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The Spawning of Ecosystems: How Cohort Effects Benefit New Ventures

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The Spawning of Ecosystems: How Cohort Effects Benefit New Ventures

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THE SPAWNING OF ECOSYSTEMS: HOW COHORT EFFECTS BENEFIT NEW VENTURES

ABSTRACT

Research has examined the process of entrepreneurial migration, whereby employees from successful industry incumbents move to new ventures. This phenomenon has been linked to direct benefits to entrepreneurial firms, offering valuable knowledge and routines obtained by employees during their tenure at incumbent firms. We propose a theoretical framework in which shared experience – a common background in beneficial knowledge management practices – creates a "cohort effect," facilitating direct ties and innovation benefits to new ventures receiving inventors from the same incumbent firms. Analyzing longitudinal data on inventor migration to 658 new biotech ventures tracked from 1990–2013, we find shared migration ties increase knowledge and market overlap between firms, enhancing their likelihood of direct engagement through alliances and employee hiring as well as the quality of knowledge they develop. Our core theoretical contribution is the identification of a migration cohort effect, in which inventors who share contemporaneous experience at incumbent firms and migrate to new ventures create unique relationships between those ventures. Where prior research on spawning and migration has focused primarily on the direct benefit of human capital transfer from incumbents to new ventures, we explore the broader network implications of similarities and interactions between firms receiving this human capital.

KEY WORDS: Technology and innovation management, New venture strategies, Knowledge management, Human capital theory

INTRODUCTION

Migration research examines the phenomenon of successful incumbent firms that act as a training ground for skilled knowledge workers, founders, and executives who subsequently leave the incumbent to join new entrepreneurial ventures (Agarwal, Echambadi, Franco, & Sarkar, 2004; Beckman, 2006; Campbell, Ganco, Franco, & Agarwal, 2012). An illustration of this phenomenon is provided by the example of three young organizations in the biotech industry: Aegerion Pharmaceuticals, Synageva Biopharma, and Akcea Therapeutics. The top executives of these three organizations shared a common work history, with prior experience at the same established incumbent firm. Marc Beer of Aegerion, Paula Soteropoulos of Akcea, and Sanj Patel of Synageva had each held prominent roles at Genzyme. As an established, highly successful biotech firm focused on developing treatments for rare diseases, Genzyme played a significant role in the development of the biotech sector in Boston (Porter & Clark, 2000). As with other prominent, ground-breaking firms such as Genentech in the biotech industry and Fairchild in the semiconductor industry (Gompers, Lerner, & Scharfstein, 2005), Genzyme served as a training ground for scientists, founders, and executives who left to join new ventures, carrying their valuable experience with them. Weisman (2015) described this phenomenon with Genzyme: "They command battalions of biotechnology workers from Kendall Square to Seattle to Stockholm. They lean on each other for business advice while poaching one another's researchers. And they share a pedigree that is pure gold in the life sciences world."

The three nascent biotech firms shared other important characteristics. They were each launched with the goal of developing "orphan drugs" designed to treat rare diseases and often eligible for governmental incentives, tax credits, and expedited drug trials. All three firms joined the RARE Corporate Alliance to collaborate in rare disease treatment and shared information and expertise as members of the National Organization for Rare Disorders. At the same time, they drew from each other's pool of talent in seeking human capital with, for example, Akcea's executive director of drug development and Aegerion's European medical director recruited from Synageva. Finally, they entered into directly overlapping markets, each developing drugs to treat genetic lipid disorders, conditions that impact metabolism and cholesterol levels and which may result in coronary heart disease.[1]

Individuals leaving the same incumbent firm to work in new ventures share a heritage that can benefit their venture and its success. We examine how the common past heritage and experience of individuals may create a beneficial cohort effect, shaping the dynamics of innovation and market strategy, knowledge sharing, and collaboration between such firms. These

[1] For example, Juxtapid, a drug developed by Aegerion, and Kynamro, a drug offered by Akcea, each target the same specific genetic disorder and received FDA approval within one month of each other.

ventures seek out specific financial, physical, or information resources in order to reduce their environmental uncertainty (Shane & Cable, 2002), with knowledge representing an increasingly important resource, particularly in technologically-intensive environments (Grant, 1996; Zhou & Li, 2012). Valuable knowledge may be gained and leveraged through established incumbent firms within an industry (Drori, Ellis, & Shapira, 2013). Such firms play an important role in seeding the market with skilled human capital for new venture creation and growth as individuals leave those firms, taking knowledge and experience with them, to work in startup ventures (Klepper, 2007). Through the migration of inventors carrying knowledge and important expertise, new ventures gain access to valuable skills in knowledge management and innovation developed during the employee's tenure with the incumbent firm.

Inventors who share contemporaneous experience at incumbent firms create unique relationships between the new ventures to which they migrate. Ventures related through inventors' common prior experiences create what we term a migration "cohort effect," with organizations sharing practices and characteristics by virtue of drawing from the same incumbent sources of human capital. In turn, we suggest that this comprises an ecosystem of firms within an industry that are linked through these prior experiences of migrating inventors. These cohort ecosystem new ventures are more likely to share unique and ongoing relationships in the domain of knowledge development, with perspectives, interactions, and success influenced by connections forged through the inventor cohort members they employ. The ecosystem relationship also provides benefits in terms of the quality of knowledge developed by the venture, an effect that may be enhanced through greater social embeddedness and cohesion of ties to other cohort members.

Our study addresses the following research question: How does the spawning of knowledge from incumbent firms, represented by inventors who move from the incumbent to new ventures, create a cohort-based ecosystem of firms that are better able to share knowledge and engage in direct exchange, resulting in the creation of higher quality knowledge? We examine these relationships among 658 VC-backed ventures which were launched in the biotech industry from 1990 to 2000 and tracked through 2013. Our data span more than 1.6 million firm dyad-year observations. We find that firms in the same cohort ecosystem have greater knowledge overlap and a greater likelihood of pursuing the same technologies, while also demonstrating a tendency to draw from cohort ecosystem firms when hiring new inventors. Ecosystem firms are also more likely to form alliances with their fellow ecosystem members. They generate knowledge of greater quality as a result of membership, though this effect is attenuated through prior direct collaboration with counterpart inventors, which may undermine the novelty of knowledge linked through experience at the incumbent firm.

Where research on spawning and migration has focused primarily on the direct benefit of human capital transfer from incumbents to new ventures, we explore the broader network implications of similarities and interactions between the set of firms receiving this human capital. Our theoretical framework demonstrates how entrepreneurial ventures may continue to benefit from their cohort ecosystem affiliations. Exploring these networks opens an interesting new path for understanding organizational performance at an intermediate level of analysis between firm and industry.

THEORETICAL BACKGROUND

Entrepreneurial Migration and Knowledge Management

Employee migration acts as an important conduit between organizations, facilitating the flow of knowledge, skills, and social connections (McKelvey, 1982; Agarwal et al., 2004; Dokko

& Rosenkopf, 2010). A vibrant stream of research into employee mobility focuses on the impact that the movement of an individual or groups of employees may have on firm outcomes (Campbell, Saxton, & Banerjee, 2014; Mawdsley & Somaya, 2016). This literature has found that employee mobility influences the ability of a firm to develop and move knowledge resources (Rao & Drazin, 2002), learn (Rosenkopf & Almeida, 2003; Song, Almeida, & Wu, 2003), enter new markets (Boeker, 1997), manage relationships (Carnahan & Somaya, 2013), and ultimately compete with other firms (Michaels, Handfield-Jones, & Axelrod, 2001; Gardner, 2005; Somaya, Williamson, & Lorinkova, 2008). Because of the significant implications for firm outcomes, organizations increasingly rely on the acquisition of key employees to help drive firm performance.

In knowledge-intensive industries where firms rely heavily on maintaining their awareness and understanding of technology developments (Cohen & Levinthal, 1990), employee mobility has even more significant implications. The acquisition or loss of key knowledge workers can introduce/deduct valuable knowledge (Rosenkopf & Almeida, 2003), abilities, routines (Aime, Johnson, Ridge, & Hill, 2010), networks (Castilla, 2005; Somaya et al., 2008) and other knowledge assets and connections that can influence important firm outcomes (Burt, 2004; Wezel, Cattani, & Pennings, 2006; Fleming, Mingo, & Chen, 2007; Campbell et al., 2012). Employee hiring thus represents a potent method for new ventures to gain access to external knowledge and promote innovation.

Knowledge management practices may be among the most critical skills obtained by technology firms through employee migration. Research into knowledge management describes how knowledge flows between and within firms in ways that influence critical firm outcomes (Hedlund, 1994; Nonaka, 1994; Spender, 1996). It explores how organizations may combine established knowledge elements in new ways, or generate new knowledge to help them achieve competitive success (Ofek & Sarvary, 2001). Knowledge management is a process of moving from differentiated to integrated states of knowledge (Alavi & Leidner, 2001), which ultimately provide greater innovation, and operational benefits (Sanchez & Mahoney, 1996; Haas & Hansen, 2007). From a knowledge management perspective, firms have been shown to use the mobility of personnel to transfer knowledge across organizational boundaries (Agarwal et al., 2004; Somaya et al., 2008; Corredoira & Rosenkopf, 2010), applying successful external practices in areas that are new to the firm (Eckardt, Skaggs, & Lepak, 2017), and extending established technologies into new geographic settings (Berry, 2015). Employee mobility thus serves as a key mechanism for not only transferring vital knowledge between firms, but also in helping firms establish beneficial practices to integrate knowledge (Inkpen & Dinur, 1998).

Lacking an organizational history or established managerial practices (Stinchcombe, 1965), entrepreneurial firms may be among those with the most to gain by acquiring knowledge management expertise through employee migration. Ventures in many industries emerge through ‘spawning’ from existing firms (Agarwal et al., 2004; Klepper, 2007; Chatterji, 2009), with new venture founders or key employees coming from established incumbents. Prior knowledge management experience at an incumbent firm (sometimes called a ‘parent’ firm) provides both know-how and opportunity for individuals building nascent entrepreneurial firms (Phillips, 2002). Knowledge management expertise transfers from parent firms to progenies as inventors bring accumulated expertise and experience from past engagement at the parent firm to their new ventures (Agarwal et al., 2004; Chatterji, 2009). In this manner, progeny ventures inherit technological experience and expertise from their parents, and such inheritance can play a critical role in their development of new technologies and innovations (Klepper, 2001). For example, Phillips (2002) illustrated how founders of new law firms in Silicon Valley establish the same routines as their previous employers, and Agarwal et al. (2004) demonstrated that both technological and marketing know-how are passed from parent firms to spinoffs. Klepper and Sleeper (2005) investigated how ventures gain knowledge, expertise, and technical information through employees' experience within established incumbents in the laser industry and then use that knowledge to fuel new ventures.

Cohort Effects of Migration Network Ties

The shared affiliations of their early employees may comprise a network of ties between new ventures. Extending beyond the dyadic concept of beneficial employee migration from an incumbent to a recipient firm, we can imagine a situation in which multiple entrepreneurial ventures gain knowledge and managerial practices by either hiring personnel or having founders who come from a single incumbent firm. This phenomenon has been noted with large, successful incumbent firms across a number of industries, including automobiles (Klepper, 2007), semiconductors (Gompers et al., 2005), and biotechnology (Bower, 2003). Through their common employee migration link to the incumbent parent organization, entrepreneurial ventures share access to the incumbent's beneficial legacy.

Inventors employed at the same parent firm are more likely to have shared experiences and knowledge management practices, leading to the development of similar perspectives on the industry and a comparable perception of market opportunities and future technological developments. New ventures connected through shared employee migration ties can be viewed in the context of generational cohorts, where inventors' prior experience at the incumbent firm is determined by the timeframe in which their tenure occurs (Stinchcombe, 1965). In this fashion, cohorts may develop comparable knowledge management practices based on similarities in prior exposure to knowledge. For example, founders and early-stage inventors in new ventures spawned from Genentech in the 1990s would have participated in the dynamic period of the early application of gene splicing technologies for human treatments. They may have absorbed strategies and routines well-suited to knowledge development and commercialization in this sort of high-growth environment. In contrast, later Genentech (now operated as a subsidiary of Hoffmann-La Roche AG) employees choosing to migrate to entrepreneurial ventures will have had their experiences shaped within a far more mature parent organization, perhaps more focused on sustaining strategies. Thus, ventures with common employee migration network ties will likely share more in common with their contemporaries in the same generational cohort.

Ties between new technology ventures with shared employee migration ties may represent an ecosystem of firms within the industry. Though they may not be connected through formal affiliations or shared ownership, the common heritage of industry experience from these early employees brings shared knowledge management practices and understanding of the innovation opportunities available in the market. Shared migration ties provide ventures with a common basis for understanding a technology, permitting greater consensus to emerge among cohort ecosystem ventures and resulting in benefits to knowledge development (Baron, Hannan, & Burton, 2001; Beckman, Burton, & O'Reilly, 2007; Bercovitz & Feldman, 2011). Prior affiliation with the same parent can help these ventures develop a common frame of reference, context and vision about the new venture (Beckman, 2006). Institutional pressures for mimetic isomorphism may also act to make it more likely that ecosystem firms drawing personnel from the same incumbent imitate similar technologies, the most salient being those that were also used by their parents (Phillips, 2002). Since mimetic isomorphism is stronger under conditions of uncertainty (DiMaggio & Powell, 1983) and launching a new venture is fraught with uncertainty, observing and reacting to experiences of other ventures in the focal firm's network may be especially likely during the start-up phase.

Important benefits may accrue to cohort ecosystem ventures that share common perspectives on knowledge development and imitate or align with each other in their pursuit of new innovations. Technologies advance through field-level developments, with aggregated efforts across individual knowledge workers, research institutions, and firms contributing to the broader trajectory of technological development (Dosi, 1982). As Powell et al. (1996b) demonstrate in their study of the biotech industry, the locus of innovation exists outside organizational boundaries in settings characterized by complex, rapidly expanding knowledge. By more readily tapping into a broader external knowledge network, migration cohort ecosystem ventures may gain advantage in observing, understanding, and exploiting emerging technological developments.

Since developing new technologies requires willingness to exchange information, ideas, and practices, working with more familiar knowledge that might have emerged from the same industry incumbent firm can accelerate the knowledge discovery and development process. To the extent that a venture employee has a better understanding of other ecosystem firms because their members came from the same incumbent firm, we would also expect them to have a greater shared understanding as to what technologies should be employed. These cohort affiliations provide new ventures with greater opportunities to build on the work of firms from the same incumbent when deciding the technological direction of the new venture. Consequently, new ventures begun by founders that have prior experience at the same incumbent firm will be better able to leverage similar technologies, leading to a greater tendency that the new venture will mimic the technology of the parent firm. We believe that this will result in two outcomes for cohort ecosystem firms: a greater likelihood of overlap in the knowledge the firms draw upon, and a greater likelihood of pursuing similar markets.

Hypothesis 1a: New ventures with shared migration cohort ties are likely to have greater knowledge overlap.

Hypothesis 1b: New ventures with shared migration cohort ties are more likely to pursue overlapping markets than firms lacking such ties.

Migration Cohort Ties and Direct Exchange

The earlier experiences of inventors employed at an incumbent firm who then move to a new venture provide the venture with technological capabilities that help in developing its initial technological trajectory. While past work focusing on inheritance by new ventures has emphasized the benefits of relatedness between the parent firm and the new venture in exploiting such an inheritance (e.g., Basu, Sahaym, Howard, & Boeker, 2015), ventures that are part of a shared migration ecosystem may find it easier to work with each other, exchange knowledge, and create higher quality innovations. Although there has not been specific research examining relationships among cohort ecosystem firms created from these migration patterns, past empirical work has demonstrated how new ventures emerging from the same parent rely on each other to both develop their own high quality innovations and advance the technological trajectory of their industry. For example, in a study of the laser industry, Klepper and Sleeper (2005) showed that nearly all the new ventures in their sample initially produced a type of laser their parent had produced, suggesting that progeny ventures exploited specific domains of technology inherited from their parents in similar ways, resulting in groups of firms that are likely to develop similar technology trajectories.

The development of new technologies often requires an exchange of knowledge and practices with external firms, and cohort ecosystem ventures are more likely to rely on each other as they pursue discovery and development of new innovations. By drawing upon similar knowledge repositories, cohort ecosystem firms may share a greater understanding and agreement in pursuing promising new technologies. Cohort affiliations create opportunities for new ventures to build on earlier work that might have originated in the parent, and ecosystem firm inventors' shared prior experience may enable useful engagement between the new ventures.

Specific ties formed between ventures provide an opportunity to reinforce benefits gained through their common association within migration cohorts. In the search for favorable new combinations of knowledge (Fleming, 2001), cohort ecosystem ventures may build on the common understanding of technology developments gained across common inventor migration (Singh & Agrawal, 2011), reinforcing their advantages through direct knowledge exchange with ecosystem counterparts. Collaborating with fellow cohort ecosystem ventures or gaining access to their personnel may underscore promising new areas of development, reveal new combinations of knowledge elements that are applicable to their own research and development, and thereby enhance the value of migration cohort ties in the creation of new knowledge and innovations.

Formal alliances offer a direct path for new firms to gain access to needed knowledge resources from their ecosystem counterparts. Cohort ecosystem ventures with a shared heritage are more likely to focus on similar technologies and face related levels of market uncertainty. A consistent finding in past research is that firms establish alliances with external organizations in an attempt to control uncertainty (Thompson, 1967; Pfeffer & Salancik, 1978; e.g., Burt, 1983). For example, when ventures compete in markets with uncertainty driven by factors such as external technology trajectories and the development of industry-level standards, they are more likely to form relationships with other ventures that share similar ideas and practices (Sjöstrand, 1992). We believe that this increased propensity to form relationships with cohort ecosystem ventures will manifest itself in a greater likelihood to create alliances.

Another way in which firms can address uncertainty and gain access to the resources they need is through the hiring of new inventors. Given that ecosystem firms are more likely to share similar knowledge trajectories and operate in the same markets, these similarities make it easier for counterpart inventors to be integrated within the hiring firm. With greater commonalities in knowledge and practices between the firms, these inventors will likely be able to transfer a greater portion of their knowledge (Campbell et al., 2012). Further, from a relational point of view, the shared heritage of the firm's founders makes it more likely that these firms will share communication channels and social ties that will make them more aware of the human capital resources of other cohort ecosystem members (Rogers & Larsen, 1984). Such communication channels have a significant impact on the firm's decisions under conditions of uncertainty, making it more likely that these firms will view each other as prime sources of human capital (Rogers, 2010).

Thus, we hypothesize that shared ecosystem ties increase the likelihood that cohort ecosystem members will form alliances and that they will draw from the key knowledge workers of their cohort counterparts when hiring new employees:

Hypothesis 2a: New ventures with shared migration cohort ties are more likely to form alliances than firms lacking such ties.

Hypothesis 2b: New ventures with shared migration cohort ties are likely to have greater exchange through direct inventor migration.

Cohort Ecosystem Benefits to Innovation

Beyond a focus of how shared ecosystem ties impact firm behavior is the question of whether such ties actually benefit the firm's performance through its ability to innovate.

Expanding our focus in this way is important as innovation is a significant aspect of performance for knowledge-based firms and can provide a critical source of competitive advantage (Ahuja & Katila, 2001). In observing innovation performance, prior research has often focused on the quality or impact of knowledge created by a firm. Consistent with the concept of innovation as a recombination of knowledge elements into new, useful forms (Fleming, 2001), higher quality knowledge is associated with greater usage and future recombination (Miller, Fern, & Cardinal, 2007). This knowledge quality perspective on innovation performance has been applied in the study of knowledge diffusion (Hoetker & Agarwal, 2007), technology M&A outcomes (Makri, Hitt, & Lane, 2010), entry into new technological niches (Kotha, Zheng, & George, 2011), and many other settings.

Building on the ideas of the search literature (e.g., Levinthal & March, 1981; Sidhu, Commandeur, & Volberda, 2007), firms may benefit from a clearer perspective and understanding of the innovation landscape in their field (Laursen & Salter, 2006). Individual ventures may be limited in the scope of their knowledge as it pertains to the exploration of new technologies (Katila & Ahuja, 2002), and may benefit through opportunities to expand the scope and breadth of their knowledge. We suggest that this represents the mechanism through which migration cohort ecosystem ventures gain advantage. The commonalities with other ecosystem firms in terms of knowledge foundations and shared understanding, possibly enhanced through direct exchange, provide ventures with a superior understanding of the innovation search space. This ultimately enables them to achieve greater innovation than they otherwise would, particularly since new ventures often have limited resources.

Migration cohort ecosystem members may more easily share knowledge and learn from each other. As a result, firms with shared ecosystem migration ties may gain meaningful benefits for innovation, including increased knowledge quality (Ahuja, 2000). Knowledge exchange between ecosystem firms may even occur through informal communication channels such as personal networks and social interactions. This then increases the absorptive capacity of the firm in its search for external knowledge, which has long been recognized as an important contributor to innovation (Cohen & Levinthal, 1990; Tsai, 2001). Shared migration ties can also make it easier to transfer tacit knowledge between firms, with individual inventors having a greater ability to detect and codify each other's knowledge (Galunic & Rodan, 1998).

Additionally, firms that share migration ties may be better able to develop a common frame of reference and vision (Boeker, 1989; Beckman, 2006), as they are more likely to share a common foundation of knowledge and understanding about a particular technology. Such a common foundation allows them to better understand how to capture and exploit knowledge resources in ways that will lead to improved firm performance (Beckman, Haunschild, & Phillips, 2004). Such ties also make it less likely that there will be significant differences in leadership and culture between cohort ecosystem members, which has been shown to influence the ability to innovate (Barkema, Bell, & Pennings, 1996; Lavie, Haunschild, & Khanna, 2012). In summary, firms with shared migration ties may be better able to share similar knowledge resources, integrating key knowledge elements into their internal innovations, resulting in higher quality knowledge being developed by the firm.

Hypothesis 3: New ventures with shared migration cohort ties are more likely to achieve greater knowledge quality.

Prior Collaboration

Direct prior collaboration at the incumbent firm between inventors who migrate to different new ventures may amplify the knowledge benefits of common migration ties for each of the cohort ecosystem firms. Prior collaboration opportunities allow individuals to gain valuable social capital that has implications for firm knowledge outcomes. Such interactions typically make it easier for actors to transfer knowledge (Uzzi & Lancaster, 2003), leading to an increase in their capacity to innovate. By having engaged in repeated exchanges during their time at the incumbent, such individuals are better able to understand and capture the potential benefits of the relationship (Uzzi, 1996; Gulati, Lavie, & Singh, 2009; Lee, 2012). These factors help enhance the flow of knowledge transfer, with past research showing that relationship-based similarity in knowledge and understanding of technology can enable more efficient and effective exchange of knowledge between firms (Lane & Lubatkin, 1998; Zahra & George, 2002; Volberda, Foss, & Lyles, 2010).

While it may seem that inventors' direct prior collaboration at the incumbent might facilitate greater knowledge quality, there is a substantial literature that suggests that connections through prior collaborations may actually undermine these benefits. Continued innovation pursuits with the same people can restrict the development and flow of new and novel information (Laursen & Salter, 2006; Nieto & Santamaría, 2007; Fitjar & Rodríguez-Pose, 2013). This is particularly true if these relationships lead the firm to limit the breadth of its external search activities (Rosenkopf & Nerkar, 2001a). A central component of innovation, particularly the development of novel knowledge, is a firm's ability to exploit external knowledge (Cohen & Levinthal, 1990). While prior collaborations are a key vehicle through which firms can access information (Powell, Koput, & Smith-Doerr, 1996a), these prior collaborations may potentially limit the ability of the firm to gain access to novel information that can help them achieve greater knowledge quality (Schilling & Phelps, 2007), differentiating their ideas from those of their ecosystem counterpart. Further, such prior relationships may lead to inertia in decision making that may further limit innovation (Davis & Eisenhardt, 2011). Prior direct collaboration between ecosystem firm inventors may reduce the novelty of knowledge that they each develop in working for their new venture. It becomes more difficult to create unique advances leveraging incumbent firm knowledge when counterpart ventures are also building from the same prior projects. The benefits of ventures in expanding and clarifying their knowledge search space are reduced when inventors' external cohort fellows possess and build upon more similar knowledge. This limits opportunities to observe variation in incumbent firm knowledge applied to new innovations. As a result, when firms share ecosystem migration ties through inventors who directly collaborated, the likelihood of creating knowledge of greater quality is reduced.

Thus, we hypothesize that more frequent prior interactions between inventors of firms with shared ecosystem migration ties will lead to decreased innovation quality for each of these firms as they work to develop new knowledge.

Hypothesis 4: The positive relationship between new ventures with shared migration cohort ties and knowledge quality is reduced as prior collaboration between cohort employees increases.

Co-Mobility

The effects of employee mobility on firm outcomes may be more pronounced when groups of individuals migrate to the new venture. Past literature has referred to this phenomenon variously as co-mobility, group mobility, cluster hiring, or team migration, with research demonstrating that co-mobility leads to performance improvements for these individuals when they transfer to a new firm with their colleagues (Groysberg, Lee, & Nanda, 2008; Campbell et al., 2014). By moving together as a group, co-mobility reduces the negative performance effect that individuals typically experience since they are able to retain a portion of their colleague-specific human capital when moving to a new firm (Huckman, Staats, & Upton, 2009).

Recent work has shifted the focus from individual-level performance to how co-mobility influences firm outcomes (Mawdsley & Somaya, 2016; Eckardt et al., 2017). For example, Eckardt and his colleagues (2017) found that co-mobility had a negative impact on firm performance as these groups of individuals coming to the firm were able to command a greater portion of the value created with the firm than were individuals who transfer alone. For firm outcomes that involve knowledge, however, it is likely that co-mobility will increase the level of knowledge quality for the recipient firm. The fact that team members transfer together from one firm to another suggests a particularly strong form of social capital that has implications for trust, coordination, combination and exchange processes that lead to the development of new knowledge (Nahapiet & Ghoshal, 1998). Such strong forms of social capital create complementarities between individuals that allow them to better share and develop tacit knowledge, as well as being able to integrate different knowledge more efficiently. In contexts where processes are often interdependent (e.g., knowledge-based firms) this increased social capital should lead to improved knowledge performance for the firm (Campbell et al., 2014). A recent, shared understanding of the local knowledge search space among migrating team members may allow them to quickly move forward in the development of new knowledge, focusing on more promising directions in the novel combination of knowledge elements. As a result, we hypothesize that co-mobility of individuals will positively moderate the relationship between shared ecosystem migration ties and knowledge quality.

Hypothesis 5: The positive relationship between new ventures with shared migration cohort ties and knowledge quality is greater when teams migrate to the new venture.

METHODS

Sample and Data Sources

This study focuses on new ventures created in the biotech industry. The biotech industry provides a dynamic environment in which entrepreneurial migration to new ventures is a relatively common practice (Stuart & Sorenson, 2003). Many of these new ventures emerge from large biotechnology or pharmaceutical companies with established market and financial positions within the industry (Bower, 2003), resulting in an ecosystem of entrepreneurial activity stemming from the incumbents. We examine relationships between firms with shared ecosystem ties among all new ventures founded in the biotech industry from the years 1990 to 2000 (which we subsequently track until 2013) that received venture capital funding. Prior research has shown that venture capital investment is a common route for new venture financing in this industry (Hand, 2007). An initial search was conducted in the Dow Jones VentureOne (now Thomson One) database, a proprietary resource that collects information on entrepreneurial ventures, their founders, and the history of their funding for all U.S. venture capital investments. This search yielded a baseline data sample of 658 VC-backed biotech ventures. Two different subsets of this sample have been studied in prior published research. Basu et al. (2015) examine 219 VC-backed biotech firms from among this larger sample, focusing on the relationship between knowledge overlap of new ventures with their organizational parents and the impact of new venture knowledge. Sahaym et al. (2016) study genealogical links of the founders of 119 of the new biotech ventures launched from 1996-1999, examining how various founder characteristics influence the degree of knowledge overlap with their parent firms. Neither of these papers explore the nature and consequences of interactions among new ventures with shared migration cohort ties, the focal topic of this study.

Prior research has explored the migration ties between incumbents and entrepreneurial ventures through the patent history of individual inventors (Basu et al., 2015). In our case, the names of all inventors for each sampled new venture were mapped to their unique individual ID codes established through the Harvard Business School project to develop disambiguated data on U.S. patent inventors (Li, Lai, D'Amour, Doolin, Sun, Torvik et al., 2014). For each patent that 1) has the new venture inventor listed as an inventor and 2) most recently pre-dates the founding date of the new venture, the firm listed as the assignee on the patent is considered an incumbent organization with which the new venture has formed an entrepreneurial migration tie. This method of establishing migration links draws on the comprehensive history of the inventor in all prior firms where he or she has been active in patenting inventions over the course of his or her career, as far back as 1975. Since the relevance of an individual's past experiences may diminish over time, technology links to incumbent organizations that occurred ten years or more prior to the founding of the new venture are excluded from the sample.

A central claim of our study is that new ventures sharing common migration links to incumbents receive similar beneficial knowledge management practices through the employees they hire. This is consistent with prior research on entrepreneurial spawning and founding teams, which has argued that individuals emerging from incumbent organizations share common experiences from their time spent working at the parent firm (Agarwal et al., 2004; Beckman, 2006). While the genealogical perspective has often focused on founders as the mechanism for the transfer of knowledge and routines from incumbent firms (Phillips, 2002; Chatterji, 2009), we examine these relationships in the specific context of migrating knowledge workers, employees possessing technological knowledge and involved in routines associated with innovation. As a result, we examine common prior organizational affiliations of the new venture's early-stage inventors who are observed to join from incumbent parent firms. It is possible that changes over time in strategy, leadership, or financial performance of the parent organization can alter the experiences of prospective new venture inventors. Thus, the results of the study may be sensitive to longer lags between the time periods of migrating inventor tenure. To address this issue, the definition of migration cohort ecosystem ties is restricted to a +/- 5 year window. The focal new venture is thus recognized to share an ecosystem tie with another venture when an employee from a common incumbent firm leaves to join the other venture during any time from five years prior to five years after the founding of the focal venture. This ensures that migrating inventors will be no more than five years apart in their exposure to routines and technologies of the incumbent organization.

The ongoing presence of inventors who migrated from common incumbent firms is also an important element of the cohort ecosystem ties. We recognize that inventors, especially in fast-paced high tech industries, may move frequently during their careers. For that reason, we observe the subsequent patenting record of inventors in our sample, noting cases in which they are later listed on patents for some 3rd party organization. We checked for cases in which all cohort tie inventors (those coming from a specific incumbent firm, which then comprise an ecosystem tie to other start-ups) departed the new ventures. This did not occur in our sample. Limiting ourselves to patenting data as the indicator of migration, we may miss some cases in which inventors depart and are simply inactive in their new firms. However, such cases would tend to have a weakening effect or add noise to our hypothesized relationships, making our empirical tests more conservative in nature.

We constructed a broad longitudinal dataset that captures dyadic relationships between all ventures in our sample, including those dyads with and without common ecosystem ties. We pair each new venture to all possible combinations of other sampled firms, observing each of these relationships over the first ten years of operation of the focal firm (thus, our study focuses on the dyad-year level of analysis). In many cases, the founding of the focal firm predates the founding of the counterpart, or alter firm in the dyad. We therefore omitted any dyad observation years in which the alter firm is not in operation. We retain all observations in which one or both of the potential dyad partners has completed a successful initial public offering (IPO), though we remove observations when one of the firms has been acquired by a 3rd party. In such cases the strategies and actions of acquired firms are likely to be determined by the acquiring organization and outside of the dynamics addressed in our theoretical framework. Applying these criteria, our full sample analyses cover 1.6 million dyad-year observations.

In order to test the influence of shared ecosystem migration ties on knowledge quality explored in hypotheses 3-5, we constructed a second dataset in a firm-year structure, capturing observations for each sampled firm over the first ten years after founding. This data structure allows us to isolate the effects of ecosystem ties (or the absence of such ties) on knowledge quality outcomes at the firm level. Furthermore, the panel structure with fixed effects models allows us to exclude time-invariant aspects such as underlying quality of firm inventors' prior incumbent firms, etc.

Dependent Variables

Our first hypotheses (H1a and H1b) focus on relational characteristics that emerge through common migration ties shared between new ventures. *Knowledge Overlap* captures the extent to which the two firms in the dyad build on common technology areas in their patented inventions. These technology areas are captured as the U.S. patent classification (USPC) codes that appear on successful patent applications of the focal firm in the observation year. Next, we construct a representation of the knowledge base of each firm. Recorded as a mathematical vector, the dimensions of the knowledge base are comprised of the unique USPC codes listed on the firm's patents, and the magnitude for each dimension of the vector is determined as the count of patents using the USPC code (e.g. Oxley & Sampson, 2004; Yayavaram & Ahuja, 2008; Olsen, Sofka, & Grimpe, 2016). Given that patents reflect the culmination of work that may have been in process for longer periods of time, we use a three year rolling aggregation of knowledge base patents in preparing the vector measures. We then calculate the Euclidean distance (e.g. Rosenkopf & Almeida, 2003) between the knowledge base vectors of the two dyad firms. Since this Euclidean distance measure ranges from zero to the square root of 2, we use a linear transformation to convert this to a knowledge overlap measure ranging from one to zero to ease interpretation of the results.[2]

Market Overlap captures the extent to which new ventures in our sample operate in the same product markets in the biotech industry. Product strategies and market actions are often difficult to observe among new ventures. However, we are able to capture a strong proxy for competitive market actions by observing the licensing agreements pursued by firms in our sample. To construct our measure, we draw from Recombinant Capital, a 3rd party source of information on agreements between firms in the biotech industry that has been frequently used in prior strategy research (e.g., Ozmel, Reuer, & Gulati, 2013; Kapoor & Klueter, 2015). We collected data on all of the licensing agreements pursued by our sampled firms over the period of the study, identifying more than 4,000 licensing agreements involving the 658 firms. These agreements capture contracts in which the firm acts as either the licensee, gaining the rights to use external drug technology, or as the licensor, authorizing other firms to use their own drug

[2] To provide examples, an alter firm that does not make any use of the technologies of the focal firm will have a maximum Euclidean distance ($\sqrt{2}$), resulting in zero knowledge overlap. In contrast, an alter firm exactly aligned with the knowledge base of the focal firm will have zero Euclidean distance, with a knowledge overlap of one.

technology. Among the young biotech firms in our study, they are more likely to serve as licensor, typically contracting with larger, established firms to obtain royalties in exchange for the use of their innovative new technologies. The data available through Recombinant Capital allow us to narrowly categorize the market space in which these agreements are focused. Each licensing agreement entry includes classifications of the "disease category" (for example, gastrointestinal, autoimmune, cardiovascular, etc.) and the "technology category" (e.g. stem cell therapy, pharmacogenomics, vaccines, etc.). Building from these data, we operationalize *Market Overlap* as a count measure reflecting the number of dyad firm licensing agreements with 3rd parties that match both the same disease category and the same technology category.[3] This offers a representation of the number of strategic actions for each venture that are executed in the same market space as their counterpart in a given time frame. While a Euclidean distance measure or similar approach could capture the extent of market activity relative to the venture's overall business, we are more closely focused on the number of discrete actions that match between the firms, indicating interest and overlap in the same market.[4]

The direct relational aspects hypothesized to occur between ventures with shared ecosystem ties involve the formation of collaborative agreements and the hiring of each other's inventors. *Alliances* measures collaborative / cooperative activity between dyad firms. This is a count measure, reflecting the number of alliances announced by dyad pairs in the year of observation. We draw this data from SDC Platinum, a 3rd party resource tracking alliances and joint ventures between organizations. We limit our measure to alliances categorized as focusing on research and development, more directly reflecting cooperative engagements that have the goal of knowledge sharing and exchange. *Inventor Migration* measures the total count of

[3] Note: licensing agreements directly between sample firms do not often occur, with a total of only 9 such events in our data. We omit these events, given that they are more indicative of a direct engagement between dyad firms.
[4] We are grateful to an anonymous reviewer for pointing out this distinction.

inventor moves between the focal and alter firm in each observation year. This is captured by identifying scientists originally listed as inventors on patents of counterpart ventures and then later having patents listed under the focal venture to identify scientists who moved between ventures. In practice, no more than one such event occurs between sample firms in any given year of observation, resulting in an outcome variable of binary distribution.

Hypotheses 3-5 explore the effects of shared ecosystem migration ties on innovation quality. *Knowledge Quality* reflects the importance of an innovation and is measured as the number of patent forward citations by external organizations within 5 years after its application (Miller et al., 2007). We aggregate this measure as the sum of external citations across all focal firm patents with application dates in the year of observation. Given the time lag in observations of forward cites, this field-level assessment of knowledge quality is not immediately observable to sample firms, reducing potential concerns of reverse causality, in which founders may choose to hire from specific incumbents based on the successful innovation track record of other ventures that have done so in the past, etc.

Independent Variables

Shared Ecosystem Migration, used in the tests of hypotheses 1-3, is a binary variable equaling 1 beginning in the year in which migrating inventors are observed to begin patenting at the destination firm and for the subsequent years of observation for the focal/alter dyad pair. As described previously, a shared tie occurs when individuals from the two firms are listed as inventors on patents filed with a common incumbent organization as the assignee, prior to the founding of their new ventures. We use a variation of this variable in the firm-year panel data structure used to test the effects of ecosystem ties on knowledge quality in hypothesis 3 and the interactions of hypotheses 4 and 5. In that case, we use the total count of shared ecosystem ties to provide a sense of the degree of common links to knowledge management practices of the incumbent, with the premise that greater linkages will further enhance the quality of knowledge developed by the new venture.

We capture the extent to which migrating inventors had direct collaboration with counterparts at other ventures through the variable, *Employee Incumbent Collaboration.* This is measured as the count of prior collaborations directly connecting inventors of the two firms, demonstrated through the concurrent listing of one or more individuals from each of the two firms as inventors on parent firm patents (i.e. patents listing the incumbent firm as assignee, with application dates prior to the founding of the new venture). This measure is distinct from shared ecosystem migrations ties; while individuals may forge an ecosystem tie through their patenting history at a common parent organization, this measure demonstrates that the individuals from the new ventures collaborated directly on projects while working for the incumbent.

Finally, we measure the cases in which multiple inventors may concurrently migrate to a new venture. *Team Migration from Incumbent* is measured as the total number of teams of two or more inventors who are observed to migrate from an incumbent to the new venture in the year of observation. In our data, this is somewhat rare, with no more than a single team observed to migrate to a given new venture in any given year. Team size of migration is also relatively small, with teams of three being the largest that are observed to concurrently migrate.

Control Variables

The models include a number of variables to control for other factors that may plausibly influence the hypothesized outcomes. We control for *Direct Patent Citation*, the count of backward citations of alter venture patents that are listed in the patents assigned to the focal venture. Direct citation may suggest a closer technological relationship between the ventures and influence the likelihood of alliance formation, inventor migration, and technological and market overlap. We also include a set of firm-level controls for both the focal and alter venture in the observed dyad. *Cumulative Amount of VC Funding* captures the cumulative amount of venture capital investment received by each venture as of the observation year. Access to greater financial resources is likely to enhance the performance of the venture. *Cumulative Rounds of VC Funding* may also have an influence, reflecting the total number of rounds of private equity venture capital obtained by the venture. This may provide an indication of the assessment of VC investors regarding the likelihood of success for the venture. *Achieved IPO* is a binary variable used to control for whether the venture successfully became publicly traded by the year of observation.

Other characteristics related to the knowledge base and scientists of the two firms may influence their likelihood of overlap, alliances, or direct migration. *Number of Inventors* is measured as the count of unique inventors listed on patents for which the firm is the assignee. A larger pool of active inventors may impact opportunities for innovation and overlap with the counterpart firm. The presence of inventors who are particularity prolific in creating new innovations may also have an effect. Prior research demonstrates that such exceptional inventors may have an important impact on organizational outcomes (Hess & Rothaermel, 2011). Thus we control for *Star Scientists,* measured as the count of individuals listed on firm patents that are in the 95th percentile of patenting productivity (i.e. number of patents on which they are listed as an inventor) among inventors in our sample. Firms may also tend to overlap or directly interact when they work in technology areas that are more similar, and we include a control variable to address this effect. *Focal, Alter Firm Same Primary Technology Area* is a binary variable that equals 1 when both firms have the same core technology area (measured as the primary USPC code which appears most frequently in their patent record) and 0 otherwise. Finally, we recognize that relationships with non-ecosystem firms may impact the tendency of the venture to interact with its incumbent ecosystem counterparts. We thus control for *Focal Firm Non-dyad Inventor Migration* and *Focal Firm Non-dyad Alliances.* We also include an additional dyadic control variable, *Focal, Alter Firm Geographic Distance*, which controls for the tendency of sample firms to overlap or interact with other firms more proximal to their own location. We follow the approach of Sorenson & Stuart (2001), using geocoded addresses of firms' headquarters to calculate the great-circle distance over the surface of the earth between each firm pair.

In the tests of hypotheses 3-5 in the firm-year panel dataset, we control for factors that may influence the quality of knowledge developed by the new venture. First, we control for the total *Number of Patents,* measured as the total count of patents of the focal firm with application dates in the year of observation. This establishes the baseline volume of innovation for each firm from which the observed forward citations are recorded. *Number of Alliances* measures the count of total alliances between the focal firm and outside organizations. We retain *Achieved IPO*, *Cumulative Rounds of VC Funding*, *Cumulative Amount of VC Funding*, *Number of Inventors*, and *Number of Star Scientists* as firm-year controls in this dataset.

We also include other control variables related to the source and breadth of the knowledge base of the new venture. Firms may have different innovation outcomes when they draw more heavily on technologies developed through basic science research at the university level. We thus control for *Citation of University Patents*, measured as the count of backward citations of patents assigned to universities that are listed in patent applications of the focal firm in the year of observation. More broadly, drawing from a greater base of prior knowledge may impact the quality of new knowledge developed by the firm (Rosenkopf & Nerkar, 2001b). We control for *Total External Backward Citations*, measured as the total count of outside patents cited in patent applications of the focal firm in the year of observation. As another measure of knowledge breadth, *Number of Firm Technology Categories* captures the total number of unique USPC codes listed in focal firm patents. Firms engaged in greater recombination of technology categories may have different outcomes in terms of the quality of knowledge they develop.

Finally, we use a series of variables to reflect broader trends and environmental conditions. *Industry Number of VC Deals* and *Industry Amount of VC Investment* track the level of activity in the private equity markets for biotech ventures, which may reflect the environmental munificence in the biotech industry, as well as the financial support for new innovation. Finally, *Number of US Drug Patents* measures the number of successful patent applications launched across all biotech ventures in the observation year.

Modeling and Study Design

Our study examines a variety of dependent variables, and we select the appropriate model specification for each of them. Our test of hypothesis 1 focuses on knowledge overlap between dyad firms. Given that this is a continuous measure ranging between zero and one, we use panel-based OLS regression. *Inventor Migration* is binary in nature, but exceedingly rare, occurring in less than 0.1% of observations. Small sample bias may create issues in maximum likelihood estimation for such rare outcomes. For that reason, we use rare events logistic regression (King & Zeng, 2001), which offers bias correction to address this problem. This is implemented through the 'relogit' command in Stata. *Market Overlap, Alliances,* and *Knowledge Quality* are count measures, ranging from zero to some non-negative integer. The appropriate model specification in this case is the Poisson distribution (Wooldridge, 2002). However, our data exhibit overdispersion, having a skewed distribution with a large incidence of zeroes (Hilbe, 2007). We choose the panel-based negative binomial specification appropriate to discrete, overdispersed dependent variables. We also incorporate firm-level fixed effects in our Hypothesis 3-5 tests of knowledge quality to eliminate variance due to firm-specific non-dynamic factors.

RESULTS

We first sought empirical evidence to establish whether firms in our sample with shared inventor cohort ecosystem ties exhibit different characteristics and performance relative to non-ecosystem firms and, more specifically, whether members tied through migration cohorts demonstrate observable similarities based on their common incumbent firm affiliation. We conducted a series of T-tests, first comparing ecosystem and non-ecosystem firms. Consistent with prior literature (e.g., Phillips, 2002; Chatterji, 2009), we find empirical evidence that new ventures drawing human capital from industry parents have advantages over their counterparts. On average, they receive 61% more VC investment (T-statistic = 4.24, p = 2.61E-05) and typically have one additional round of funding beyond their non-ecosystem counterparts (T-statistic = 3.58, p = 3.71E-04). Next, we explored basic dyadic characteristics that might support the treatment of ecosystem organizations as a distinct empirical grouping among the new ventures in our sample. Examining the effect of ecosystem dyads, firms average 10.7 times the number of patent citations of technologies held by ecosystem counterparts than those held by non-ecosystem firms (T-statistic = 10.76, p = 5.43E-27). The average number of alliances is 9 times greater between ecosystem tied firms (T-statistic = 12.55, p = 3.88E-36), and the average number of inventor migrations is 17 times greater (T-statistic = 92.48, p ~ 0). Comparing the knowledge overlap between technologies of new ventures in our sample, pairs of ecosystem firms have an average overlap that is roughly twice as great as the knowledge overlap between non-ecosystem firms (T-statistic = 210.30, p ~ 0).

The descriptive statistics and bivariate correlations for the new venture dyadic dataset are shown in Table 1. The results of the regression models predicting knowledge and market overlap between dyad partners are shown in Table 2.

<< Insert Tables 1 and 2 about here >>

Model 1 incorporates all of the control variables for the knowledge overlap model. A number of the controls are significant; for example, having the same core technology area, greater VC support (rounds and funding) of both focal and alter firms, and number of non-dyad alliances, inventors, and star scientists tend to enhance the level of knowledge overlap. In Model 2 of Table 2, we add the direct effect of shared ecosystem migration ties. The coefficient of the independent variable associated with ecosystem ties has a positive, highly significant effect on knowledge dependence (**β**=0.007, p=<.001). In our sample, the presence of ecosystem ties increases the level of knowledge overlap by 165%. This provides strong support for hypothesis 1a. We repeat the same steps for the analysis of market overlap, incorporating control variables in Model 3 and the direct effect of shared cohort ecosystem ties in Model 4. In support of hypothesis 1b, the coefficient associated with shared ecosystem migration ties is again positive and significant (**β**=0.895, p<.001), with shared ecosystem ties increasing the level of market overlap by 66%.

We test the effects of ecosystem migration ties on alliances and direct inventor migration in Table 3.

<< Insert Table 3 about here >>

Among the control variables, working in the same primary technology area, IPO status of both the focal and alter firms, and the tendency of both firms to engage in other alliances show relatively consistent, positive effects on both dependent variables. Greater geographic distance between the firms shows a generally negative effect. Model 6 includes the shared ecosystem migration effect on alliances. The coefficient for this variable is positive and significant (**β**=1.461, p<.001), offering support for hypothesis 2a. This is also true in the model 8 test of shared ties on direct migration (**β**=1.716, p<.001), revealing support for hypothesis 2b. In terms of effect sizes, having a shared migration relationship increases the likelihood of forming an alliance by 39%, and the likelihood of direct inventor migration by 22%.

Finally, we examine the effects of shared migration cohort ecosystem ties on innovation outcomes. We test this relationship using the firm-year data structure described earlier, and we provide the descriptive statistics and bivariate correlations of this second data structure in Table 4. The results of the regression analyses are shown in Table 5.

<< Insert Tables 4 and 5 about here >>

Model 9 incorporates control variables for the models predicting knowledge quality. As shown in Model 9, the number of firm patents, citation of university technologies, and the broader level of drug patenting at the US level are positively associated with greater knowledge quality. Model 10 then includes the direct effects of shared migration ties, employee incumbent collaboration, and team migration. The coefficient for number of shared ecosystem migration ties is positive and significant (**β**=0.070, p<.05), demonstrating support for hypothesis 3. With regard to effect size, having an additional shared ecosystem tie led to a 3.1% increase in knowledge quality for the focal firm. In Model 11, we add the interaction effects between shared ecosystem ties and incumbent collaboration. The coefficient of this variable is negative and significant (**β**=-

0.030, p<.001), showing support for hypothesis 4. This is consistent with the theoretical framework suggesting that shared ties may reduce the novelty of knowledge management practices and routines that the migrating employee brings to the new venture. Finally, Model 12 tests the interaction of shared ecosystem ties with team migration. We find no significance for this effect and no support in our empirical sample for hypothesis 5, that migrating teams in the ecosystem context will further enhance the knowledge quality of the new venture. Model 13 provides the fully loaded specification, including all study variables, and the findings in Model 13 are consistent with the other results in Table 5.

Robustness Tests

We conduct a number of additional tests to ensure the robustness of our findings, using alternative approaches to modelling the effects of shared ecosystem migration cohort ties. The first set of these tests is shown in Table 6.

<< Insert Table 6 about here >>

Heterogeneity in the advancement of innovations at a technology class level across the US patent record may impact our tests of knowledge quality. Some USPC classes may be more prone to external citation, skewing their effects on a given firm's overall measure of knowledge quality (Lanjouw & Schankerman, 2004). In Models 14-18 of Table 6, we conduct robustness tests to address this potential issue. First, we standardize the external forward citations of sample firm patents based on the distribution of all patents in the US patent record with the same primary USPC code having application dates in the year of observation. We then calculate the average standardized score across all firm-year patents. This results in a knowledge quality dependent variable ranging from zero to one. Given this distribution, we employ general linearized regression models. Our findings are fully consistent with the baseline results reported in Table 5 – significant support for hypotheses 3 and 4, with no observed significance for hypothesis 5.

Recognizing that management strategies are inherently endogenous, with founders and managers executing strategies contingent on their assessment of the environment and their firm's capabilities (Shaver, 1998), we account for potential endogenous effects through instrumental variable analysis in our Model 19 test of the effects of shared migration ties on knowledge quality. To select appropriate instruments, we first select the relational characteristic, *Total Inventor Migration*, the count of inventors moving to the focal firm from other firms in the sample. From a conceptual standpoint, the migration of inventors between the firms should not necessarily have a direct effect on the quality of knowledge developed by the focal firm. Secondly, we include an instrument reflecting the general munificence of the environment of the focal firm, capturing *State R&D Spending.* This should plausibly impact resources that may be available in encouraging the formation of shared migration ecosystems, while having no direct effect on a specific firm's knowledge quality. From a statistical standpoint, the instrumental variable diagnostics provide support for these measures as valid instruments, successfully rejecting the null hypothesis that the instruments are under-identified (Anderson LM statistic of 132.3***), while failing to reject the null hypothesis that they are over-identified (Sargan statistic value of 0.32). The results of the instrumental variable analysis shown in Model 19 of Table 6 are consistent with the baseline results demonstrating that shared ecosystem migration ties have a positive effect on knowledge quality (**β**=0.029, p<.05). This again provides support for hypothesis 3.

In Table 7, we again address endogeneity through instrumental variable analysis, this time to support the results of hypotheses 1-2, that shared migration ties impact knowledge overlap, market overlap, alliances, and direct inventor migration.

<< Insert Table 7 about here >>

Given the dyad-year structure used in testing these hypotheses, we select other instruments as proxies for shared ecosystem migration ties that are more suited to the dyadic setting. For the tests of models 20-22, we selected and tested two instruments. *Focal, alter firm in non-compete enforcement states* is a binary variable valued as 1 if both of the dyad partners are founded in states that have historically enforced employee non-compete agreements (Marx, Strumsky, & Fleming, 2009). This environmental factor is likely to impact the degree to which inventors are free to move from incumbent firms to entrepreneurial ventures, forming migration cohort ties. We also use *Citations of Parent Firm Technology*, reflecting the number of times the new venture directly references the patented technologies of the incumbent firm in its own inventions. Incumbent firms offering a stronger base of useful technologies may be likely to spawn more ecosystem ventures, thus increasing the likelihood of shared migration ties. In the model 23 test of effects on direct inventor migration, we retain the non-compete state variable and add *Focal Firm State R&D Spending* as an instrument. As previously described, firms in a more intensively supported R&D environment may be more likely to emerge as ventures in the connected ecosystem, with incumbent firm inventors recognizing greater environmental advantages in migrating to progeny firms.

As shown in models 20, 21, and 22 of Table 7, the results of our instrumental variable analysis are consistent with the baseline findings – ecosystem migration ties have a positive, significant effect on knowledge overlap, market overlap, and alliances between dyad partners. In all three of these models, the Anderson LM statistic is significant, rejecting the null hypothesis that the set of instruments is underspecified in representing the independent variable of shared ecosystem ties. Furthermore, the Sargan test is not significant, failing to reject the null hypothesis that the instruments are not over-specified. The results of model 23 are consistent in showing a positive, significant effect of shared ties on direct migration between ventures. However, the Sargan statistic is significant (4.41, $p<.05$), rejecting the null hypothesis that the instruments are not over-specified. This may be due to the relatively poor fit of the chosen instruments. In any event, we are unable to fully rule out the potential for endogeneity in our empirical results for hypothesis 2b.

It is possible that observations in our dyad-pair data structure may over-inflate instances in which the dyad firms do not share an ecosystem migration tie. To address this concern, we construct an additional set of analyses in Table 8 that employs a matched pair strategy (e.g. Chen, 2015; Boivie, Graffin, Oliver, & Withers, 2016) to more carefully isolate the role of shared migration ties between firms.

<< Insert Table 8 about here >>

We identify all dyad-year observations involving shared migration tie firms and match each of them with a corresponding dyadic observation of firms that do not have a shared migration tie relationship. For our matching criteria, we use year, number of focal firm patents, difference in number of patents between focal and alter firm, focal firm cumulative VC funding, difference in focal and alter firm cumulative funding, and the binary variable reflecting whether the focal and alter firm operate in the same core technology area. Using the propensity score matching approach in Stata ('psmatch2'), we thus identify 201,311 dyad-year observations with not shared migration links matched to the 201,311 observations of firms that do share such a relationship. In models 24-28, we report the regression analyses associated with this matched pair sample. Once again, we find positive, significant effects of shared ecosystem migration ties on all four of the outcome variables in hypotheses 1 to 2 and the knowledge quality outcome of hypothesis 3.

We pursue other tests to address an important limitation of conventional regression analyses, that shared innovation and market behaviors in a given migration cohort ecosystem pair are assumed to be independent of external ties (Gulati, 1995). On its face, this may be an implausible assumption. As an example in the context of our study, it is possible that new ventures in the biotech industry may be cognizant of the technology advances and market actions among other ecosystem members, in some cases choosing to respond to these developments by adapting their own innovation and market strategies. Conventional regression techniques are unable to address this dependence on the broader network structure (Stuart, 1998; Kim, Howard, Cox Pahnke, & Boeker, 2016). To ensure that these issues are not undermining the findings of H1a/b, we conduct a robustness test using stochastic actor-oriented models (SAOMs), a longitudinal method of social network analysis that allows inferential statistical tests of factors impacting the evolution of actors' behaviors in a social network tie context and, importantly, relaxes the assumption of independence between ties (Snijders, 2005; Snijders et al., 2010). SAOMs are based on the notion that network actors may choose in each period of time to maintain, pursue, or discontinue behaviors shared with other actors, based on their own short-term preferences and constraints. These preferences and constraints are captured through an objective function (Snijders, 2010):

$$f_i(\beta, x) = \sum_k \beta_k \, s_{ki}(x)$$

For each actor *i*, the objective function, $f_i(\beta, x)$ reflects his or her (or in our case, the firm's) value in changing or maintaining shared behaviors based on network structural and actor covariates, $s_{ki}(x)$, with statistical parameters of the effects of each covariate represented by β_k. When aggregated across all actors in the network, this provides a framework for modeling the broader evolution of the network structure.

We restructured our data in a format suitable for longitudinal social network analysis. Specifically, we dichotomized the knowledge overlap and market overlap variables, coding them as 1 for values that exceeded the mean value plus one standard deviation, and zero otherwise. This provides indicators of shared behaviors in innovation and market focus, firms that are exceptionally similar in the technologies and disease categories they pursue. These data are then organized into a series of network tie sociomatrices – 658 x 658 arrays of 1's and 0's representing the presence or lack of a shared behavior between dyad firms in each year. We focus on the period 2000 through 2005 for the SAOM analysis.[5] All dyadic controls and independent variables (e.g. *Direct Patent Citation*; *Focal, Alter Firm Same Primary Technology Area*) are structured in a similar fashion, using observation year sociomatrices. All firm-level variables (such as amount and rounds of VC funding, number of inventors, etc.) are structured as vectors capturing the corresponding value of each covariate for each firm in the year of observation. We use R SIENA (simulation investigation for empirical network analysis) to implement the SAOM analysis (Ripley, Snijders, Boda, Voros, & Preciado, 2015), with results shown in Table 9.

<< Insert Table 9 about here >>

The control variables for the social network analyses of the shared knowledge and market overlap dependent variables are included in Models 29 and 31.of Table 9. Additionally, we

[5] This is based on two issues – first, all of the sample firms will have reached their founding date by 2000 and are available for network tie formation; secondly, SAOM analysis and the associated tools currently available face significant computational limits when modeling large networks and/or long term panel structures involving network evolution across many time periods.

include network structural effects to account for general tendencies for tie formation and dependence between network ties. *Outdegree (density)* essentially acts as an intercept in social network analysis, capturing baseline tie formation (Wasserman & Pattison, 1996) and generally yielding a negative coefficient due to the underlying costs of forming and maintaining ties. *Transitive Triads* is a network term capturing the tendency for the formation of triangle structures in the network. Transitive effects are often observed in social networks, with concurrent ties between actors *a* and *b,* as well as *b* and *c* often leading to triadic closure through tie formation between *a* and *c* (Madhavan, Gnyawali, & He, 2004; Kim et al., 2016). The significance of this term in the models of Table 9 provides evidence in support of dependence between network ties in explaining shared behaviors.

Models 30 and 32 include the hypothesized direct effects on knowledge overlap and market overlap. Several steps are taken in SAOM analysis to ensure model fit and significance (Snijders et al., 2011). Following these conventions in each case, we ensure the maximum convergence ratio for the overall model is below 0.25 and that the t-statistics for each model parameter is under 0.1. In testing the predicted effects, we find consistent support for the role shared ecosystem migration ties in the formation of high knowledge overlap relationships ($\boldsymbol{\beta}$=0.292, p<.001) and high market overlap relationships ($\boldsymbol{\beta}$=0.157, p<.001). This demonstrates that shared migration relationships still play an important role in the hypothesized outcomes, even when accounting for broader structural relationships in the network of market and knowledge similarities between firms.

DISCUSSION

The central finding of this study is that cohort ecosystems matter. Migration from a successful incumbent creates enduring connections between the entrepreneurial firms to which the incumbent's former inventors move. Prior research on knowledge worker migration has largely focused on the beneficial transfer of human capital, with new employees bringing valuable knowledge management practices and organizational routines associated with innovation. Our work takes a more ambitious view, suggesting broader consequences of inventor migration. We offer evidence that ventures connected through migration cohort ecosystems share meaningful, ongoing links that shape their subsequent development of new knowledge and technologies. From a network perspective, these ventures represent an intermediate network structure within their field. Based on their migration ecosystem affiliations, they are more likely to share knowledge and focus on similar markets, as well as engage in alliances and cross-hiring of inventors, all of which result in the creation of higher quality knowledge.

We suggest that the key mechanism through which ventures belonging to migration cohort ecosystems benefit is the broadening of their knowledge search. The shared foundations and perspectives stemming from incumbent firm inventor migration connect them to a broader structure of nascent organizations in their field. Ecosystem firms are thus not constrained by the limits of their own resources and innovation capabilities; they gain a wider perspective of the innovation landscape by more readily observing and understanding promising new combinations of knowledge elements emerging from their ecosystem fellows. With this widening and focusing of their own search efforts, they are able to enhance the quality of their own developed knowledge.

Future Research

The migration cohort ecosystem view opens important new avenues for research. The presence of intermediate groupings of firms bound by the shared history of their inventors may help explain the evolution and pace of technological advancement. Industries undoubtedly differ in the degree to which they are 'seeded' by capable early incumbent firms that offer the training ground for future employees of new ventures. We might consider how much of this effect is beneficial to society, and whether there are tipping points at which strong, early incumbents dominate and stifle field-level development. Innovation researchers may also delve more deeply into the cohort ecosystem effects on the knowledge search landscape. Factors such as technological complexity and modularity likely play a role in determining the benefits of these ecosystems. Perhaps increasingly complex technologies with unpredictable interdependencies can only be advanced through a cross-organizational search process enabled by migration cohort connections.

Beyond the focus on knowledge development, there are many other relationships and outcomes that may be explored in the context of incumbent ecosystem cohorts. For example, do ecosystem firms exhibit coordinated action at a group level? Outside of dyadic overlap and exchange, they may be more likely to organize or cooperate as factions, leveraging their shared heritage in the broader competition against other industry competitors. Also, the notion of discrete ecosystem structures may lead to comparisons between ties that stem from different incumbents. Perhaps certain parent firms are more suited to spawning successful generational spinoffs, or specific moderating factors of founder and entrepreneurial employee experience obtained from the parent may increase chances for survival and success.

We offer important extensions to established research on employee migration. We demonstrate that patterns of migration can have an important impact on inter-organizational relationships, leading to unique structures of migration-based affiliation between firms within an industry. Shared knowledge among firms tied through common migration may shape the direction of innovation and competition in technologically-intensive fields. These effects may have significant implications for how we view and understand organizational boundaries and how policymakers should address regulations governing hiring practices in competitive technology fields.

Finally, this study contributes to the theory of organizational spawning and the study of entrepreneurship. By introducing the novel concept of incumbent ecosystems, our findings offer a broader perspective of the spawning phenomenon, capturing the dynamics and interactions among multiple progeny firms. In this initial application of the incumbent ecosystem concept, we demonstrate how the collective migration of knowledge workers by cohort ecosystem firms influences the extent of overlap, cooperation, and employee hiring between them. In this manner, ecosystem cohort relationships represent a distinctive resource for new ventures, enhancing shared knowledge and exchange.

Limitations

While this study illustrates important relationships between new ventures in incumbent firm ecosystems, it raises other questions about the persistence and strength of these effects. Founders may leave an incumbent firm purposely because they want to move into different technologies, products, and markets that may not be supported by the incumbent firm, thus limiting or negating any shared incumbent imprint. In larger incumbent firms with many technologies, emerging founders and migrating knowledge workers may have been familiar with or shared only a limited exposure to similar knowledge management practices, limiting the cohort ecosystem effect. The effects of ecosystem membership may also diminish over time as firms grow and diversify in such a way that they no longer share a significant foundation of knowledge with other cohort ecosystem firms. This may occur through mechanisms such as shifting consumer preferences, the hiring of new personnel who alter the knowledge base of the firm, changes in alliance portfolio (Lavie, 2007), market competitiveness, and firm transitions into other technological areas.

It is difficult to exclude all possible alternative explanations of the dynamics of overlap and direct engagement between ventures in our study. However, we feel that the study design, controls, and robustness tests are effective in addressing the most plausible alternative explanations for our findings. For example, controls such as the extent to which ventures draw from university patents and geographic distance address aspects of transaction costs in the choice to pursue external alliances and hiring vs. inwardly focused innovation. Controls for innovation capacity with respect to number of inventors, presence of star scientists, and level of VC funding provide proxies for the quality of resources offered by potential alliance and inventor migration partners. Finally, our robustness test employing stochastic actor-oriented models addresses potential explanations from network theory, such as the impact of dependence between ties on the adoption of shared behaviors.

Additional value may be gained from examining the impact of ecosystem cohort ties on other strategic actions with different measures of success. Our study focused on innovation outcomes, yet other firm outcomes such as survival, growth, and overall performance may also be affected by similar mechanisms. Beyond the measurement of alliance formation, market and knowledge overlap, and direct employee hiring, other outcomes such as product launches or successful IPO offerings may help us better gauge the influence of ecosystem effects. Similarly, we would expect organizational characteristics such as firm age, industry, size, and decentralization, as well as firm-specific capabilities, to influence these relationships. Research should also consider how power imbalances between firms combine with shared ecosystem ties (Casciaro & Piskorski, 2005) to impact the results found in this study.

CONCLUSION

Prior research has focused on the direct benefits of employee migration from industry incumbents to entrepreneurial firms. This study extends that literature by exploring the cohort effect that emerges between new ventures hiring key knowledge workers from the same incumbents, thus forging connections within a common ecosystem of firms. Drawing from a broad, longitudinal sample of new ventures in the biotech industry launched from 1990-2000 and tracked until 2013, we find that ventures with shared ecosystem migration ties are more likely to overlap in knowledge development and product markets, with an increased probability of directly engaging in alliances and the hiring of their fellow cohort ecosystem members' inventors. Furthermore, ecosystem members tend to create knowledge of higher quality, an effect which is diminished when their employees share prior direct technology development experience with collaborators at the previous firm.

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Table 1. Descriptive Statistics and Correlations, Dyad-Year Sample

	Variable	Mean	S.D.	1	2	3	4	5	6	7
1	Knowledge Overlap	5.E-03	0.05							
2	Market Overlap	0.04	0.29	.062						
3	Alliances	3.E-04	0.02	.021	.092					
4	Inventor Migration	1.E-03	0.03	.013	.032	.011				
5	Shared Ecosystem Migration	0.12	0.33	.072	.103	.018	.046			
6	Direct Patent Citation	7.E-04	0.10	.036	.010	.023	.011	.011		
7	Focal Firm - Achieved IPO	0.17	0.38	.011	.100	.013	.022	.133	.002	
8	Focal Firm - Cumulative Rounds of VC Funding	2.41	2.52	.045	.072	.006	.012	.062	.003	.202
9	Focal Firm - Cumulative Amount of VC Funding	18.06	31.38	.057	.079	.005	.017	.071	.005	.205
10	Focal Firm - Non-dyad Inventor Migration	0.77	2.00	.040	.073	.014	.046	.179	.010	.232
11	Focal Firm - Non-dyad Alliances	0.87	1.74	.047	.131	.017	.030	.147	.002	.374
12	Focal Firm - Number of Inventors	0.80	3.05	.069	.031	.004	.018	.062	.010	.093
13	Focal Firm - Star Scientists	0.06	0.40	.056	.025	.003	.016	.049	.015	.082
14	Alter Firm - Achieved IPO	0.17	0.38	.018	.099	.013	.029	.133	.007	.009
15	Alter Firm - Cumulative Rounds of VC Funding	2.40	2.51	.051	.059	.006	.014	.063	.009	.025
16	Alter Firm - Cumulative Amount of VC Funding	18.04	31.37	.065	.068	.005	.017	.072	.008	.024
17	Alter Firm - Number of Inventors	0.80	3.05	.091	.040	.004	.012	.062	.008	.005
18	Alter Firm - Star Scientists	0.06	0.40	.077	.025	.003	.010	.049	.008	.004
19	Focal, Alter Firm Same Primary Technology Area	0.00	0.04	.389	.028	.019	.006	.020	.022	.005
20	Focal, Alter Firm Geographic Distance	2180	1585	-.011	-.002	-.004	-.002	-.041	-.002	.009
21	Focal, Alter Firm in Non-Compete Enforcement States	0.21	0.41	.044	.030	.007	.010	.135	.005	.057
22	Focal Firm - Citation of Incumbent Firm Technology	2.E-01	2.26	.009	.004	3.E-04	.004	.010	.002	.004
23	Focal Firm - State R&D Spending ($B)	19238	16827	.037	.032	.003	.007	.067	.005	.112

Correlations greater than |.0015| are significant at the $p<.05$ level.

Table 1. (Continued)

	Variable	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
9	Focal Firm - Cumulative Amount of VC Funding	.528														
10	Focal Firm - Non-dyad Inventor Migration	.132	.161													
11	Focal Firm - Non-dyad Alliances	.215	.234	.309												
12	Focal Firm - Number of Inventors	.108	.168	.192	.111											
13	Focal Firm - Star Scientists	.077	.122	.142	.079	.730										
14	Alter Firm - Achieved IPO	.025	.025	.002	.006	.005	.004									
15	Alter Firm - Cumulative Rounds of VC Funding	.092	.112	-.001	.018	.023	.018	.203								
16	Alter Firm - Cumulative Amount of VC Funding	.112	.144	-.012	.016	.024	.021	.205	.529							
17	Alter Firm - Number of Inventors	.023	.024	.008	.011	.010	.007	.093	.109	.168						
18	Alter Firm - Star Scientists	.018	.021	.003	.009	.007	.006	.082	.078	.122	.731					
19	Focal, Alter Firm Same Primary Technology Area	.011	.013	.021	.022	.023	.019	.005	.011	.013	.023	.019				
20	Focal, Alter Firm Geographic Distance	.001	.005	.007	.008	.004	.003	.009	.001	.005	.004	.003	1.E-04			
21	Focal, Alter Firm in Non-Compete Enforcement States	.018	.028	.037	.049	.042	.026	.057	.018	.027	.042	.027	.005	-.377		
22	Focal Firm - Citation of Incumbent Firm Technology	.025	4.E-04	.021	.008	.043	.012	.002	.007	.009	.004	.002	.007	-1.E-04	-.006	
23	Focal Firm - State R&D Spending ($B)	.114	.138	.067	.088	.103	.069	.018	.064	.075	.018	.013	.004	.047	.444	-.012

Correlations greater than |.0015| are significant at the p<.05 level.

Table 2. Regression Analysis – Cohort Effects on Knowledge and Market Overlap

Outcome Variable	Knowledge Overlap		Market Overlap	
Model Type	*Panel OLS Regression*		*Panel Negative Binomial Regression*	
	Model 1	Model 2	Model 3	Model 4
Independent Variables				
Shared Ecosystem Migration (H1a, H1b)		0.007*** (1.56E-04)		0.895*** (0.019)
Control Variables				
Direct Patent Citation	0.010*** (3.54E-04)	0.009*** (3.54E-04)	0.033 (0.022)	0.029 (0.020)
Focal Firm - Achieved IPO	-0.001*** (1.15E-04)	-0.002*** (1.16E-04)	0.660*** (0.014)	0.602*** (0.014)
Focal Firm - Cumulative Rounds of VC Funding	2.50E-04*** (2.03E-05)	2.58E-04*** (2.03E-05)	0.092*** (0.003)	0.092*** (0.003)
Focal Firm - Cumulative Amount of VC Funding	4.14E-05*** (1.63E-06)	4.09E-05*** (1.63E-06)	0.005*** (1.97E-04)	0.005*** (1.94E-04)
Focal Firm - Non-dyad Inventor Migration	2.47E-04*** (1.96E-05)	1.57E-04*** (1.97E-05)	0.019*** (0.002)	0.008*** (0.002)
Focal Firm - Non-dyad Alliances	5.42E-04*** (2.36E-05)	4.76E-04*** (2.37E-05)	0.128*** (0.002)	0.120*** (0.002)
Focal Firm - Number of Inventors	7.95E-04*** (1.90E-05)	7.86E-04*** (1.89E-05)	0.004+ (0.002)	0.002 (0.002)
Focal Firm - Star Scientists	6.90E-04*** (1.24E-04)	6.86E-04*** (1.24E-04)	0.040** (0.013)	0.040** (0.013)
Alter Firm - Achieved IPO	-1.63E-04 (1.12E-04)	-6.23E-04*** (1.12E-04)	0.727*** (0.014)	0.628*** (0.014)
Alter Firm - Cumulative Rounds of VC Funding	3.05E-04*** (2.03E-05)	3.04E-04*** (2.02E-05)	0.060*** (0.003)	0.060*** (0.003)
Alter Firm - Cumulative Amount of VC Funding	5.49E-05*** (1.62E-06)	5.33E-05*** (1.62E-06)	0.007*** (2.14E-04)	0.007*** (2.12E-04)
Alter Firm - Number of Inventors	0.001*** (1.88E-05)	0.001*** (1.87E-05)	0.024*** (0.002)	0.023*** (0.002)
Alter Firm - Star Scientists	0.002*** (1.24E-04)	0.002*** (1.24E-04)	-0.089*** (0.013)	-0.088*** (0.013)
Focal, Alter Firm Same Primary Technology Area	0.427*** (9.614E-04)	0.427*** (9.60E-04)	0.286*** (0.064)	0.236*** (0.063)
Focal, Alter Firm Geographic Distance	-3.43E-07*** (3.11E-08)	-2.79E-07*** (3.11E-08)	-1.20E-05** (4.57E-06)	-1.05E-06 (4.60E-06)
Constant	2.62E-04** (9.93E-05)	-4.23E-04*** (1.00E-04)	-2.113*** (0.025)	-2.288*** (0.025)
Sample Size - # of Firm-Dyads	1,621,171	1,621,171	1,621,171	1,621,171
Model Wald Chi^2	2.27E+05***	2.29E+05***	2.95E+05***	3.20E+05***

+p<.1, *p<.05, **p<.01, ***p<.001

Table 3. Regression Analysis – Cohort Effects on Alliances and Inventor Migration

Outcome Variable	Alliances		Inventor Migration	
Model Type	*Panel Negative Binomial Regression*		*Rare Events Logistic Regression*	
	Model 5	Model 6	Model 7	Model 8
Independent Variables				
Shared Ecosystem Migration (H2a, H2b)		1.461*** (0.126)		1.716*** (0.057)
Control Variables				
Direct Patent Citation	0.046 (0.061)	0.035 (0.059)	0.052+ (0.028)	0.043+ (0.026)
Focal Firm - Achieved IPO	0.885*** (0.130)	0.713*** (0.131)	0.589*** (0.065)	0.374*** (0.064)
Focal Firm - Cumulative Rounds of VC Funding	0.044+ (0.022)	0.039+ (0.023)	0.030** (0.010)	0.017 (0.010)
Focal Firm - Cumulative Amount of VC Funding	0.002 (0.002)	0.001 (0.002)	0.004*** (3.69E-04)	0.004*** (4.67E-04)
Focal Firm - Non-dyad Inventor Migration	0.028* (0.013)	0.009 (0.013)	0.102*** (0.003)	0.081*** (0.008)
Focal Firm - Non-dyad Alliances	0.190*** (0.016)	0.174*** (0.016)	0.106*** (0.007)	0.081*** (0.008)
Focal Firm - Number of Inventors	0.018 (0.015)	0.017 (0.016)	0.019*** (0.005)	0.020*** (0.005)
Focal Firm - Star Scientists	-0.022 (0.126)	-0.029 (0.127)	0.096* (0.044)	0.090*** (0.045)
Alter Firm - Achieved IPO	1.412*** (0.121)	1.167*** (0.123)	1.442*** (0.056)	1.130*** (0.057)
Alter Firm - Cumulative Rounds of VC Funding	0.032 (0.023)	0.029 (0.023)	0.045*** (0.010)	0.030** (0.010)
Alter Firm - Cumulative Amount of VC Funding	0.002 (0.002)	0.001 (0.002)	0.004*** (4.38E-04)	0.004*** (5.30E-04)
Alter Firm - Number of Inventors	0.030+ (0.016)	0.026 (0.016)	0.016** (0.006)	0.014* (0.006)
Alter Firm - Star Scientists	-0.100 (0.138)	-0.085 (0.136)	0.013 (0.054)	0.021 (0.053)
Focal, Alter Firm Same Primary Technology Area	1.511*** (0.345)	1.272*** (0.343)	1.145*** (0.294)	0.844** (0.296)
Focal, Alter Firm Geographic Distance	-1.42E-04*** (3.67E-05)	-1.16E-04** (3.69E-05)	-3.87E-05* (1.55E-05)	-6.27E-06 (1.50E-05)
Constant	-3.749*** (0.274)	-4.204*** (0.275)	-8.276*** (0.059)	-8.580*** (0.060)
Sample Size - # of Firm-Dyads	1,621,171	1,621,171	1,621,171	1,621,171
Model Wald Chi^2	660.08***	805.22***	3.82E+04***	4.56E+04***

+p<.1, *p<.05, **p<.01, ***p<.001

Table 4. Descriptive Statistics and Correlations, Firm-Year Sample

	Variable	Mean	S.D.	1	2	3	4	5	6	7
1	Knowledge Quality	4.53	20.84							
2	Number of Shared Ecosystem Migration Ties	0.54	1.23	.206						
3	Employee Incumbent Collaboration	0.53	2.81	.062	.181					
4	Team Migration from Incumbent	0.08	0.33	-.023	.013	.060				
5	Number of Patents	1.72	6.98	.332	.315	.101	-.009			
6	Number of Alliances	0.79	1.62	.133	.278	.136	-.017	.357		
7	Achieved IPO	0.17	0.37	.113	.313	.097	-.015	.243	.354	
8	Cumulative Rounds of VC Funding	2.34	2.55	.029	.171	.109	.069	.100	.210	.195
9	Cumulative Amount of VC Funding	18.71	34.12	-.006	.164	.109	.076	.133	.215	.229
10	Number of Inventors	0.59	2.84	.080	.101	.224	.114	.122	.102	.098
11	Number of Star Scientists	0.05	0.38	.096	.092	.146	.060	.158	.068	.082
12	Citation of University Patents	1.31	7.70	.148	.123	.292	.052	.201	.102	.072
13	Total External Backward Citations	15.65	87.33	.131	.094	.262	.094	.175	.077	.067
14	Number of Firm Technology Categories	0.44	1.68	.104	.098	.243	.141	.120	.102	.069
15	Industry Number of VC Deals	516	214	-.138	-.011	.059	.118	.033	.095	.128
16	Industry Amount of VC Investment	3051	1880	-.147	-.013	.047	.115	.027	.090	.122
17	Number of US Drug Patents	3275	899	-.061	.000	.076	.058	.076	.112	.081
18	State R&D Spending ($B)	18940	17398	.016	.115	.135	.038	.047	.090	.145
19	Total Inventor Migration	0.65	1.79	.292	.327	.169	.011	.546	.304	.220

Correlations greater than |.027| are significant at the p<.05 level.

Table 4. (Continued)

	Variable	8	9	10	11	12	13	14	15	16	17	18
9	Cumulative Amount of VC Funding	.550										
10	Number of Inventors	.102	.146									
11	Number of Star Scientists	.071	.109	.788								
12	Citation of University Patents	.097	.077	.242	.305							
13	Total External Backward Citations	.076	.085	.545	.559	.744						
14	Number of Firm Technology Categories	.104	.139	.941	.735	.264	.555					
15	Industry Number of VC Deals	.376	.391	.068	.049	.057	.063	.071				
16	Industry Amount of VC Investment	.366	.386	.056	.042	.054	.054	.057	.950			
17	Number of US Drug Patents	.216	.148	.093	.045	.105	.099	.119	.506	.476		
18	State R&D Spending ($B)	.156	.175	.103	.068	.059	.068	.115	.279	.282	.163	
19	Total Inventor Migration	.123	.128	.189	.134	.235	.217	.200	.026	.017	.129	.062

Correlations greater than |.027| are significant at the p<.05 level.

Table 5. Regression Analysis – Cohort Tie Effects on Knowledge Quality

Outcome Variable	*Knowledge Quality*				
Model Type	*Panel Fixed Effects Negative Binomial Models*				
	Model 9	Model 10	Model 11	Model 12	Model 13
Independent Variables					
Number of Shared Ecosystem Migration Ties (H3)	-	0.070* (0.040)	0.091* (0.041)	0.072* (0.040)	0.093* (0.042)
Employee Incumbent Collaboration	-	-0.020 (0.017)	0.063* (0.026)	-0.020 (0.017)	0.063* (0.026)
Team Migration from Incumbent	-	-0.233 (0.687)	-0.176 (0.683)	0.392 (1.150)	-0.060 (0.729)
Shared Ecosystem Ties X Incumbent Collaboration (H4)	-	-	-0.030*** (0.008)	-	-0.030*** (0.008)
Shared Ecosystem Ties X Team Migration (H5)	-	-	-	-0.142 (0.235)	-0.107 (0.234)
Control Variables					
Number of Patents	0.04*** (0.002)	0.017*** (0.004)	0.017*** (0.005)	0.017*** (0.005)	0.017*** (0.005)
Number of Alliances	0.026 (0.018)	0.029 (0.019)	0.030 (0.018)	0.028 (0.019)	0.030 (0.018)
Achieved IPO	0.051 (0.091)	-0.063 (0.118)	-0.065 (0.177)	-0.062 (0.118)	-0.064 (0.117)
Cumulative Rounds of VC Funding	0.038* (0.018)	0.091** (0.030)	0.091** (0.030)	0.094** (0.030)	0.093** (0.030)
Cumulative Amount of VC Funding	-0.004* (0.002)	-0.011*** (0.002)	-0.012*** (0.002	-0.012*** (0.002)	-0.012*** (0.002)
Number of Inventors	8.94E-04 (0.028)	0.068* (0.031)	0.058+ (0.031)	0.069* (0.031)	0.029+ (0.032)
Number of Star Scientists	0.152+ (0.092)	0.058 (0.102)	0.094 (0.098)	0.052 (0.102)	0.091 (0.098)
Citation of University Patents	0.021*** (0.003)	0.029*** (0.004)	0.029*** (0.004)	0.028*** (0.004)	0.028*** (0.004)
Total External Backward Citations	-0.002*** (2.37E-04)	-0.003*** (4.13E-04)	-0.003*** (3.95E-04)	-0.003*** (4.18E-04)	-0.003*** (4.09E-04)
Number of Firm Technology Categories	0.377 (0.041)	0.530*** (0.048)	0.552*** (0.049)	0.532*** (0.048)	0.552*** (0.049)
Industry Number of VC Deals	-9.15E-04 (6.16E-04)	1.11E-04 (6.64E-04)	1.23E-04 (6.62E-04)	8.94E-05 (6.65E-04)	1.05E-04 (6.63E-04)
Industry Amount of VC Investment	-2.97E-04*** (7.03E-05)	-3.60E-04*** (7.17E-05)	-3.55E-04*** (7.15E-05)	-3.57E-04*** (7.19E-05)	-3.52E-04*** (7.17E-05)
Number of US Drug Patents	4.54E-04*** (4.66E-05)	3.34E-04*** (5.22E-05)	3.20E-04*** (5.21E-05)	3.32E-04*** (5.23E-05)	3.19E-04*** (5.21E-05)
Constant	-2.574*** (0.148)	-2.584*** (0.404)	-2.641*** (0.398)	-2.595*** (0.405)	-2.650*** (0.399)
Model Chi^2	856.07***	1.79E+03***	1.84E+03***	1.79E+03***	1.84E+03***
Sample Size - # of Firm-Years	5,167	5,167	5,167	5,167	5,167

+p<.1, *p<.05, **p<.01, ***p<.001

Table 6. Robustness Tests - Knowledge Quality

Outcome Variable	*Knowledge Quality (Standardized by Technology Category and Year)*					
Model Type	*General Linearized Models*					*GMM IV Regression*
	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19
Independent Variables						
Number of Shared Ecosystem Migration Ties (H3)	-	0.126**	0.155***	0.128**	0.158***	0.029*
		(0.042)	(0.042)	(0.042)	(0.042)	(0.014)
Employee Incumbent Collaboration	-	0.040***	0.060***	0.040***	0.061***	-0.002*
		(0.012)	(0.015)	(0.012)	(0.015)	(0.001)
Team Migration from Incumbent	-	0.057	0.067	0.057	0.066	-0.029***
		(2.053)	(2.053)	(2.053)	(2.053)	(0.008)
Shared Ecosystem Ties X Incumbent Collaboration (H4)	-	-	-0.010*	-	-0.011*	-
			(0.005)		(0.006)	
Shared Ecosystem Ties X Team Migration (H5)	-	-	-	-0.046	-0.068	-
				(0.139)	(0.143)	
Control Variables						
Number of Patents	0.018**	0.016**	0.016*	0.016**	0.016*	-6.98E-04
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(7.08E-04)
Number of Alliances	-0.053	-0.067	-0.066	-0.068	-0.068	-0.004
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.002)
Achieved IPO	-0.302	-0.530*	-0.498*	-0.536*	-0.505*	-0.018
	(0.221)	(0.235)	(0.233)	(0.236)	(0.234)	(0.013)
Cumulative Rounds of VC Funding	0.042	0.025	0.034	0.025	0.035	-0.001
	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.002)
Cumulative Amount of VC Funding	0.005**	0.005*	0.005**	0.005*	0.005**	-2.09E-04*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(1.04E-04)
Number of Inventors	-0.108**	-0.107**	-0.109***	-0.107**	-0.109***	0.022***
	(0.037)	(0.034)	(0.034)	(0.034)	(0.034)	(0.003)
Number of Star Scientists	0.057	0.071	0.073	0.067	0.068	-0.063***
	(0.167)	(0.160)	(0.158)	(0.160)	(0.159)	(0.012)
Citation of University Patents	0.027***	0.020**	0.020**	0.019**	0.019**	3.12E-04
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(5.27E-04)
Total External Backward Citations	2.36E-04	5.53E-04	5.25E-04	6.08E-04	6.04E-04	4.69E-04***
	(7.03E-04)	(6.75E-04)	(6.75E-04)	(6.98E-04)	(7.00E-04)	(5.41E-05)
Number of Firm Technology Categories	0.456***	0.435***	0.436***	0.435***	0.436***	0.078***
	(0.060)	(0.056)	(0.056)	(0.057)	(0.056)	(0.005)
Industry Number of VC Deals	2.07E-04	1.52E-04	1.12E-04	1.73E-04	1.44E-04	-1.12E-04*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(4.59E-05)
Industry Amount of VC Investment	-4.42E-04**	-4.27E-04**	-4.37E-04**	-4.27E-04**	-4.36E-04**	4.41E-06
	(1.64E-04)	(1.67E-04)	(1.67E-04)	(1.67E-04)	(1.67E-04)	(5.12E-06)
Number of US Drug Patents	5.10E-04***	5.15E-04***	5.22E-04***	5.13E-04***	5.20E-04***	3.48E-06
	(1.10E-04)	(1.10E-04)	(1.10E-04)	(1.10E-04)	(1.10E-04)	(3.80E-06)
Constant	-4.566***	-4.634***	-4.670***	-4.636***	-4.674***	0.022
	(0.380)	(0.384)	(0.385)	(0.384)	(0.386)	(0.014)
Model Chi^2	321.11***	361.26***	360.96***	361.12***	360.84***	-
F-Value	-	-	-	-	-	346.44***
Sample Size - # of Firm-Years	5,167	5,167	5,167	5,167	5,167	4,929
Anderson LM statistic	-	-	-	-	-	132.30***
Sargan statistic	-	-	-	-	-	0.32

Instruments

Sibling Coopetition: Total Inventor Migration, State R&D Spending

+p<.1, *p<.05, **p<.01, ***p<.001

Table 7. Robustness Tests – Cohort Dyad Outcomes

Outcome Variable	Knowledge Overlap	Market Overlap	Alliances	Inventor Migration
Model Type	*GMM IV Regression*	*GMM IV Regression*	*GMM IV Regression*	*GMM IV Regression*
	Model 20	Model 21	Model 22	Model 23
Independent Variables				
Shared Ecosystem Migration	0.049*** (0.001)	0.115*** (0.007)	0.003*** (5.75E-04)	0.004*** (7.51E-04)
Control Variables				
Direct Patent Citation	0.013*** (4.00E-04)	0.021*** (0.002)	0.006*** (2.05E-04)	0.003*** (2.62E-04)
Focal Firm - Achieved IPO	-0.005*** (1.29E-04)	0.030*** (7.63E-04)	2.76E-04*** (6.62E-05)	2.68E-04** (8.63E-05)
Focal Firm - Cumulative Rounds of VC Funding	2.28E-04*** (1.81E-05)	0.002*** (1.06E-04)	1.01E-05 (9.25E-06)	-2.32E-05+ (1.19E-05)
Focal Firm - Cumulative Amount of VC Funding	3.77E-05*** (1.47E-06)	2.17E-04*** (8.68E-06)	-1.49E-06* (7.54E-07)	2.97E-06** (9.65E-07)
Focal Firm - Non-dyad Inventor Migration	-7.58E-04*** (3.24E-05)	0.001*** (1.91E-04)	4.30E-05** (1.66E-05)	5.05E-04*** (2.16E-05)
Focal Firm - Non-dyad Alliances	5.72E-05+ (2.94E-05)	0.014*** (1.73E-04)	1.30E-04*** (1.50E-05)	2.04E-04*** (1.92E-05)
Focal Firm - Number of Inventors	6.14E-04*** (1.86E-05)	-1.43E-04 (1.10E-04)	-1.69E-06 (9.53E-06)	2.16E-05+ (1.22E-05)
Focal Firm - Star Scientists	0.001*** (1.41E-04)	0.002* (8.31E-04)	-5.42E-05 (7.21E-05)	4.92E-04*** (9.24E-05)
Alter Firm - Achieved IPO	-0.005*** (1.56E-04)	0.054*** (9.20E-04)	4.96E-04*** (7.98E-05)	0.002*** (1.04E-04)
Alter Firm - Cumulative Rounds of VC Funding	2.37E-04*** (1.82E-05)	0.002*** (1.07E-04)	1.70E-05+ (9.29E-06)	2.74E-05* (1.20E-05)
Alter Firm - Cumulative Amount of VC Funding	3.97E-05*** (1.51E-06)	2.51E-04*** (8.89E-06)	-1.94E-07 (7.72E-07)	7.22E-06*** (9.91E-07)
Alter Firm - Number of Inventors	7.60E-04*** (1.90E-05)	0.002*** (1.12E-04)	7.30E-06 (9.73E-06)	4.35E-05*** (1.25E-05)
Alter Firm - Star Scientists	0.003*** (1.41E-04)	-0.008*** (8.33E-04)	-5.67E-05 (7.23E-05)	8.36E-05 (9.25E-05)
Focal, Alter Firm Same Primary Technology Area	0.556*** (0.001)	0.173*** (0.006)	0.013*** (5.62E-04)	0.003*** (7.19E-04)
Focal, Alter Firm Geographic Distance	9.00E-08*** (1.15E-04)	3.28E-07* (1.55E-07)	-3.65E-08** (1.34E-08)	-6.64E-09 (1.74E-08)
Constant	-0.003*** (1.15E-04)	-0.023*** (6.77E-04)	-2.76E-04*** (5.88E-05)	-7.18E-04*** (7.35E-05)
Sample Size - # of Firm-Dyads	1,621,171	1,621,171	1,621,171	1,621,171
Model F Statistic	1.90E+04***	3.71E+03***	146.22***	368.69***
Anderson LM statistic	1.8E+04***	1.8E+04***	1.8E+04***	1.8E+04***
Sargan statistic	1.68	1.11	0.28	4.41*

Instruments

Shared Ecosystem Migration: Focal, Alter Firm in Non-compete Enforcement States; Citations of Parent Firm Technology (in inventor migration model): Focal, Alter Firm in Non-compete Enforcement States; Focal Firm State R&D Spending

+p<.1, *p<.05, **p<.01, ***p<.001

Table 8. Robustness Tests – Cohort Dyad Outcomes, Propensity Score Matching

Outcome Variable	Knowledge Overlap	Market Overlap	Alliances	Inventor Migration	Knowledge Quality
Model Type	*Panel OLS Regression*	*Panel Negative Binomial Regression*	*Panel Negative Binomial Regression*	*Rare Events Logistic Regression*	*Panel Negative Binomial Regression*
	Model 24	Model 25	Model 26	Model 27	Model 28
Independent Variables					
Shared Ecosystem Migration	0.005*** (2.84E-04)	0.700*** (0.022)	1.092*** (0.175)	1.048*** (0.073)	0.042* (0.006)
Control Variables					
Direct Patent Citation	0.007*** (4.86E-04)	0.028 (0.019)	0.046 (0.060)	0.044* (0.021)	0.013 (0.015)
Focal Firm - Achieved IPO	-0.002*** (2.67E-04)	0.591*** (0.019)	0.749*** (0.157)	0.382*** (0.071)	0.029*** (0.007)
Focal Firm - Cumulative Rounds of VC Funding	4.78E-04*** (5.24E-05)	0.088*** (0.004)	0.032 (0.028)	0.022+ (0.012)	0.110*** (0.001)
Focal Firm - Cumulative Amount of VC Funding	3.70E-05*** (3.01E-06)	0.003*** (2.06E-04)	-6.44E-04 (0.002)	0.003*** (4.86E-04)	-0.004*** (1.22E-04)
Focal Firm - Non-sibling Inventor Migration	-9.32E-05** (3.63E-05)	0.008*** (0.002)	0.007 (0.014)	0.072*** (0.004)	0.094*** (3.94E-04)
Focal Firm - Non-sibling Alliances	5.88E-04*** (4.91E-05)	0.093*** (0.002)	0.147*** (0.018)	0.074*** (0.008)	0.049*** (7.71E-04)
Focal Firm - Number of Inventors	0.002*** (4.60E-05)	0.004 (0.003)	0.009 (0.020)	0.020*** (0.006)	0.061*** (0.001)
Focal Firm - Star Scientists	0.002*** (2.48E-04)	0.045** (0.015)	0.039 (0.136)	0.110* (0.047)	0.142*** (0.005)
Alter Firm - Achieved IPO	-9.32E-04*** (2.58E-04)	0.650*** (0.019)	1.186*** (0.148)	1.139*** (0.064)	-0.154*** (0.007)
Alter Firm - Cumulative Rounds of VC Funding	5.87E-04*** (5.22E-05)	0.052*** (0.004)	0.018 (0.028)	0.028* (0.011)	0.008*** (0.001)
Alter Firm - Cumulative Amount of VC Funding	4.54E-04*** (3.01E-06)	0.004*** (2.24E-04)	-7.36E-04 (0.002)	0.002*** (5.57E-04)	-0.011*** (1.22E-04)
Alter Firm - Number of Inventors	0.002*** (4.54E-05)	0.020*** (0.002)	0.013 (0.020)	0.016* (0.007)	0.013*** (0.001)
Alter Firm - Star Scientists	0.003*** (2.48E-04)	-0.015 (0.016)	0.030 (0.144)	0.020 (0.056)	-0.120*** (0.008)
Focal, Alter Firm Same Primary Technology Area	0.456*** (0.001)	0.418*** (0.064)	1.356*** (0.345)	0.688* (0.293)	0.325*** (0.030)
Focal, Alter Firm Geographic Distance	-7.85E-07*** (8.47E-08)	1.70E-05** (6.54E-06)	-1.33E-04** (4.51E-05)	-1.53E-05 (1.69E-05)	9.05E-06*** (1.83E-06)
Constant	-0.002*** (2.92E-04)	-2.278*** (0.038)	-3.934*** (0.338)	-7.770*** (0.084)	-2.000*** (0.009)
Sample Size - # of Firm-Dyads	402,622	402,622	402,622	402,622	402,622
Model Wald Chi^2	1.27E+05***	1.29E+04***	344.64***	1.85E+03***	1.40E+05***

+p<.1, *p<.05, **p<.01, ***p<.001

Table 9. Robustness Tests – Stochastic Actor-Oriented Models

Outcome Variable	High Knowledge Overlap		High Market Overlap	
Model Type	*Stochastic Actor-Based Models for Network Dynamics*			
	Model 29	Model 30	Model 31	Model 32
Rate Parameters				
2001	41.703	41.436	95.968	98.112
	(1.512)	(1.447)	(3.514)	(3.760)
2002	23.255	23.275	89.735	90.777
	(0.786)	(0.788)	(2.424)	(2.517)
2003	24.648	24.736	75.891	76.116
	(0.789)	(0.821)	(1.995)	(2.027)
2004	33.498	33.512	85.495	85.137
	(1.191)	(1.182)	(3.364)	(3.276)
2005	20.683	20.662	65.416	65.664
	(1.029)	(1.050)	(1.876)	(1.919)
Network Structural Effects				
Outdegree (Density)	-7.633***	-7.653***	-6.017***	-6.148***
	(0.068)	(0.076)	(0.127)	(0.123)
Transitive Triads	5.566***	5.526***	4.450***	4.571***
	(0.078)	(0.089)	(0.135)	(0.129)
Independent Variables				
Shared Ecosystem Migration	-	0.292***	-	0.157***
		(0.021)		(0.010)
Control Variables				
Direct Patent Citation	0.044*	0.041*	0.036*	0.032*
	(0.018)	(0.018)	(0.015)	(0.015)
Focal Firm - Achieved IPO	-0.730***	-0.765***	-0.078***	-0.095***
	(0.040)	(0.042)	(0.010)	0.010)
Focal Firm - Cumulative Rounds of VC Funding	-0.041***	-0.042***	-0.015***	-0.016***
	(0.006)	(0.006)	(0.002)	(0.002)
Focal Firm - Cumulative Amount of VC Funding	-0.001	-0.001**	0.005***	0.005***
	(9.0E-04)	(1.0E-04)	(1.0E-04)	(1.0E-04)
Focal Firm - Non-sibling Inventor Migration	0.070***	0.061***	0.038***	0.034***
	(0.008)	(0.007)	(0.002)	(0.002)
Focal Firm - Non-sibling Alliances	0.082***	0.080***	0.109***	0.108***
	(0.006)	(0.006)	(0.002)	(0.002)
Focal Firm - Number of Inventors	0.031***	0.031***	0.013***	0.012***
	(0.004)	(0.004)	(0.002)	(0.002)
Focal Firm - Star Scientists	0.015	0.015	0.017	0.022
	(0.025)	(0.027)	(0.016)	(0.016)
Alter Firm - Achieved IPO	-0.183***	-0.156***	0.001	0.010
	(0.021)	(0.020)	(0.007)	(0.007)
Alter Firm - Cumulative Rounds of VC Funding	0.301***	0.283***	0.063*	0.067*
	(0.072)	(0.073)	(0.027)	(0.027)
Alter Firm - Cumulative Amount of VC Funding	-0.222	-0.165	1.333***	1.350***
	(0.160)	(0.158)	(0.071)	(0.069)
Alter Firm - Number of Inventors	1.540***	1.402***	0.291*	0.249*
	(0.195)	(0.194)	(0.113)	(0.114)
Alter Firm - Star Scientists	-0.505**	-0.402*	0.389*	0.474**
	(0.189)	(0.195)	(0.152)	(0.154)
Focal, Alter Firm Same Primary Technology Area	1.000***	0.989***	0.441***	0.408***
	(0.090)	(0.095)	(0.067)	(0.066)
Focal, Alter Firm Geographic Distance	-1.0E-04	-1.0E-04	-1.0E-04	-1.0E-04
	(1.0E-04)	(1.0E-04)	(1.0E-04)	(1.0E-04)

+p<.1, *p<.05, **p<.01, ***p<.001

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