is more resource rich than the periphery (Tsai & Ghoshal, 1998). However, it is not possible for every firm to set up in the center. Firms that have greater initial endowments of social, financial, and technical capital can leverage these to outmaneuver less capable firms in order to occupy these positions. Firms that are less endowed to begin with do not get this head start. They are often marginalized and shouldered into the periphery. Second, firms that occupy the center tend to have more status and influence in the network (Brass & Burkhardt, 1993; Ibarra, 1993). This influence gives central firms a greater deal of power in choosing what other firms they would like to have as exchange partners. Because the locus of control is in central firms’ hands, they act as gatekeepers in deciding who gets to connect with firms in the center of the network. Firms with larger initial endowments make for
more attractive exchange partners to existing firms because they bring a greater pool of resources and capabilities to the relationship. At the same time, they are new and have not gained a great deal of status and influence in their own right. Thus, they pose less of an initial competitive threat and may be more easily cowed. Thus, better-endowed firms are more likely to be chosen by existing central firms. Less endowed firms do not receive these invitations or have their own refused. Combined, jostling for position by entering firms and gatekeeping by existing firms suggests that there is differential selection into the center: more capable firms are the ones that are allowed into the center of the network.

Better firms sort into the center and worse ones sort into the periphery, on average, and the center of the network contains the myriad benefits chronicled by networks research. This suggests that there is a Matthew effect for firms that enter into the center. Not only should they be better off due to their higher initial endowments, but they also have access to better resources going forward. The distribution of performance outcomes for firms that enter into the center should be unilaterally better than the distribution of performance outcomes for firms that enter into the periphery. Figure 1 represents this visually.

[insert Figure 1 about here]

Entering into the center of the network gives firms an initial resource advantage and may improve mean outcomes, as suggested by Figure 1. However, there are other dynamics that, over time, could make the center less advantageous. An important dynamic is the process of search and learning. Operating in the center of the network promotes a predictable pattern of behavior. It influences the expectation of reciprocal exchange with prior partners and supports it at a lower cost (Katz, 1982; Marsden & Campbell, 1984). Firms get better at finding and exploiting resource complementarities as more dimensions of expertise are uncovered (McPherson, Smith-Lovin, & Cook, 2001; Uzzi & Spiro, 2005). They design long-term interfirm strategies with a densely connected group and are able to build trust with this group (Dahlander & McFarland, 2013; Sorenson & Stuart, 2001). Trust
promotes the ability to mobilize resources, so firms in the center are relatively more incentivized than those in the periphery to engage with the same exchange partners again (Ahuja, 2000; Coleman, 1988). Organization theory suggests that tradeoff between exploration and exploitation suggests that the behaviors inherent in operating in the center or the periphery may reflect diverging motivations for external search (March, 1991). Firms that are predominantly explorers tend to face a wider range of outcomes because their search patterns introduce more variance into their behavior (Gupta, Smith, & Shalley, 2006). Conversely, firms that are exploiters experience a smaller range of outcomes because they do not jump around their search landscape as much, reducing the variance for any one type of firm.

The tradeoff between exploration and exploitation suggests that experiencing better performance outcomes may not be about who has the best access to resources. Instead, it may be about who has the greatest motivation for external search (March, 1991). The benefits of the center of the network may be a double-edged sword that actually removes the motivation for external search. This can occur for social-structural reasons. When firms enter into the center, they gain a modicum of status by associating with high status, influential firms, rather than earning it via their own success. This tension creates a middle status conformity problem (Phillips & Zuckerman, 2001). Deviation from prevalent models high status and influential firms espouse may carry severe penalties and can result in expulsion from the center (McPherson et al., 1992). Engaging in exchange relationships with other actors that have more status or power may provide exclusive opportunities, but these commitments often become binding. Expectations of reciprocity, or outright obedience, impact the strategic choices a firm makes. The motivation for external search may also be removed for cognitive reasons. In the center, firms find success by facilitating consistent interaction among a connected core of actors (Obstfeld, 2005). Yet, experiencing early positive returns in this manner can produce myopia that discourages exploration out of this mold (Levinthal & March, 1993). After experiencing success in a particular manner, firms’ future behavior is tinged by a competency trap that removes the desire to break out of the firms’ existing search architecture (Denrell &
March, 2001; Levitt & March, 1988). Similarly, working with the same group of firms repeatedly is good for refining existing information and working habits (McPherson et al., 2001; Obstfeld, 2005). But, it closes off the clustered individuals from new and distant information (Guimera, Uzzi, Spiro, & Amaral, 2005; Reagans, Zuckerman, & McEvily, 2004). It encourages an overreliance on existing frameworks of action rather than the development of new strategies (Uzzi, 1997). In addition, working groups that are more familiar with each other tend to bring in prior mental models into new work and are blinded to new information and sources for ideas from far afield (Perreffi & Negro, 2007; Skilton & Dooley, 2010).

On the other hand, in the periphery a firm is free to explore and adopt its own preferred strategy and to pursue the opportunities it wishes, which promotes external search. There are fewer resources available to capture and exploit. Instead, firms are motivated to explore the landscape for novel ideas and strategies to employ. In the periphery, benefits arise from networks comprised of disconnected individuals rather than connected others (Lazer & Friedman, 2007). Firms form sparsely knit arrangements that are a structurally diverse web (Granovetter, 1973). This web integrates information and resources from disparate regions of the market (Burt, 2004). External search with new combinations of ideas implies greater variability that can produce unforeseen breakthroughs (Fleming, 2001). This allows firms in the periphery to access distant information that is often locally unavailable (Reagans & Zuckerman, 2001; Van Alstyne & Brynjolfsson, 2005), combine the information in new ways beyond the additive effect of each resource alone (Burt, 2004; Reagans & McEvily, 2003), and use it to create strategic opportunities that existing firms have not been able to capture (Zaheer & McEvily, 1999).

The periphery is not a resource rich area, which limits the potential for long-term viability. Yet, it is also socially and cognitively freeing. The very foundation of what makes the center consistent and reliable can remove the motivation for external search. On the other hand, the adverse conditions present in the periphery may increase the motivation for external search. This presents two possible treatment effects. Under the homogeneous treatment effect, entering firms are uniformly exposed
to the increased motivation to search, and the resulting tendency toward exploration sometimes results in the discovery of great strategies and ideas. It is also possible to conceive of a heterogeneous treatment effect. The heterogeneous treatment effect follows from returning to the fact that not all firms that would like to get into the center can do so. In general, this sorting process reflects firms’ actual endowments and capabilities, and the less capable firms are selected into the periphery and fail. However, there may be some more capable firms that end up in the periphery “by accident.” For the more capable firms that end up in the periphery, the same adverse conditions here that motivate them to be more exploratory may also stimulate them to outperform other capable firms in the center. These lead to the same predictions: the factors active in the periphery influences the variance of the firms located there. This leads to a different set of predictions than those of Figure 1. It no longer appears to be the case that the periphery should produce unilaterally worse outcomes. Instead, the explorative tendencies of the periphery should increase the likelihood of very bad outcomes, but also allow for the possibility of very good ones. On the other hand, the exploitative tendencies that make the center more stable should reduce the likelihood of very bad outcomes, but also stifle the possibility of very good ones. Thus, the center is a buffer from extreme outcomes, but this buffer cuts both ways. In the periphery, no buffer exists. Firms are free to make their own way—if they find success, it uniquely their own, but if they do not, then there is no insurance against failure. I expect firms that enter in the periphery of the network to end up in the tails of the performance distribution for all firms. Firms that enter into the center of the network should end up closer to the center of the performance distribution for all firms.

**Hypothesis 1.** *The more central (peripheral) in the network a firm’s starting position is, the less (more) likely it is to experience left-tail performance outcomes.*

**Hypothesis 2.** *The more central (peripheral) in the network a firm’s starting position is, the less (more) likely it is to experience right-tail performance outcomes.*

Figure 2 represents this visually. In addition, this setup represents a conservative
test of my hypothesis because of positive selection. Firms that are better endowed should be entering into the center, while firms that are worse endowed should set up at the periphery, where resources are fewer. Therefore, if firms that enter into the periphery consistently find right-tail success at a higher rate then firms at the center, this result is all the more striking.

[insert Figure 2 about here]

**Empirical Setting**

The co-investment networks of venture capital firms are a useful place to test these predictions. For venture capital firms, engaging in collaborative investments with other firms is just as important as interfirm competition. Firms engage in investments with other venture capital firms as part of syndicate groups. These arrangements help to diversify the risk associated with any one venture, break down information asymmetries between firms investing in different rounds of a project, and build complementary and diverse expertise for evaluating, managing, and mobilizing resources for startup ventures (Admati & Pfleiderer, 1994; Bygrave, 1987; Lerner, 1994; Sah & Stiglitz, 1984; Wilson, 1968). As this process repeats itself, venture capitalists develop a network of co-funders over time. Any particular venture capitalist’s network can grow to take on a variety of structures. This will depend on the type of investments undertaken, the number of investments pursued, and the other venture capitalists a focal firm works with. At the population level, these individual events aggregate to form the larger venture capital co-investment network.

Research has shown that networks are important for venture capitalists and the entrepreneurs they fund (Hochberg, Ljungqvist, & Lu, 2007). Networks determine access and exposure to information and resources (Aldrich & Zimmer, 1986; Hochberg, Ljungqvist, & Lu, 2007). They contribute to brand image and provide a support system when times are tough (Stuart, Hoang, & Hybels, 1999). They also determine the flow of deals a company is exposed to and eventually pursues (Sorenson & Stuart, 2001). In light of these results, it is evident that the co-investment
network influences the strategies venture capital firms are able to pursue.

To better understand the micro mechanisms of this process, I conducted a series of semi-structured interviews with eighteen venture capitalists. These individuals worked at firms operating in locations ranging from the Silicon Valley in California to New Delhi, India.1 I spoke to venture capitalists about the considerations they made when determining what made others more attractive exchange partners, how they used their interfirm networks, and also how they would like to position themselves in the network.

All venture capitalists described the most advantageous network location as the center. They spoke about the desire to be a part of the densely connected group at the center and the benefits this would confer. They describe the venture capitalists located here in glowing terms: as having more status, better visibility and brand recognition, more resources, easier access to limited partner funds, and more hits and prior success for their investments. This is consistent with the unilateral core-periphery dynamic depicted in Figure 1, where, among a group of entrants, those that position themselves in the center should experience unambiguously better outcomes.

Venture capitalists also spoke about the desire for stability and consistency above all. One remarked on balancing risk with potential success, “Unicorns are nice, but we can’t pursue them as a strategy.” Another described the center of the network as a comfortable place, commenting, “We could really sit back and make everything we need to off of just our managing fees alone—there’s no real need to explore elsewhere.” One venture capitalist said fondly of a group of investors he had worked with before, “You have a group of people you know you can get together and the project is going to hit a certain outcome.” Overall, the interviews suggested that venture capitalists value the center as the most resource and information rich location in the network. They also value the center for its ability to grant consistency and

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1I gathered an initial sample of six firms through these firms’ connection to Stanford Graduate School of Business’ Curriculum Development Department. I then used a snowball sample to contact additional venture capital firms for interview. Building the sample this way introduces the possibility for survivor bias to tinge the kinds of responses venture capitalists’ give. In interviews, however, venture capitalists spoke freely about their own experiences and biases as well as interfirm social interactions more broadly. Importantly, these comments often took the perspective of less successful and well-known firms. This balance in venture capitalist responses alleviates concerns about the qualitative results only reflecting a one-sided view, i.e., a portrait of success.
ensure long-term survival. All else equal, a venture capitalist would always prefer to locate in the center instead of trying to “get lucky” in the periphery and face the risk of failing.

However, my interviews uncovered drawbacks to the center as well. The center appears to promote a closing off effect where venture capitalists engage with the same investors on the same projects over and over again. Some of the mechanisms reflect the social-structural constraints of the center. Venture capitalists also spoke of the social pressure that exists as a byproduct of investing with other firms. One told the story of investing together with an influential, high-status firm earlier in his firm’s history. He said that the visibility was good, but it created expectations: “It got very hard to say no to the deals they would send across our desk.” He described the situation where regardless of his firm’s own strategy or preferences, the more powerful firm impacted his investment behavior and was able to influence the less powerful firm to follow its wishes. Another venture capitalist explained that interacting in the center was necessary because of the ability to mobilize resources there, but expressed reticence at what the costs down the road could be. “There are people you want to call, and people you have to call,” he said. Other mechanisms parallel the cognitive constraints outlined in the literature. The same venture capitalist that reflected fondly on his working group commented that the group “knew what worked”—they generally took on the same kinds of projects when reconvening again. Another mentioned that when deciding what other firms would be best in a syndicate for a particular project, he often based the decision on prior experience. Once two firms established a particular working relationship, they tended to rely on the tie again. Importantly, the tie seems to be used for the same kinds of investments when it is reused.

Venture capitalists spoke of the periphery in terms of its untapped, yet unknown potential. One said, “We know there’s a huge volume of deals out there, but they require a lot more sifting through.” At the same time, he explained that a good deal coming from a relatively unknown area could provide a huge opportunity if his firm could secure a large equity stake by being one of the first to fund it. “The deals
coming from the denser part of the network are better," he said, "but they're already scooped." He went on to explain that he knew he was guaranteed a higher rate of success on a given deal of the latter type. But the ceiling on how profitable it could be for the firm is much lower because the advantageous equity positions are already taken. In this sense, the very best deals represent strategic opportunities that are yet to be captured by other firms. Because there is more room for these opportunities to move around the periphery without getting snapped up, unicorns can be picked up from here.

My interviews enhanced my understanding about the tradeoffs present in the center and periphery of the network. In the center, there is a steady stream of deals available to choose from, and it is easy to mobilize resources. As a venture capital firm gains experience working with other firms, other firms are more likely to come to it with deals in the future as well. At the same time, this process creates a cycle where venture capitalists located in the center end up working on the same people on the same kinds of projects over and over again. On the other hand, in the periphery, venture capitalists may not get dependable deals coming across their desk as often, but they get deals from far afield. And, they have the freedom to pursue the investments they choose. The center of the network guarantees stability and consistent returns. The periphery of the network motivates external search that is beneficial for exploration. While exploration can be risky, it also increases the likelihood of discovering great, uncaptured ideas. For venture capitalists, I argue that entering into the center of the co-investment network decreases left-tail outcomes, which I define as death. But, entering into the center of the co-investment network should also decrease right-tail outcomes, which I define as successful initial public offerings and positive acquisitions achieved by a venture capitalist’s investment portfolio. I test these predictions by measuring these variables as a function of the network location of other members of first syndicate group a venture capital firm participates in.
Research Design and Measurement

I use the venture capital firm-level co-investment network as my strategic research setting. To test my predictions, I built several sources of data and integrated several others. I compiled information about funding events from Preqin Venture Deals Analyst, which populates its database using filings that must be reported when a venture capital firm invests in a startup. It matches these to the startup companies on the receiving end of the funds. This catalogue of events contains 14,197 unique venture capital firms engaging in 65,123 investments. These events occur over an observation window of 1981 to late 2014. While some venture capitalists stake out investments as single firms, the majority of investments are undertaken as a part of a syndicate group. About half of the syndicates are comprised of groups of three of larger. Figure 3 illustrates the frequency distribution of syndicate size.

Dependent Variables: Venture Capital Outcomes

My analysis centers on how network entry influences the variance of venture capital performance outcomes. To investigate the spread of performance, I center on outcomes that occur at the tails of the performance distribution. In the right tail, I focus on performance outcomes that venture capitalists agree upon to be highly desired and also difficult to attain. These outcomes include successful initial public offerings and positive acquisitions of startups the firm has invested in. These outcomes correspond with what the interviews illustrated about what venture capitalists aspire to and how they perform and have also been used in prior research as a measure of venture capital firm success (Hochberg, Ljungqvist, & Lu, 2007). Taking a company public is a highly desired outcome. One venture capitalist remarked about the qualities he looks for in entrepreneurs, “What we want is an entrepreneur that is in it until the end. Their goal is to IPO.” Initial public offerings are also extremely rare. Of the 34,622 startup firms that receive venture funding in the data,
only 86 of these go public. I compile initial public offering data from ThompsonOne. Having a startup acquired confers less prestige, but positive acquisitions are also a desired outcome. They provide positive media attention and grant status, brand recognition, and large inflows of cash to the firm. I integrate acquisition data from Crunchbase because they compile acquisition events based on media coverage as well as financial filings. While acquisitions made for a slight loss or no gain do not gain a lot of media attention, those sold for positive gains do. Reading the tenor of the media coverage for acquisition events allows us to build a pool of acquisitions that represent strongly positive events for the companies involved. They are less rare than initial public offerings, but are also very uncommon. Only 1,217 out of the 34,622 startup firms in the data experience this outcome. Following this, I define the variable \textit{Acquisition or IPO} as the yearly count of companies a venture capital firm has invested in that have been acquired or IPO’d.\footnote{More than one venture capitalist can invest in a particular startup, either as a part of a syndicate group or on separate funding rounds. So, the sum of \textit{Acquisitions or IPO} across all firm-year observations is greater than the raw 1,217 count observed among startups.}

In the left tail, I focus on outcomes that are a result of poor performance and are agreed upon to be undesired. We characterize the left tail as firm death. A venture capital firm “dies” when it is unable to attract capital from limited partners to raise a new fund. Limited partners decide whether or not to allocate capital for a new fund based upon a venture capitalist’s investment history. Limited partners look for a portfolio that has a proven track record of success with securing follow-on rounds, for example, or one that shows high potential for future success. If they are satisfied with the venture capitalist’s progress, they will raise another round. Another limited partner may decide to raise a round as well. Venture capital firms compete with each other to secure the most lucrative deals with the best entrepreneurs; in a more passive sense they also compete for limited partner funds. If no limited partner is interested in working with the venture capital firm, it is unable to raise a fund and eventually dies when its active funds run out and it is unable to invest any more. In accordance with this, I consider a venture capital firm as no longer active when it does not invest for over two years since its last funding event and name this variable \textit{Defunct}.\footnote{More than one venture capitalist can invest in a particular startup, either as a part of a syndicate group or on separate funding rounds. So, the sum of \textit{Acquisitions or IPO} across all firm-year observations is greater than the raw 1,217 count observed among startups.}
Investment skills are transferrable across organizational housing. So, the individual venture capitalists of a defunct firm could decide to cut the losses sustained and reorganize as a new firm. However, this does not appear to be how venture capitalists behave. When approaching the fund raising and renewing window with a portfolio that is inadequate, some venture capitalists engage in what some call “logo collecting.” This practice involves buying into the late stages of high status deals for a large amount of capital but without a large share of equity (and therefore without a large potential for profit). The collectors then “put the logo on their mantle,” as one venture capitalist put it, and use this apparent portfolio boost to try to attract quality entrepreneurs and lobby for renewing or raising a limited partner fund. Venture capital firms in this position also try to gain extensions on their funds, and may do so by making a case for why a particular company needs more time to develop. This pattern of reactions to potential failure indicates that it is agreed upon to be an undesirable outcome. The negative language used to describe the struggles of firms in this position also indicates that there is a stigma associated with poor performance. These observations illustrate that firm death is an effective measure of a left-tail outcome for a venture capital firm.

**Independent Variables: Co-investment Network and Additional Controls**

The investment history of each venture capital firm provides the foundation for building the co-investment network. Firms can send and receive ties by investing in portfolio companies with one another. When two firms invest as a part of the same syndicate, they become tied bidirectionally. The network is comprised of a densely connected center with a surrounding periphery. I depict this visually in Figure 4, where each vertex is shaded by the highest $k$-core to which it belongs. The $k$-core of a network is the subgraph for which the degree of each node in the subgraph is $k$ or more (Seidman, 1983). The coreness of a node $k$ corresponds to the highest $k$-core to which it belongs. Vertices with the lowest coreness are colored in the lowest color frequencies (red and orange) and gradually build up to the highest (indigo
and violet) as the coreness becomes high. In 2014, the highest-degree $k$-core in the venture capital co-investment network is 46. There are 161 firms in this $k$-core, which has a clustering coefficient of .56. The clustering coefficient, calculated as the global probability that any firm’s ties are also connected to each other, decreases as the coreness decreases. Figure 5 depicts the number of firms and the clustering coefficient in each $k$-core. A firm becomes central in the network by maintaining connections through making investments with other venture capital firms. I measure a venture capitalist’s degree centrality as the number of other firms they connect with by engaging in investments with them. The variable *Centrality of entry* represents the sum of the centralities of each of the other venture capitalists that participate in the first investment a brand new focal firm makes. This variable is an imprint, so it is set upon entry and remains the same for the focal venture capital firm’s lifetime.

[insert Figure 4 about here]

[Insert Figure 5 about here]

I incorporate three additional controls. The first, *Syndicate size*, measures the total number of venture capital firms participating in the syndicate round the focal firm is involved in. This helps to alleviate the possibility that syndicate groups that are more central are simply comprised of more members. The second, *Deal size*, measures the size of the funding round the focal venture capital firm participates in. The purpose of this variable is to consider the possibility that syndicate groups that are more central tend to invest in larger funding rounds. If the mechanism of action that produces my effect were driven primarily by the size of the funding round an entering firm is exposed to, I should not expect to see any leftover effect for the centrality variable after deal size is taken into account. The third control accounts for the possibility that venture capital firms may enter together or that new firms might attract one another, which could tend to place these firms into the periphery more often. The variable *New syndicate* is equal to 1 when the average age in years of the firms in the syndicate round the focal firm participates in is less than or equal to 1. That is, the variable indicates when all of the other firms in a focal firm’s
syndicate round are less than a year old (age is counted discretely beginning at 1 year). I present descriptive statistics of all variables in Table 1.\textsuperscript{3} \textit{Centrality of entry} is scaled down by a factor of $10^4$ to improve the visual presentation of the results; the scaling does not affect the substantive content. \textit{Deal size} is reported in millions, USD.

[insert Table 1 about here]

Modeling Strategy

To incorporate network characteristics for each of the syndicates, I build a data structure that models the co-investment network as it evolves. I generate a cross section of the co-investment network at each time interval in the data and compute network characteristics for every node at each interval. For each focal venture capital firm $i$ that participates in an investment at time $t'$, the other members of its syndicate are represented by $j_l$, where there are $l + 1$ total members in the syndicate. For each syndicate investment, I take the network characteristics $x_{jt'}$ for each of the $l$ other participants on the investment and match these back to the corresponding focal firm $i$ for that investment. This builds an index of all the investments a firm participates in, which includes the corresponding network characteristics for its co-investors (on that project) at that point in time. Each firm’s network imprint is comprised of the $x_{jt'}$ from the members of its initial syndicate group. Since the imprint never changes for a particular firm, $t'$ represents the time a firm makes its first investment and enters the risk set.\textsuperscript{4}

I also observe all subsequent investments each firm makes, and track how well these portfolio companies perform. Through monitoring a firm’s investment activity,

\textsuperscript{3}It is worth nothing that firms that do not die have more observations than those that do not, and skew the mean of Defunct down. The mean of Defunct is close to 30%, but about 48% of unique firms go defunct. When predicting this outcome, I model whether a firm ever goes defunct, represented as the function of the the firm’s one-time imprint and matching variables. Thus, the total number observations for this model equals the number of unique firms in the dataset, 14,197.

\textsuperscript{4}As intimated by Figure 3, some firms’ first investments are undertaken alone. I want to ensure that it is not singleton investors that are driving the centrality effects. To rule out this possibility, I re-run both sets of models including only firms that invest first as a part of a syndicate. These results are presented in Appendix A.
it is also evident whether the firm becomes defunct. I use the firm’s investment trajectory to compile these network and performance outcomes for each firm \( i \) in each year \( t \), so that I have a yearly panel where the unit of analysis is venture capital firm-years. This provides approximately 37,000 firm-year observations. I model the dependent variable right-tail and left-tail performance outcomes as a function of the \( x_{jt'} \) and the controls. For this analysis, I predict the success and failure of each firm using the combined centrality of the other venture capital firms that participated in its first investment. This model is estimated

\[
\text{performance}_{it} = \mu_t + \beta x_{jt'} + \gamma \text{controls}_{it'} + \alpha_i + \epsilon_{it} \quad (1)
\]

where \( \mu_t \) is an intercept that varies over each year, \( \beta \) is a coefficient, \( \gamma \) is a coefficient vector, \( \alpha_i \) is an error term that varies over venture capital firms, and \( \epsilon_{it} \) is an error term that varies over venture capital firms over each year.

I supplement this basic model with a Coarsened Exact Matching design. One matching setup focuses on the initial characteristics of the entering venture capital firms, and the other on the characteristics of the entering venture capital firm’s initial investment. Supplementing the baseline model with a matching design accomplishes two goals. First, Coarsened Exact Matching is a useful tool for estimating causal treatment effects.\(^5\) The use of this identification strategy is to get as clean an effect of network entry as possible. This setup allows us to eliminate characteristics of venture capital firms or investments that might make them systematically appear in one area or another of the network. By doing this, I control in the analysis for characteristics of first syndicate groups that are correlated with centrality but that may represent different mechanisms than the ones I advance.

There remains the issue that venture capital firms’ characteristics are observed as they enter the risk set by making investments. This process occurs simultaneously to the network imprint rather than before it, so matching on firm characteristics at this stage does not create true pretreatment groups. I modify the analysis to avoid this pitfall. The modified setup takes advantage of the fact that while the portfolios

\(^5\) See Appendix B for an elaboration on the Coarsened Exact Matching Approach and my identification strategy.
of venture capital firms may outperform one another, the return on any independent investment in the portfolio is random. Similar to stock market returns, a venture capital firm may invest in five biotech companies and experience the success that one of them “hits.” But, which of the five goes on to be hit is ex ante subject to chance. My identification strategy uses this fact, and measures the network imprint as the centrality of the first syndicate of an investment that “hits.” Here, the firm enters the risk set when it makes its first investment that goes on to receive a follow-on round of funding. Here, and the corresponding network variables represent the other syndicate members' network positions at the time this eventually successful investment is made. For approximately 85% of firms, this follow-on investment is not the first investment they make. This data structure implies that for this matching setup, 85% of firms are in a true pretreatment group. I use this matching setup to strengthen the robustness of this identification strategy.

The second goal of matching focuses on accounting for the finite observation window. To model left-tail outcomes, I use a logistic regression to model the likelihood of becoming defunct. However, the regression needs to account for right censoring in the data. I model the hazard of a venture capital firm becoming defunct using a form of event analysis. My research question investigates the effect of a group of network variables and a set of controls on the hazard of becoming defunct. It is less concerned with the particular relationship between a venture capital firm’s age and this hazard. I want to focus directly on the covariates and do away with this underlying nuisance function. An obvious choice for this would be the Cox proportional hazards estimator, which would serve this goal while simultaneously avoiding imposing a functional form. However, I observe a venture capital firm’s death by its lack of investing rather than its investing activity. Because the data are compiled based on investment activity, incorporating firm death into a Cox estimator creates the mechanical issue of inflating the data using artificial data points to mark when a firm becomes defunct. To avoid this, I use a matching design that creates strata based on when venture capital firms make their first investment (i.e., enter the risk set). I alleviate the problem of there being disproportionately more zeros in the De-
funct variable for newer firms because these firms are only compared against other firms that enter at the same time. By building treatment-control cohorts of firms that exist in parallel in the same portion of the observation window, I do not have a censoring problem.

The right-tail measure is a discrete outcome. I use count models to analyze the number of successful acquisitions and IPOs managed. The variance is greater than the mean for Acquisition or IPO. A goodness of fit test for a Poisson distribution under the null hypothesis that this variable represents a Poisson process reports a $\chi^2$ statistic of 55203.3 with 43338 degrees of freedom. I reject the null that the data represent a Poisson process. I turn to the negative binomial class of models, since they are better equipped to deal with overdispersed data (Hilbe, 2011). I perform a likelihood-ratio test with the null hypothesis that the dispersion parameter in the baseline negative binomial model is the same as the Poisson. This test reports a $\chi^2$ statistic of approximately 25,000 with one degree of freedom. I reject the null that the dispersion parameter is the same as the Poisson. One additional consideration is the heavy skewness in the data. Because these counts are tail events, it is likely for many firm-year observations to not have any or have very few events occur. It is impossible for a firm to have negative acquisitions or IPOs occur, while it is possible to have very many. I provide two additional robustness checks to ensure that our results are not driven erroneously by the shape of distribution of Acquisition or IPO. To account for excess zeros in the data, I run a zero-inflated negative binomial regression to incorporate for the possibility of both structural and sampling zeros in the data (Lambert, 1992). To account for excess skew in the data, I run a quantile regression estimating the median level of acquisitions and IPOs to avoid for the possibility that the results are driven by outliers over-influencing the mean (Cade & Noon, 2003). I use an estimation procedure adapted for use with count data using the jittering method exposited by Machado and Silva Santos (2005) and implemented by

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6I also considered an alternative to the zero-inflated negative binomial, a hurdle model that treats all zeros as structural. The hurdle model produces similar results as the zero-inflated model. I use Vuong’s likelihood-ratio test for non-nested models to compare fit (1989). The null hypothesis is that the models fit the underlying data generating process equally well, while the alternative is that one model fits the data better. The test produces a $z$ statistic of 25.80 in favor of the zero-inflated negative binomial; I report the zero-inflated model in the results.
Miranda (2008). I use 100 jittered samples to build the average-jittering estimator to calculate the parameters of the model.

All models include year fixed effects and non-matching models cluster standard errors at the venture capital firm level.

Results

I regress the right-tail and left-tail performance outcomes, Acquisition and IPO and Defunct, respectively, on the network variable Centrality of entry and a set of controls.

Does Initial Attachment influence Left-Tail Outcomes?

Hypothesis 1 stated that attaching into the center should decrease the likelihood of experiencing left-tail outcomes, while attaching in the periphery should increase the likelihood of experiencing left-tail outcomes. The analysis investigates whether entering into the core or periphery influences a firm’s chances of survival. To accomplish this, I regress the outcome variable Defunct on the network attachment variable Centrality of entry and a set of controls. The results are contained in Table 2.

Column 1 reports the results of a negative binomial regression of Defunct on Centrality of entry, Syndicate Size, Deal Size, and New syndicate. The coefficient on Centrality of entry is negative and statistically significant, the coefficient on Syndicate size is positive and significant, and the coefficients on Deal size and New syndicate are not significant. This suggests that entering into the center is associated with a better chance of survival. Conversely, making an initial attachment in the periphery exposes a firm to a greater risk of death. This result provides support for Hypothesis 1.
Does Initial Attachment Influence Right-Tail Outcomes?

Hypothesis 2 stated that attaching into the center should decrease the likelihood of experiencing right-tail outcomes, while attaching in the periphery should increase the likelihood of experiencing right-tail outcomes. The next analysis investigates whether entering into the core or periphery influences a firm’s chances of runaway success. I regress the outcome variable *Acquisition or IPO* on the network attachment variable *Centrality of entry* and a set of controls. Table 2 contains this result.

Column 2 reports the results of a negative binomial regression of *Acquisition or IPO* on *Centrality of entry*, *Syndicate Size*, *Deal Size*, and *New syndicate*. The coefficient on *Centrality of entry* is negative and statistically significant, the coefficient on *Syndicate size* is positive and significant, the coefficient on *Deal size* is not significant, and the coefficient on *New syndicate* is positive and significant. These results suggest that entering into the center is associated with a lower likelihood of extreme success. Conversely, making the initial attachment in the periphery provides a better opportunity for runaway success. This provides support for Hypothesis 2.

Robustness Checks I: Identification

In discussing the research design, I outlined a matching strategy that would help us to rule out the possibility that venture capitalists with certain types of characteristics would systematically enter into different parts of the network. In doing so, this would avoid the potential for underlying heterogeneity in initial endowments or strategies to be the driver of the results. The matching using investment characteristics serves a parallel function by ruling out the possibility that venture capital firms with different endowments or strategies are systematically tied to first investments that are located in one part of the network or another. Each of these regressions of *Defunct* and *Acquisition or IPO* on *Centrality of entry* and the set of controls follow a Coarsened Exact Matching algorithm. The first algorithm focuses on venture capital firm characteristics. As outlined in the research design, for this group I use for the network entry variable the first investment a venture capital firm makes that...
eventually receives follow-on funding in order to build true pretreatment treatment-control groups in the data. The second algorithm focuses on characteristics of the investment itself. The results are presented in Table 3.

Column 1 contains a negative binomial regression of Defunct on Centrality of entry, Syndicate Size, Deal Size, and New syndicate matching on venture capital firm characteristics. The coefficient on Centrality of entry is negative and statistically significant, the coefficient on Syndicate size is positive and significant, the coefficient on Deal size is not significant, and the coefficient on New syndicate is positive and significant. This result indicates that entering in the center is associated with an increased likelihood of survival. On the other hand, entering in the periphery is associated with an heightened chance of dying. Column 2 repeats this regression matching on investment characteristics. The coefficient on Centrality of entry is negative and significant, the coefficient on Syndicate size is positive and significant, the coefficient on Deal size is positive and significant, and the coefficient on New syndicate is positive and significant. The core result of the two models is that entering into the center depresses the likelihood of becoming defunct. This bolsters the support for Hypothesis 1.

Columns 3 and 4 repeat this process for the right-tail outcomes. Column 3 contains a negative binomial regression of Acquisitions or IPO on Centrality of entry, Syndicate size, Deal size, and New syndicate matching on venture capital firm characteristics. The coefficient on Centrality of entry is negative and significant, the coefficient on Syndicate size is positive and significant, the coefficient on Deal size is positive and significant, and the coefficient on New syndicate is not significant. This suggests that firms that enter into the center of the network are less likely to experience runaway success. On the other hand, firms that enter into the periphery are more likely to experience outcomes in the right tail. Column 4 repeats this regression, matching on investment characteristics. The coefficient on Centrality of entry is negative and significant, the coefficient on Syndicate size is positive and significant, the coefficient on Deal size is positive and significant, and the coefficient on New syndicate is not significant. Together, the two models illustrate that entering
into the center inhibits the chances of runaway success. This result validates the findings of Hypothesis 2.

Robustness Checks II: The distribution of right-tail performance outcomes

The negative binomial model accounts for overdispersion in the count of acquisitions and IPOs. However, there was additional concern that the shape of the distribution might influence the results. Many firms do not experience acquisitions at all, and some firms experience many. I employ two additional estimation procedures to address this. The zero-inflated negative binomial accounts for the excess zeros present in the data. The quantile regression estimating the median, rather than the mean level of acquisitions and IPOs, takes the skewness of the data into account. The results are presented in Table 4.

Columns 1 and 2 report the results of a zero-inflated negative binomial regression of Acquisition and IPO on Centrality of entry, Syndicate size, Deal size, and New syndicate. The negative binomial portion of the model indicates that Centrality of entry is negative and significant, Syndicate size is not significant, Deal size is not significant, and New syndicate is positive and significant. The logistic portion of the model indicates that entering in the center not associated with structural zeros, increased syndicate size indicates fewer structural zeros, a larger deal size indicates fewer structural zeros, and a new new syndicate is not associated with structural zeros. The model suggests that firms may experience acquisitions for both structural and sampling reasons. But, even when accounting for the data generating process, firms that enter into the center are less likely to experience right-tail outcomes.

Column 3 contains the results of a quantile regression, adjusted for count data, estimating the median level of Acquisition and IPO as a function of Centrality of entry, Syndicate size, Deal size, and New syndicate. The coefficient on Centrality of entry is negative and significant, the coefficient on Syndicate size is positive and significant, the coefficient on Deal size is not significant, and the coefficient on New syndicate is positive and significant. The result indicates that entering in the center
is associated with a decreased median likelihood of Acquisitions or IPO. The model suggests that the previous results are not driven by outliers with extremely high counts of acquisitions and IPOs. The models in Columns 1 and 2 and Column 3 indicate that even taking into account potential irregularities in the distribution of right-tail outcomes, the results are not model dependent. These results provide further support for Hypotheses 1 and 2.

**Discussion and Conclusion**

My models describe the relationship between the place a new venture capital firm enters the network and the outcomes it experiences. The first major finding is that venture capital firms that enter in the center of the network are less likely to become defunct. On the other hand, firms that enter in the periphery are more likely to shut down. This result is consistent with the idea that the core of the network provides a safety blanket. It provides consistent access to resources and quality exchange partners. This stability allows firms to survive. This idea is summarized in the arguments leading up to Hypothesis 1.

I go on to explore outcomes in the right tail as well. Venture capital firms that enter into the center of the network are less likely to experience extreme positive performance outcomes. Conversely, firms that enter into the periphery of the network are more likely to achieve performance outcomes in the right tail. This result is more surprising. It might seem that for firms that are otherwise equal, entering into relatively more central positions should promote uniformly better outcomes. This is the naïve illustration in Figure 1. However, organization theory suggests that there is more to the puzzle than is initially obvious (March, 1991). It belies the fact that the benefits that make the center more attractive to firms often reflect the exploitation of safe bets. This means that organizations that “grow up” here take on a pattern of behavior geared towards capitalizing on already available resources. This hedging behavior promotes interacting with the same exchange partners, doing the same kinds of work. This is great for exploitation. Firms build up a specific
repertoire of expertise and can execute a specific kind of strategy very well, as one venture capitalist remarked about having a near certainty with which they could pursue certain kinds of deals. Because of the pressure for maintaining a consistent pattern of interaction with other firms, some venture capitalists were influenced into pursuing deals that did not let them explore their own individual strategies.

Taken together, these factors cut both ways. These examples illustrate that the center can be a very constraining place as well, with influences stemming from both cognitive and social-structural mechanisms. While the periphery does have other problems, notably, the lack of organic resources and notoriety located there, it is relatively less constraining in important ways. The periphery promotes external, rather than internal, search. It is home to relatively uncharted idea space, and its sparse population affords the ability connect these ideas and capitalize on them in novel ways. One venture capitalist commented about making deals with high status, well-connected firms, “People will be aggressive when trying to take rewards.” Deals made in the center required a great deal of cooperative sharing and jostling for position in order to negotiate high returns. On relatively unknown ideas firms could source themselves, though, the firms’ successes and failures were all their own. This applies to both the financial and social dimensions of a successful deal. For already-exploited deals where a lot of firms are sharing the pie, they must share the financial windfall the investment brings in smaller slices. On the social side, they also share the credit, and each of them gains a smaller boost to brand image and recognition. Often, firms will engage in public or private squabbles over who deserves the credit for a shared success. One venture capitalist described this as “the particularly nasty part of the business.” So, the periphery has the potential for a unique snowball effect. The deals here are not vetted and are on average of lower quality, but come from far afield, enough so that some may have a wild chance of success. For those that are executed successfully, firms gain huge returns because the deal is not “scooped” and the windfall does not have to be shared as widely. Firms also gain huge social returns in status and brand recognition because it is obvious to others that they are primarily responsible for the success. They can turn around and leverage both of
these types of rewards into attracting new deals from high quality entrepreneurs, and be the “first one in” on these deals to gain large returns in the next cycle, repeating the process.

These firms may also be invited to join higher quality deals being brokered by existing venture capital firms as well. Because of their own independent success, the status differential in these exchange relationships may be smaller. This could afford them the protection of not being as easily maneuvered into exploitative investing as a firm that made its initial investment in a high status group. In this way, it seems like a firm could eventually thrive by adopting the most effective strategies promoted in the center and in the periphery. Straddling a bridge between the two would appear to be a way to capture the benefits of both. This raises an important question. In this paper, I develop a theory of network entry. I show that network imprinting has implications for the tendency to explore versus the tendency to exploit and that this impacts the variance of firm performance. But, how a firm’s initial ties and formative investments interact with its local network remains an intriguing puzzle. There is more work to be done on this topic. In particular, it is worth investigating explicitly how network entry impacts the shape and evolution of the network itself. Even more intriguing, the tradeoffs associated with occupying each type of network position imply that experiencing a success or failure in a different part of the network may have greatly differential effects on a firm’s life. This research will help us understand the way that these factors, often studied in isolation, interact to shape the way that a firm forges strategic opportunities and social relationships.
Rereferences


Rossman, G., Esparza, N., & Bonacich, P. (2010). I’d like to thank the academy,
Figures and Tables

Figure 1. Firm Entry and Network Imprinting Under the Matthew Effect

The solid line —— represents firms that enter into the center. The dashed line - - - represents firms that enter into the periphery.
Figure 2. Firm Entry and Network Imprinting Under Exploration and Exploitation

The solid line —— represents firms that enter into the center. The dashed line —— represents firms that enter into the periphery.

freq(\textit{performance})
Figure 3. Distribution of Syndicate Group Size
Vertices with the lowest coreness are colored in the lowest color frequencies (red and orange) and gradually build up to the highest (indigo and violet) as the coreness becomes high.
Figure 5. $k$-core Size and Clustering Coefficient by Degree of $k$-core
Table 1. Descriptive Statistics: Venture Capital Firms, 1981-2014

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Mean</th>
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<th>Maximum</th>
<th>Variance</th>
</tr>
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<td>Defunct</td>
<td>0.304</td>
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<td>1</td>
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<td>Acquisition or IPO</td>
<td>0.235</td>
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<td>36</td>
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<td>Centrality of entry</td>
<td>0.010</td>
<td>0</td>
<td>0.344</td>
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<td>Syndicate size</td>
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Centrality of entry is scaled down by a factor of $10^4$, and Deal size is scaled down by a factor of $10^6$. 

40
Table 2: Performance of a Venture Capital Firm as a Function of the Centrality of the First Syndicate Group at the Time of Entry: Baseline Models

<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>(2)</th>
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<tbody>
<tr>
<td>Centrality of entry</td>
<td>-3.242***</td>
<td>-8.360***</td>
</tr>
<tr>
<td></td>
<td>(0.844)</td>
<td>(2.072)</td>
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<tr>
<td>Syndicate size</td>
<td>0.0403***</td>
<td>0.0780***</td>
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<tr>
<td></td>
<td>(0.0108)</td>
<td>(0.0235)</td>
</tr>
<tr>
<td>Deal size</td>
<td>0.0008</td>
<td>0.0011</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>New Syndicate</td>
<td>-0.0518</td>
<td>0.632***</td>
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<tr>
<td></td>
<td>(0.0677)</td>
<td>(0.153)</td>
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<tr>
<td>Constant</td>
<td>279.2***</td>
<td>-512.0***</td>
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<tr>
<td></td>
<td>(9.424)</td>
<td>(14.52)</td>
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<tr>
<td>Observations</td>
<td>14,197</td>
<td>43,339</td>
</tr>
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<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
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Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 3: Performance of a Venture Capital Firm as a Function of the Centrality of the First Syndicate Group at the Time of Entry: Matching Models

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<td>Acquisition or IPO</td>
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<td>-15.11***</td>
<td>-7.762***</td>
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<td></td>
<td>(2.601)</td>
<td>(0.911)</td>
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<td>Syndicate size</td>
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<td>(0.000663)</td>
<td>(0.000417)</td>
<td>(0.00106)</td>
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<tr>
<td>New Syndicate</td>
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<td>0.277***</td>
<td>0.0681</td>
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<td>(0.134)</td>
<td>(0.0654)</td>
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<td>(0.0807)</td>
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<td>Constant</td>
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<td>-601.2***</td>
<td>-546.6***</td>
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<td></td>
<td>(0.0607)</td>
<td>(0.0261)</td>
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*** p<0.01, ** p<0.05, * p<0.1
Table 4: Performance of a Venture Capital Firm as a Function of the Centrality of the First Syndicate Group at the Time of Entry: Distribution Models

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Acquisition or IPO</th>
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<th>(2) Acquisition or IPO</th>
<th>(3) Acquisition or IPO</th>
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<tbody>
<tr>
<td>Centrality of entry</td>
<td>-7.295**</td>
<td>1.104</td>
<td>-1.980**</td>
<td></td>
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<tr>
<td></td>
<td>(3.472)</td>
<td>(2.746)</td>
<td>(0.950)</td>
<td></td>
</tr>
<tr>
<td>Syndicate size</td>
<td>-0.00316</td>
<td>-0.193***</td>
<td>0.0697***</td>
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</tr>
<tr>
<td></td>
<td>(0.0220)</td>
<td>(0.00915)</td>
<td>(0.0050)</td>
<td></td>
</tr>
<tr>
<td>Deal size</td>
<td>-0.000361</td>
<td>-0.00348***</td>
<td>0.0007</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000614)</td>
<td>(0.000789)</td>
<td>(0.0005)</td>
<td></td>
</tr>
<tr>
<td>New Syndicate</td>
<td>0.385***</td>
<td>0.0337</td>
<td>0.505***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.160)</td>
<td>(0.0537)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-404.2***</td>
<td>0.196**</td>
<td>-380.7***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(22.32)</td>
<td>(0.0793)</td>
<td>(10.26)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>36,883</td>
<td>36,883</td>
<td>43,339</td>
<td></td>
</tr>
<tr>
<td>Model design</td>
<td>Zero-inflated negative binomial</td>
<td>Zero-inflated negative binomial</td>
<td>Quantile (median)</td>
<td></td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Appendix A: Ruling Out Singletons

Following the note from Footnote 3, there was a concern that the results could be driven by venture capital firms that enter as singletons. To rule out this possibility, I re-run both models including only firms that invest first as a part of a syndicate. The results are presented in the table below, and indicate that the pattern of results are consistent with those presented earlier, whether singleton entrants are included or not.

Table A1: Performance of a Venture Capital Firm as a Function of the Centrality of the First Syndicate Group at the Time of Entry: Syndicate Entrants Only

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Defunct</th>
<th>Acquisition or IPO</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td></td>
</tr>
<tr>
<td>Centrality of entry</td>
<td>-3.118***</td>
<td>-8.483***</td>
</tr>
<tr>
<td>(0.852)</td>
<td>(2.068)</td>
<td></td>
</tr>
<tr>
<td>Syndicate size</td>
<td>0.0116</td>
<td>0.0955***</td>
</tr>
<tr>
<td>(0.0122)</td>
<td>(0.0257)</td>
<td></td>
</tr>
<tr>
<td>Deal size</td>
<td>0.000824</td>
<td>-0.000542</td>
</tr>
<tr>
<td>(0.000570)</td>
<td>(0.000498)</td>
<td></td>
</tr>
<tr>
<td>New Syndicate</td>
<td>-0.136*</td>
<td>0.663***</td>
</tr>
<tr>
<td>(0.0702)</td>
<td>(0.161)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>287.9***</td>
<td>-530.8***</td>
</tr>
<tr>
<td>(10.51)</td>
<td>(15.50)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>10,948</td>
<td>33,374</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Appendix B: Coarsened Exact Matching

I employ a Coarsened Exact Matching algorithm, part of the Monotonic Imbalance Bounding class of matching strategies outlined by Iacus, King, and Porro (2011b) and later further illustrated by the same (Iacus, King, & Porro, 2011a). The Coarsened Exact Matching algorithm is designed to take a group of covariates, break each apart into optimally sized bins so that the difference between covariate values within each bin are empirically negligible, and then perform an exact match for each data point on the distance between the vector of these bins. After this process is complete, the estimation can be carried out on the original uncoarsened data incorporating the counterfactual matching generated by the coarsened strata.

I chose this matching estimator because it provides an advantage over traditional approaches such as propensity score matching or nearest neighbor Mahalanobis for several reasons. First, it removes imbalances not just at the mean of the covariates, but along interactions, quantiles, and other moments. Second, it provides a way to remove treated and control data points that lie outside of the shared support of the data that does not rely on the propensity score itself to identify it. This helps the matching process avoid forcing matches based on extrapolating treated and control units at extreme values of the data with no common empirical support. Last, the algorithm ensures that the binning decisions made about the distance between treatment and control units on one dimension do not affect the balance between the groups on another dimension. In classical matching methods, when imbalance on a covariate persists after the matching procedure is completed, researchers must decide how to redefine the procedure to improve it. But, the change that improves the balance on one covariate may decrease it for the others. With Coarsened Exact Matching, the maximum bound of imbalance is determined inherently by the degree of coarsening. Since changing the coarsening choice for any one covariate cannot make the maximum bound of imbalance higher for any other covariate, each coarsening improvement reduces the maximum imbalance for the total set of covariates. These factors result in a matching solution that is maximally balanced at the level of the distribution of each covariate without requiring model dependence. The differ-
ences in other covariates that remain between treated and control units occur only within maximally balanced strata, such that they are empirically indistinguishable. This also reduces model dependence. Within these strata, we can make a strong comparison between treatment and control groups. This comparison isolates the mechanism of interest, the treatment variable, without interference or confounding from the other covariates.

As outlined in section 4.3, the matching approach focusing on characteristics of the venture capital firm uses as the network imprint the first investment a venture capital firm makes that goes on to receive a follow-on round. I match on the location of the venture capital firm, the modal industry it invests in up to the imprint round, the modal stage (early or late stage ventures) it invests in up to the imprint round, and the year that the investment occurs. The second matching approach focuses on the characteristics of the first investment a focal firm makes. This approach matches on the size of the syndicate, the size of the deal, the location of the startup company being invested in, the industry of the startup being invested in, the stage of the startup, and the year that the investment occurs. Table B1 details the breakdown of industry, location, and stage for the observed data.

The coarsened exact matching algorithm chooses an optimal bin width for each stratum. To guide this choice, I use the binning method developed by Shimazaki and Shinomoto (2007). This binning procedure is unique in that it does not require any assumptions about the probability density function of the data (e.g., normality, smoothness), as does Scott’s rule, for example, and instead only that the data follow a Poisson process. Because the underlying rate that produces the observed data is unknown, it is not possible to compute the bandwidth arrangement that maximizes the goodness-of-fit directly from the underlying rate. Instead, the Shimazaki and Shinomoto method reverse engineers the problem and computes a set of potential bandwidths, each with a goodness-of-fit to the observed data. It then uses the data to select from the computed bandwidths the one that maximizes the goodness-of-fit and has the lowest estimated error. This method is conducive to my covariates because they are not normally distributed and the method not require us to make
any additional distributional assumptions about the underlying rate.

Table B1. Overview of Additional Matching Variables

<table>
<thead>
<tr>
<th>Industry</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet</td>
<td>8,030</td>
<td>18.53</td>
</tr>
<tr>
<td>Medical</td>
<td>13,286</td>
<td>30.66</td>
</tr>
<tr>
<td>Other</td>
<td>3,556</td>
<td>8.21</td>
</tr>
<tr>
<td>Other Tech</td>
<td>10,451</td>
<td>24.11</td>
</tr>
<tr>
<td>Software</td>
<td>8,016</td>
<td>18.5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>43,339</strong></td>
<td><strong>100</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Location</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asia</td>
<td>4,043</td>
<td>9.33</td>
</tr>
<tr>
<td>California</td>
<td>10,619</td>
<td>24.5</td>
</tr>
<tr>
<td>Europe</td>
<td>7,636</td>
<td>17.62</td>
</tr>
<tr>
<td>Other</td>
<td>4,213</td>
<td>9.72</td>
</tr>
<tr>
<td>Non-California US</td>
<td>16,828</td>
<td>38.83</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>43,339</strong></td>
<td><strong>100</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early</td>
<td>28,453</td>
<td>65.65</td>
</tr>
<tr>
<td>Late</td>
<td>14,886</td>
<td>34.35</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>43,339</strong></td>
<td><strong>100</strong></td>
</tr>
</tbody>
</table>

Early stage ventures represent Seed or Series A funding rounds.