Exploring the Role of Network Characteristics, Knowledge Quality, and Inertia on the Evolution of Scientific Networks

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Despite decades of network research, the crucial question, “How do networks evolve?” has not been sufficiently explored. The authors explore this question by analyzing the co-authorship networks in the U.S. biotechnology firms. Building on network management and network inertia perspectives, the authors build a model predicting that the structural changes in the firms’ co-authorship networks are dependent on the specific characteristics of firms’ initial networks, the firm’s age and size. The authors then extend the model by incorporating a measure of the impact of the quality of the knowledge produced by the network ties using the prominence and inertia perspectives, which lead to the incorporation of competing hypotheses and moderating relationships in the model of scientific network evolution. The authors then test the model using longitudinal analysis of 367 U.S. biotechnology firms over a span of 17 years. The authors find that firms’ existing tie-specific characteristics in the form of a firm’s existing network size, tie strength, and the knowledge quality are significant determinants of network evolution, but that this influence is tempered by organizational inertia.

Keywords: network dynamics; network evolution; co-authorship networks; biotechnology industry; longitudinal analysis

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Introduction

Research on innovation has long recognized the need to build external networks in order to access new knowledge. Networks are important mechanisms for organizations to gather information and access complementary assets and resources. Networks play a significant role in an organization’s success and survival by representing critical avenues for the acquisition of resources necessary for its survival and growth (Aldrich & Reese, 1993; Gulati, 1998), which in turn enhances innovation (Vanhaverbeke, Gilsing, Beerkins, & Duysters, 2009) and increases performance (Baum, Calabrese, & Silverman, 2000; Rothaermel, 2001).

Recent empirical studies have provided evidence that collaborative networks and relationship-specific assets enable organizations to access resources that may not be available through market exchanges (Arya & Lin, 2007). This is even more prevalent for knowledge-intensive industries, such as biotechnology, where the co-authorship of scientific papers plays a crucial role (McMillan, Narin, & Deeds, 2000). Prior studies examining co-authorship networks found that firms whose researchers engaged in joint research and publishing with other institutions were more effective at sourcing novel scientific information (Demirkan & Demirkan, 2011; Oliver, 2004; Zucker, Darby, & Armstrong, 2002). However, none of these studies examined how these firms’ scientific networks evolved over time.

Despite the abundance of research on networks, the evolution of networks over time remains an underexplored issue (Parkhe, Wasserman, & Ralston, 2006; Zaheer & Soda, 2009). Prior research on networks has mainly focused on the impact of networks on firms rather than exploring the nature and the evolution of networks. There is a dearth of research examining why certain ties are established while others are destroyed or how these networks change over time (Koka & Prescott, 2008; Madhavan, Koka, & Prescott, 1998). One of the few exceptions that demonstrate that networks evolve over time is Koka and Prescott (2002). Koka and Prescott discovered that many firms in the global steel industry sought to increase the diversity and quality of the information in their alliance networks, by adding and dropping partners. Changing their network members enabled these firms to address shortcomings in their network.

We know very little about how a particular firm’s network is likely to change over time and what factors influence this change; these are the questions we hope to shed some light on in this paper. Our study contributes to the literature on networks by developing and testing a model of network evolution that incorporates three streams of thought, managerial capacity, inertia, and prominence. By studying how the characteristics of the focal firms’ scientific network influence the development of the structure of the firms’ network in the future we expand the field’s understanding of the evolution of scientific networks and provide findings that have implications for social networks in general. We have chosen to study scientific co-authorship networks in biotechnology because their importance to innovative activity in biotechnology is well established (McMillan et al., 2000; Powell, Koput, & Smith-Doerr, 1996). Co-authorships allow us to track network collaborations over time, as well as the quality of the knowledge produced by these collaborations. Finally, co-authorship networks are more flexible and adaptable in response to changing environmental and organizational conditions because they are much less formalized and constrained by contracts than alliance
networks. This adaptability provides us with rich data that we base our analysis of the evolution of firms’ scientific networks.

We posit that a dynamic view of how changes in the firms’ relationships in one period affect the structure of the firms’ collaborative networks in subsequent periods is critical in developing a better understanding of (1) how such networks are organized, (2) how firms benefit from changes in structure of their relationships, and (3) how firms manage their relationships. Addressing the aforementioned research questions suggests the need to examine the sources of network change at the structural level. Prior research mentions the need to look into the tie strengthening and tie loosening aspects of network change as well as the creation and deletion of network ties (Koka, Madhavan, & Prescott 2006). While we concur with these four dimensions, in this research we restrict ourselves to studying the additions and subtractions from firms’ networks over time.

This paper addresses these issues using a longitudinal analysis of the co-authorship networks of biotechnology firms. We highlight the significance of the characteristics of firms’ existing networks in understanding the dynamics of their networks and their future networking behavior.

Theoretical Background and Hypotheses

The Network Dynamics

The literature suggests that the need to combine complementary assets (Powell et al., 1996) and to acquire resources necessary for firm survival and growth (Gulati, 1998) play a significant role in the membership, shape, and structure of firms’ networks. Others have argued that existing ties provide the basis for the establishment of new ties (Gulati & Gargiulo, 1998; Walker, Kogut, & Shan, 1997). The assumption that networks are vehicles to acquire resources has shaped our understanding of the formation and dissolution of firms’ network ties, leading the empirical research to examine these phenomena as discrete events in time, not a point in the continuing evolution of firms’ networks. As valuable as this approach has been, focusing solely on the formation/dissolution of network ties as discrete events suffers from some theoretical and methodological deficiencies. First, these studies are unable to examine the transformation of the network over time and they mostly overlook the influence of the characteristics of the existing network, such as the size, the tie strength, and the quality of the joint product, on the firm’s network in the future. With a few exceptions (Ebers, 1999; Gulati, 1995), research has ignored the effects of the characteristics of existing network-based relationships on the formation or the dissolution of future ties. Second, they suffer from a sample selection bias, since this research only includes firms that form new network ties or that dissolves their old network ties without ever looking into the firm’s preexisting network of embedded relationships (Kim, Oh, & Swaminathan, 2006). The view of networks as dynamic processes that are formed, dissolved, and reformed on a continuous basis has led to calls for an examination of the processes that initiate change in firms’ networks across time (Koka et al., 2006; Zaheer & Soda, 2009). Building on this stream of literature, we view networks as a continuous process of terminating and forming ties.
Tie-Specific Determinants of Scientific Network Dynamics

The motivating factor for the creation and expansion of a research network is the expansion, recombination, and exploitation of the knowledge that exists among collaborating firms (Ahuja, 2000; Kogut & Zander, 1992; Powell et al., 1996). Over time firms need to adjust the configuration of their network to expand their knowledge base in pursuit of the development of novel and profitable new products and to accommodate changing demands from their environment (Ebers, 1999). Gaps between the firms’ needs, what is available from their network, or new opportunities for collaboration arise, motivating the firms to initiate changes in their network.

Firms’ scientific networks are collaborations between scientists and are organized based on convergence of interests and research needs, which are subject to change (Kogut & Zander, 1992). Over time, firms are likely to add new members to their network and drop members who are no longer providing valuable resources. In addition, the partners available to the firm will change based on the prominence of the firm, which is a function of their prior research activities (Rosenkopf & Padula, 2008). Successes are likely to expand the pool of potential network members creating new opportunities for the firm to access valuable complementary assets.

When changing their networks, firms are likely to consider the benefits that they are receiving from their existing network relationships. Ties that provide benefits to the firm are likely to persist (Kim et al., 2006); unproductive ties may be culled and lead to a contraction of the firm’s network. Moreover, particular characteristics of firms’ existing network might lead to differences in the configuration of its future ties, which leads us to focus on how specific features of firms’ existing scientific collaborative networks influence change in the network in subsequent periods. The specific network characteristics we will examine are network size, network tie strength, and quality of the knowledge produced by the firm’s network.

Firms’ existing collaborative network size is the number of partners that a biotechnology firm currently enjoys. This characteristic not only acts as an indicator for the potential of knowledge flows to the focal firm, but it also shows the extent of influence that the firm has in the overall scientific collaborative network (Koka & Prescott, 2008). Network size influences the evolution of the network because firms begin by referencing their existing network as they consider the need to add or subtract members to meet their changing research needs. In addition the prominence that accrues to the firm as their network grows is likely to enhance the ability of the focal firm to attract new and potentially valuable members.

Firms’ strength of existing ties in the network both enables and constrains changes in the network (Granovetter, 1973). Collaboration among organizations is risky due to imperfect information about partners’ capabilities, reliability, and motives (Oxley, 1997). This risk is even more salient in the biotechnology where the industry is highly uncertain (Pisano, 2006) and firms face substantial risk of expropriation of their key knowledge assets (Alvarez & Barney, 2001). Due to the risky and uncertain environment in biotechnology, firms are likely to repeat ties that work leading to a network of strong ties that deter change. The history of collaborations, familiarity, and trust with research partners reduce the biotechnology firms’ perceived benefit from new partners, and in turn this reduces their perceived need to change their network.
It is critical to consider the impact of the quality of the knowledge created through the firm’s network on network evolution. Scientific collaborative networks have become one of the main sources of novel knowledge (McMillan et al., 2000) and the know-how needed to complement the firm’s existing knowledge (Rooijakkers, Hagedoorn, & van Kranenburg, 2005). When biotechnology firms have successful and valuable outcomes from their collaborative networks, this is likely to affect the future evolution of their network, but how it affects that evolution is uncertain. On one hand, theory would suggest that success is an indicator of a network that is providing the assets the firm requires and hence decreases the motivation to make changes to the network. On the other hand, the increased prominence that accrues to the focal firm from successful outcomes increases the partnership opportunities available to the firm and motivates the firm to expand its network.

The aforementioned forces do not exist in a vacuum nor are they likely to operate independent of one another. In light of this, it is important to explore the interplay between the inertial forces (network size, tie strength, firm size and age) and knowledge quality, which opens new opportunities for the firm, on the evolution of firms’ collaborative networks. We develop and test hypotheses about the impact of the interactions between these inertial forces and the opportunities created by a rise in the prominence provided by high-quality publications on the evolution of firms’ scientific collaborative networks.

**Network Size**

Larger networks are suggested to be facilitating factors for collective knowledge generation and learning (Powell et al., 1996), and thus positively related to firm performance. For example, in their research, Collins and Clark (2003) found that those firms with larger top management team networks experienced increased firm performance. Deeds, DeCarolis, and Coombs (1999) found that resource flows into the firm increased with the size of their alliance network. There are limits to the returns to network size, and several articles have documented declining marginal returns to alliance networks (Deeds & Hill, 1996; Rothaermel, 2001). However, the evidence is supportive of the proposition that increased network size benefits firm performance.

Similar to large organizations, large networks require effective structures and mechanisms to coordinate the different inputs and interests in the network; having large networks, no matter how successful they are, imposes significant management costs on the focal firm (Ford & McDowell, 1999; Hakansson & Ford, 2002). Firms can face these costs in various ways. For example, in looking into knowledge networks Hansen (2002) mentions that network relationships can imply different costs to the firm. He finds that accessing knowledge via networks requires maintenance costs, while within-network knowledge transfer requires time to help others in the network.

Considering the potential costs and the limits to managerial attentions, managers face a trade-off between the benefits of working within a large network versus the time and energy required to maintain productive relationships with their network members (Goerzen, 2005). Given limited time, energy, and attention, as size increases, the efficiency of communication between the network members is likely to decrease, which is consistent with increasing
network maintenance costs (Burt, 1992). While keeping large networks is desirable, the complexities created by the interdependencies between network members often make it difficult, if not impossible, for the firm to effectively manage its network (Rothaermel & Deeds, 2006). Additional members in the network increase the potential for goal and value conflicts, the amount of coordination required between members, and the difficulty of negotiating agreement among the members (McFadyen & Cannella, 2004). Aral and Van Alstyne (2011) demonstrate that the time and effort required managing the network increase with its size. Given the potential costs faced by firms with larger networks, managers of these firms are likely to be cautious about adding additional ties to their network, leading to substantially more inertia in larger networks. Thus, our Hypothesis 1 becomes:

**Hypothesis 1(a):** Network size will be negatively associated with network growth in subsequent periods.

As firms develop their networks in response to opportunities, they are likely to create redundancy in their networks. Emerging opportunities create significant ambiguity and uncertainty about the knowledge and skills needed and the quality of potential partners. Under these conditions, biotechnology firms are likely to engage in redundant ties. Limited network diversity, especially within a large and growing network, creates a danger that due to the similarity of partners in the network, the network will become less effective at generating new knowledge (Dyer & Nobeoka, 2000). As noted earlier, firms will evaluate the benefits received from their existing network ties and cull unproductive ties. As the firm begins to reach the limits of its effective network size, it will have greater incentive to cull redundant ties to create room to access the new knowledge and skills it requires. Redundant network ties are likely to have limited performance benefit since they suffer from a similarity of ideas, skills, and knowledge. As Burt (1992: 64) points out, larger networks increase the possibility of having diverse members and are “the best guarantee of having a contact present where useful information is aired.” Since information in more local, smaller networks tends to be redundant, structurally diverse contacts that reach across larger networks should provide channels through which novel information flows (Burt, 1992). Differences in the characteristics and strategies of the partners within a larger network create diversity of information, which not only enables novel combinations of knowledge in the network but also generates better performance outcomes when industry faces a radical change (Koka & Prescott, 2002, 2008).

We expect firms to cull redundant ties first, since they provide few benefits and the firm retains access to the knowledge via other ties. At the same time as new opportunities arise that demand the firm access new knowledge, the firm will be looking to add novel ties to replace the culled redundant ties. Over time this process will decrease redundancy in a firm’s network and increase the diversity. This impact will be greater as the pressure to manage the portfolio of ties increases with the size of the firm’s network. This leads to the conclusion that larger networks will include a greater diversity of ties. Therefore:

**Hypothesis 1(b):** Network size will be positively associated with network diversity in subsequent periods.

Management issues in a network context can be exceedingly complex not only due to the embedded and reciprocal character of network relationships (Ford & McDowell, 1999;
Hakansson & Ford, 2002), but also due to the need to create trust and routines that allow the partners to work efficiently together while protecting their knowledge assets. Networks also add to firms’ organizational costs by adding substantially to the firm’s management structure (Goerzen, 2005). These issues become even more complicated with the addition of new members. Prior research has noted that young or new firms face particular difficulties and are more prone to failure than older firms, due to immature routines and unstable relationships, or put simply due to the liability of newness (Stinchcombe, 1965). Over time, firms gain experience managing network relations, increasing their productivity and allowing them to manage their network more efficiently (Kale, Dyer, & Singh, 2001). As firms age, network management routines become stable, allowing the firm to effectively expand its network. Therefore, older firms will be better positioned to expand large networks by adding new members than younger firms with large networks.

Hypothesis 2: The relationship between the network size and network growth will be positively moderated by firm age.

The liability of newness might at the same time be liability of smallness (Freeman, Carroll, & Hannan, 1983). In most studies, liability of newness coexists with the liability of smallness (Bruderl & Schussler, 1990; Singh & Lumsden, 1990). Liability of smallness contributes to the explanations of why new organizations have more tendencies to fail (Baum & Amburgey, 2002). An increase in firm size increases the probability of the accumulation of specific firm-level resources and competencies (Rosenberg, 1976), while smaller firms have difficulties in accessing most basic resources such as difficulties in raising capital (Aldrich & Auster, 1986). Larger firms are more likely to set up knowledge management policies such as promoting a culture of sharing information and knowledge as well as rules (Kremp & Mairesse, 2004) that enhance their ability to manage larger networks. This suggests that for larger biotechnology firms, constraints caused by the management of their networks might not be as critical as they are within small firms. If firms have already built the structures to manage their collaborative networks, growing the network will be less of a challenge. For such firms, larger networks might mean larger associated benefits, and a change toward more new members and growth could be expected.

Hypothesis 3: The relationship between the network size and network growth will be positively moderated by firm size.

Network Tie Strength

Granovetter (1973) defines relational strength in terms of the time and emotions invested in a relationship in addition to the reciprocity involved between actors. From this standpoint, the duration of network ties with one specific partner could be a measure of the success of a certain relationship (Geringer & Hebert, 1991). For example, Parkhe (1993) found out that in a strategic alliance, the level of perceived opportunistic behavior is negatively related to the history of cooperation. This suggests that the stronger and more repeated the relationships
are, the better the cooperative and collaborative performance between the partners is. As noted earlier, high level of uncertainty and risk in the biotechnology industry may induce the firms to ally more frequently and more intensely with existing partners. Repeated collaboration increases the ability to predict the potential success of a given project with a given partner (Gulati, 1995), increasing trust among the partners and inducing firms to continue to look for ways to work together rather than bring new members into the network. This tendency underlies the findings that repeated and strong ties enhance both relational and cognitive lock-in (Gargiulo & Bernassi, 1999).

Firms that are entrenched in their network through strong ties risk the ability to adapt to changing internal and external environments (Uzzi, 1997). Because of this cognitive lock-in and the costs of building trust with potential new partners, strong ties constrain further change in the network. Firms with network ties that are characterized by strong, repetitive, and long-lasting network relationships will be less likely to include new members and expand their networks. Overall, because attachment and commitment to a relationship can affect the members’ attitudes (Salancik, 1995), firms that are characterized by such commitments will find it difficult to initiate a change in their networks.

**Hypothesis 4(a):** Network tie strength within firms’ networks will be negatively associated with network growth in subsequent periods.

Network diversity, on the other hand, reflects the variety of backgrounds and knowledge bases of the members in the network (Ruef, Aldrich, & Carter, 2003). While bringing in further diversity to the network will enhance the richness and the quality of information exchanged (McPherson, Smith-Lovin, & Cook, 2001), diversity of ties also means more complex and more difficult relationships to manage. Kim et al. (2006) point out that strong ties constitute partner-specific routines and structures in the network that result in network inertia. In collaborative networks that are characterized by strong ties, members institutionalize an understanding of the specific styles of their existing ties (Doz, Olk, & Ring, 2000). They establish a common understanding of each other that strengthens the relationships. Recent research has shown that firms benefit more from collaborations that are longer in duration (Demirkan & Demirkan, 2011). In such cases, changing network ties to increase diversity might mean a complete abandonment of the existing and stable set of routines and structures in the network and potential disruption of innovative activities. This may eventually hurt the success of the existing network ties. Accordingly;

**Hypothesis 4(b):** Network tie strength within firms’ networks will be negatively associated with network diversity in subsequent periods.

As we argued previously, network size creates inertial forces that deter network growth, as does the existence of strong ties in a network. Raub and Weessie (1990) note that the higher the tie strength, the lower the risk of cutting ties because such behavior may give the firm a negative reputation in a context where trust and mutual understanding is important. Building on this finding, we argue that firms with large networks and strong ties will have a lower propensity to cull redundant ties, but they also recognize the need to change their
network in response to the changes in the environment. This leads firms with large networks and strong ties to grow faster than firms with large networks and weak ties, but because they do not cut as many ties their network remains less diverse. This leads to our next set of hypotheses:

**Hypothesis 5(a):** The relationship between network size and network growth will be positively moderated by network tie strength.

**Hypothesis 5(b):** The relationship between network size and network diversity will be negatively moderated by network tie strength.

### Knowledge Quality

In reviewing the network literature we found competing theoretical explanations from the inertia perspective and the prominence perspective on the impact of quality of the knowledge on network evolution. The inertia perspective supports the old adage “if it ain’t broke don’t fix it,” indicating that knowledge quality should be negatively related to changes in the network. In contrast, the prominence perspective argues that high-quality knowledge production increases firm prominence, which opens up new partnership opportunities that expand the firm’s network. In the following paragraphs we will develop these competing hypotheses.

From a network inertia perspective (Kim et al., 2006), firms that have success in their existing networks will not see the need to initiate a change in their networks through the addition of new members to their network. As firms build collaborative relationships for a variety of resources, they develop a network profile or portfolio of ties and partners over time. The value of these ties is reinforced if they are accompanied by high-quality knowledge output. This embedded action causes the biotechnology firms to rely on and be constrained to a narrower set of relationships that perpetuates itself over time. In such cases, quality of knowledge becomes a constraining factor for further change in the network.

**Hypothesis 6(a):** Knowledge quality within a firm’s network will be negatively associated with network growth in subsequent periods.

From an “inertia”-based perspective (Hannan & Freeman, 1984; Kim et al., 2006), success in existing collaborative networks would also inhibit a further diversity in a firm’s network, since the success would induce the firm to stick with its current collaborators. Firms in general, and biotechnology firms in particular, introduce diversity to their network in order to improve the creative potential, increase the ability to implement new ideas of the members, and generate more innovation and quality knowledge (Demirkan & Demirkan, 2011). Accordingly, we assert that firms whose networks are already producing quality knowledge will perceive less need to introduce diversity to their network.

Therefore, we suggest that:

**Hypothesis 6(b):** Knowledge quality within a firm’s network will be negatively associated with network diversity in subsequent periods.
The prominence perspective (Rosenkopf & Padula, 2008) suggests a competing set of hypotheses. The prominence perspective suggests that the biotechnology firms’ relative attractiveness in the market for partners is also likely to change based on the firm’s prominence, which is a function of the prior research activities, successes, and failures (Koka & Prescott, 2008; Rosenkopf & Padula, 2008). Successes are likely to expand the pool of potential network members and create new opportunities for the firm to gain access to complementary assets through new scientific collaborations. The prominence perspective suggests that better performing members of the network achieve prominence within the industry and the network (Stuart, 1998). For example, Ozcan and Eisenhardt (2009) find that after financial success, the partners within the strategic alliance network of the wireless gaming industry gained prominence. Similarly, we suggest that quality of knowledge created within a firm’s scientific collaboration network is a measure of success and also enhances a biotechnology firm’s prominence. Such prominence makes the firm more visible and attractive as a potential future network partner, increasing the opportunities to collaborate that are available to the firm. This leads to prominent members of the industry being in advantageous positions to enter into beneficial new collaborative efforts previously unavailable to them. This will lead to growth and increased diversity in their network. Given the robustness of the prominence arguments we propose a second set of competing hypotheses regarding the relationship between knowledge quality and network change.

Hypothesis 6(c): Knowledge quality within a firm’s network will be positively associated with network growth in subsequent periods.

Hypothesis 6(d): Knowledge quality within a firm’s network will be positively associated with network diversity in subsequent periods.

However, it is equally important to recognize the role of inertial forces in this relationship. We propose the previously discussed inertial forces as boundary conditions in the relationships between knowledge quality and network change. Such interplay between the inertial forces of network size, tie strength, and firm age and knowledge quality deters firms’ entry in to new partnering opportunities and the evolution of firms’ collaborative networks.

We have previously noted that managers face a trade-off between the benefits of working within a large network versus the time and energy required to maintain productive relationships with their network members. Firms that already have larger networks will find it harder to accommodate the new partners available to them due to the increased prominence that accrues to them from the creation of high-quality knowledge. The demands for efficiently benefiting from new partners in the network and demands for efficiently managing the relationships with new partners may contradict. Therefore, the existence of larger networks for the biotechnology firm will act as a constraint on prominence’s effect on network growth and diversity.

Capitalizing on prominence requires change via adding new members to the existing network (Gulati & Gargiulo 1998; Powell et al., 1996). While prominence is likely to expand the pool of potential network members and create new opportunities for the firm to engage in new scientific collaborations, the existence of strong ties with existing partners is an inertial factor mitigating against change in network growth and network diversity. Raun and Weessie
(1990) note that the higher the tie strength, the lower the risk of cutting ties because such behavior may give the firm a negative reputation in a context where trust and mutual understanding is important. Strong ties lock in the biotechnology firm to its existing network even when new opportunities for change stemming from prominence are available.

Researchers have long argued that a firm’s likelihood of engaging in strategic change depends on its age due to the pressures of inertia. In other words, older firms are less likely to engage in change due to committing themselves to existing courses of action (Hannan & Freeman, 1984). And in the case of older biotechnology firms, the pressures of inertia may suppress the pressures of prominence especially when the outcome from existing collaborative networks is characterized with high quality knowledge outcomes.

Overall, we hypothesize that:

**Hypothesis 7(a):** The relationship between knowledge quality within a firm’s network and network growth will be negatively moderated by the inertial forces of network size, tie strength, and firm age.

**Hypothesis 7(b):** The relationship between knowledge quality within a firm’s network and network diversity will be negatively moderated by the inertial forces of network size, tie strength, and firm age.

We summarize these relationships in Figure 1.

### Data and Methodology

**Data**

We chose the U.S. biotechnology industry as our research setting. We collected inter-firm network data based on the co-authorships of the focal firm. Studies based on research collaborations at the co-authorship and scientist level are quite extensive (Oliver, 2004; Oliver & Liebeskind, 1998; Zucker et al., 2002). It is important to study the individual-level networks, such as co-authorship networks, that occur at the inter-organizational levels in order to get a full picture of inter-organizational networks in this industry (Oliver & Liebeskind, 1998).

We identified a sample of publicly traded biotechnology firms that are listed in Recombinant Capital (ReCap). ReCap is a comprehensive database that documents the variety of activities in the global biotechnology industry (Hoang & Rothaermel, 2005). We developed our co-authorship network based on these firms. Each network consisted of a focal biotechnology firm and a set of alters, namely, research institutions, universities, or pharmaceutical firms, connected to the focal firm by the co-authorship of a research paper. For each biotechnology firm in our sample using the ISI-Science Citation Index (SCI), we identified the organizations that the researchers from the specific biotechnology firm had co-authored a scientific article with for each year. Using SCI we tracked the co-authorships from each biotechnology company in our sample for a period of 17 years (from 1990 to 2006).

Scientific developments such as genetic engineering, which enabled the formation of the biotechnology industry, were accomplished during the mid-1970s in university labs. The
industry has experienced the founding of hundreds of small science-based biotechnology firms in the 1980s and the industry reached its maturity stage in the 1990s with the commercialization of new drugs. Since the evolving structure of the collaborative networks is the focus of this study, we started data collection from the mature stage of the biotechnology industry. Subsequently, our study covers publicly traded biotechnology firms between 1990 and 2006. We obtained yearly patent counts, co-authorship network data, and firm attribute data for the firms in our sample. The panel used for the analysis includes specific variables for the period 1990-2006. Due to some missing variables as well as three-year lagged in, 3,056 observations of 367 firms remained in the sample. The panel used in the regression analysis is unbalanced because there are missing values for some of the variables in the sample.

**Variable Definition and Operationalization**

**Dependent variables.** We use two network structure variables as our dependent variables: network growth and network diversity. A firm’s network in our sample consists of the total number of co-authorship ties that a firm has with other institutions over a three-year period (Bae & Gargiulo, 2004).
**Network growth** is operationalized as the ratio of new ties within a given year \( t \) to the overall network size in the same year. This measure captures the growth in the network via the addition of new members. Network members are considered to be “new” if they had not appeared in the firm’s network within the past three years.

In measuring **network diversity**, we followed the methodology developed by Baum et al. (2000). Diversity in the network is based on the Hirschman-Herfindahl index and computes diversity as one minus the sum of the squared proportions of a firm’s number of collaborations with a specific partner in year \( t \), divided by its total number of co-authorship collaborations. Network diversity is measured as \( ND_{ij} = [1 - \sum_{j} (PC_{ij})^2]/TC_i \), where \( PC_{ij} \) is the proportion of a firm \( i \)’s number of collaborations with a specific partner \( j \), and \( TC_i \) is firm \( i \)’s total number of co-authorship collaborations. For example, a firm with total co-authorship collaborations of six (five with organization A and 1 with organization B) would score \([1 – (5/6)^2 + (1/6)^2]/6 = 0.046\). In our sample, network diversity ranges between 0 and 0.9375 with values closer to 1 showing more diversification while values closer to 0 showing less diversification in the network.

**Independent Variables**

We measured a biotechnology firm’s **network size** for a given year \( t \) as the firm’s total number of its network partners within a three-year moving window (Bae & Gargiulo, 2004). In order to measure the **network tie strength** between the network partners, we counted the number of times that a focal firm collaborated with network members who were in the network for three consecutive years and then computed the percentage of times that the focal firm has collaborated with these partners relative to the others. That is, partners who are in the network for three consecutive years are considered as strong ties, whereas the rest are coded as weak ties.

**Knowledge quality** is measured by looking at the output of the specific research collaborations for a given year \( t \). We analyzed the quality of the articles published in highest ranking journals. Journal rankings are taken from ISI’s Journal Citation Rankings (JCR): Science edition. Based on citation analysis, Journal Citation Rankings measures the impact of a journal by its usefulness to other journals (ISI, 2006). From JCR, we looked at the individual journal rank within discipline (JRK) of every journal that the focal firm’s scientists published in collaboration with other organizations. JRK is measured by the following equation: \( 1 – (n – 1)/N \), where \( n = \) descending ranking number within discipline and \( N = \) total number of journals in the discipline (ISI, 2006). JRK ranges between 0 and 1. We classified a high-ranking journal as the journal with a JRK = 1. Knowledge quality is the total number of a firm’s publications in collaboration with its network partners where JRK = 1.

**Control Variables**

We controlled the **firm size** by using the natural logarithm of total assets as a proxy. We also controlled for the **firm age**. The incorporation dates of each biotechnology firm are taken from Mergent Online. We controlled for **R&D intensity**. We collected R&D data from
Compustat and computed R&D intensity as the R&D expenditures over total sales. We also controlled for the profitability and liquidity of the focal firms. Profitability was captured by the return on equity variable (the ratio of net income to total equity) and liquidity was captured by the current ratio (ratio of current assets to current liabilities) of the firm. Over time, there might be differences in the innovative performance of all firms. Therefore, we also controlled for time variant effects by including dummies for every year from 1990 to 2006. In general, it is also necessary to control for the firm effects; however, since our data are longitudinal panel data, firm effects are captured with the data.

Model Specification and Analysis

In this study, we have panel data over 17 years. Our panel has observations on cross-section units \( i = 1, 2, \ldots, 368 \) of firms, over time periods \( t = 1990, 1991, \ldots, 2006 \). An ordinary least square analysis may result in biased estimates because of unobserved heterogeneity. In such cases, a recognized option is to estimate fixed effects models to control for unobserved time-invariant factors associated with grouped observations (Yamaguchi, 1986), in our case the firm-level unobserved heterogeneity. Since only a fixed effects model would not account for autocorrelation and heteroskedasticity in time series data, the standard errors are adjusted for heteroskedasticity and autocorrelation by a firm identifier using Stata’s “cluster” command (Rogers, 1993).

A firm’s current network structure may be influenced by unobserved factors such as the existence of its prior (or initial) level of established relationships. When uncorrected this might introduce potential sample selection bias (Berk, 1983). In order to correct for such a possibility in these models, we followed Heckman’s two stage procedure (Heckman, 1979; Wooldridge, 1995). We first estimated a probit model of the likelihood of a firm’s having an initial network for a given year (if a firm has an initial network or not) and generated the Inverse Mill’s Ratio (IMR). We then estimated a fixed effects model of the determinants of a firm’s network structure using the IMR from the first stage as a control variable. This method eventually yields unbiased estimators of the predictors of the second model (Greene, 1997).

In our first stage model we used independent variables that are suggested to affect the likelihood of a firm’s having an initial network. For this stage, we used variables that are not in direct control of the firm for further network creation. These variables are the ones that lead to the formation of a firm’s initial network. For instance, firm size and firm age are important indicators of firm-level resources and hence its capacity to form network-based relationships (Powell & Brantley, 1991). A biotechnology firm’s patenting performance is a measure of its success and attractiveness to network partners. This is measured by using issued patents, which is the number of patents granted for a firm within a year (Ahuja, 2000). A firm’s region of establishment in certain areas also affects its initial networking. Location variables are based on the 10 largest that show significant level of biotech activity. Studies of technology clusters, such as biotechnology, have yielded explanations that focus on the development of social networks (Almeida & Kogut, 1999; Casper, 2007). Year controls are also included in the first stage probit model. The dependent variable is a network dummy variable indicating whether or not firms will have initial networks (0 = no initial network,
1 = have initial network). Equation 1 presents the variables that are used for the first stage probit model to determine the network formation as:

\[ \text{Network Formation Dummy}_{i,t+1} = \alpha + \beta_1 \text{Firm Size} + \beta_2 \text{Firm Age} + \beta_3 \text{Issued Patents} + \sum \text{Location Dummy} + \text{error}. \] (1)

We generated the IMR from the first stage probit model and used it as a control variable in the second stage regressions (Greene, 1997). Since we have a panel data, we use a fixed effects regression model in our second stage regressions by clustering according to firm identifiers. We present our second stage results in a hierarchical way that enables us to investigate the added variance of independent variables in addition to the base model. Table 1 reports the means, standard deviations, and correlations for the variables in the second stage Heckman models.

**Results**

Table 1 reports the means, standard deviations, and correlations for the variables in our models. Firm size is measured by the natural logarithm of total assets and the mean value is 1.520, which is the size of the average company. On average, 23% of the firms have a growing network with at least one new member in their network. Network diversity is based on the Hirschman-Herfindahl index and it varies between 0 and 1 in which the value 1 indicates highly diversified firms. Mean diversity score is .33, which shows that on average our sample firms are not highly diversified. On average our firms have a return on equity (ROE) of −34%, which is common for the biotechnology industry. R&D intensity has a mean of 9.96, indicating firms invest approximately 9.96 times of their total sales in a year. Average current ratio of our sample firms is 2.01. This indicates that our sample firms do not have liquidity issues in the short run, namely, they can pay their current liabilities with their current assets comfortably on time. The average value of the IMR is 0.45.

Average network size is 10.72, indicating there are approximately 11 organizations in the scientific network of the firm. Network tie strength is measured by the percentage of times that the focal firm collaborated with the partners that are in the firm’s network for three consecutive years relative to others. On average, 24% of our sample firms collaborations were strong ties. Our firms and their partners have on average 2.01 high quality publications per year.

Table 2 reports the results of the second stage regression variables, which shows the effects of tie-specific variables on network growth.

Control variables such as firm age, firm size, firm profitability, firm R&D, firm liquidity, and IMR are entered in the equation first (Model 1), then independent variables such as network size, tie strength, and knowledge quality are entered second in the regression model (Model 2). Lastly, we entered the interaction variables to our full model (Model 3).

According to Model 3, Hypothesis 1(a) is supported at the \( p < .05 \) level. This result shows that network size is negatively associated with network growth. The relation between network ties strength and network growth is negative as hypothesized in Hypothesis 4(a) and significant at \( p < .01 \) level, supporting Hypothesis 4(a). The coefficient for knowledge quality
Table 1
Descriptive Statistics and Correlations (N = 3,056)

<table>
<thead>
<tr>
<th>Number</th>
<th>Variable</th>
<th>M</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
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<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<tr>
<td>1</td>
<td>Network growth</td>
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<td>.32</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>2</td>
<td>Network diversity</td>
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<td>.37</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>3</td>
<td>Firm size</td>
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<td>.77</td>
<td>.07**</td>
<td>.27**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>4</td>
<td>Firm age</td>
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<td>9.07</td>
<td>.12**</td>
<td>.24*</td>
<td>.23**</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>5</td>
<td>Firm profitability</td>
<td>−.34</td>
<td>1.65</td>
<td>−.03</td>
<td>−.01*</td>
<td>.37**</td>
<td>−.00</td>
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<tr>
<td>6</td>
<td>Firm R&amp;D</td>
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<td>.03</td>
<td>.01</td>
<td>.01</td>
<td>.03</td>
<td></td>
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<tr>
<td>7</td>
<td>Firm liquidity</td>
<td>2.01</td>
<td>10.2</td>
<td>−.03</td>
<td>−.03*</td>
<td>−.06**</td>
<td>−.00</td>
<td>−.04**</td>
<td>−.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Inverse Mill’s Ratio</td>
<td>.45</td>
<td>.36</td>
<td>−.15**</td>
<td>−.35**</td>
<td>−.62**</td>
<td>−.35**</td>
<td>−.21**</td>
<td>.00</td>
<td>.06**</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Network size</td>
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<td>34.2</td>
<td>.08**</td>
<td>.35**</td>
<td>.35**</td>
<td>.13**</td>
<td>.02</td>
<td>−.00</td>
<td>−.00</td>
<td>−.21**</td>
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<td></td>
</tr>
<tr>
<td>10</td>
<td>Tie strength</td>
<td>.24</td>
<td>.33</td>
<td>.17**</td>
<td>.60**</td>
<td>.32**</td>
<td>.24**</td>
<td>.00</td>
<td>.03</td>
<td>−.03</td>
<td>−.34**</td>
<td>.42**</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Knowledge quality</td>
<td>2.01</td>
<td>2.97</td>
<td>.42**</td>
<td>.62**</td>
<td>.24**</td>
<td>.17**</td>
<td>−.00</td>
<td>.01</td>
<td>−.02</td>
<td>−.22</td>
<td>.66**</td>
<td>.56**</td>
</tr>
</tbody>
</table>

*p < .05. **p < .01.

is positive and significant at p < .01 level in Model 3, which supports Hypothesis 6(c) and not Hypothesis 6(a). This result supports arguments based on the prominence perspective.

Model 3 also presents the interaction effects between network size and firm age, firm size, and tie strength. Results for Model 3 support Hypotheses 2 and 5(a) at the p < .01 and p < .05 levels, respectively. Hypothesis 3 is marginally supported at p < .10 significance level. These interaction effects are depicted in Figures 2, 3, and 4.

Hypothesis 7(a) explores the moderating role of inertial forces of network size, tie strength, and firm age in the relationship between knowledge quality within a firm’s network and network growth. The moderating role of tie strength is supported, but there is no support for the moderating role of network size and firm age. The interaction term between knowledge quality and network size is negative and significant at p < .01 level. This interaction effect is depicted in Figure 5. These results are not caused by multicollinearity, because the variance inflation factors (VIFs) between linear and interaction terms are 1.49, well below the cutoff point of 10 (Cohen, Cohen, West, & Aiken, 2003).

We test Hypotheses 1(b), 4(b), 5(b), and 6(b/d) in Model 6, in Table 3. The positive association between network size and network diversity is supported at the p < .01 level. Similarly, the negative direct effect of network tie strength and network diversity also received strong support. Knowledge quality is found to be positively associated with network diversity at the p < .01 level, which supports Hypothesis 6(d) and does not support Hypothesis 6(b). That is, Hypotheses 1(b), 4(b), and 6(d) are supported, whereas Hypothesis 6(b) is not supported.

Hypothesis 5(b) is supported at the p < .01 level, indicating that tie strength negatively moderates the relationship between network size and network diversity. In Hypothesis 7(b) we predicted a moderating effect of inertial forces of network size, tie strength, and firm age between the knowledge quality and network diversity. This hypothesis has received support at the p < .05 level for the moderating role of network size and at the p < .01 level for the moderating role of tie strength. These interaction effects are depicted in Figures 6, 7, and 8,
respectively. VIFs in Model 6 between linear and interaction terms were 1.69, also below the cutoff point of 10 (Cohen et al., 2003).

**Robustness Checks**

We took several steps to ensure that our findings are robust. Following Bae and Gargiulo (2004), we measured new members in the network within a three-year window. Since our collaboration network is based on co-authorships, we need to take into account a potential longer gestation period for the research and look into alternative windows for counting new members. Accordingly, we re-ran our Model 3, (1) using 5-year window and (2) counting true new and old ties over a 17-year period. Using different time frames in determining new members did not change our results.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient (SE)</th>
<th>t-stat</th>
<th>Coefficient (SE)</th>
<th>t-stat</th>
<th>Coefficient (SE)</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>.725 (.06)</td>
<td>12.08**</td>
<td>.181 (.09)</td>
<td>2.10*</td>
<td>2.515 (1.03)</td>
<td>2.44*</td>
</tr>
<tr>
<td>Firm size</td>
<td>.009 (.02)</td>
<td>.62</td>
<td>.015 (.02)</td>
<td>–.74</td>
<td>1.632 (.42)</td>
<td>3.92**</td>
</tr>
<tr>
<td>Firm age</td>
<td>.012 (.02)</td>
<td>3.48***</td>
<td>.010 (.02)</td>
<td>2.28*</td>
<td>.153 (.04)</td>
<td>3.69**</td>
</tr>
<tr>
<td>Firm profitability</td>
<td>.004 (.00)</td>
<td>.67</td>
<td>.001 (.00)</td>
<td>.39</td>
<td>.119 (.07)</td>
<td>1.72†</td>
</tr>
<tr>
<td>Firm R&amp;D Intensity × 10^6</td>
<td>–4.601 (.00)</td>
<td>1.02</td>
<td>–4.032 (.00)</td>
<td>–.09</td>
<td>–1.707 (.00)</td>
<td>–.57</td>
</tr>
<tr>
<td>Firm liquidity</td>
<td>.002 (.00)</td>
<td>1.23</td>
<td>.000 (.00)</td>
<td>.33</td>
<td>.002 (.00)</td>
<td>.96</td>
</tr>
<tr>
<td>Inverse Mill’s Ratio</td>
<td>–.014 (.05)</td>
<td>.26</td>
<td>–.218 (.05)</td>
<td>–.33</td>
<td>–.005 (.10)</td>
<td>–.05</td>
</tr>
<tr>
<td>Network size</td>
<td>–.001 (.00)</td>
<td>–2.45*</td>
<td>–.285 (.13)</td>
<td>–2.24*</td>
<td>–.387 (.98)</td>
<td>–3.99**</td>
</tr>
<tr>
<td>Tie strength</td>
<td>–.063 (.02)</td>
<td>–2.45*</td>
<td>–.387 (.98)</td>
<td>–3.99**</td>
<td>–.005 (.10)</td>
<td>–.05</td>
</tr>
<tr>
<td>Knowledge quality</td>
<td>.006 (.00)</td>
<td>2.37*</td>
<td>.451 (.12)</td>
<td>3.64**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Network Size × Firm Age</td>
<td>.019 (.01)</td>
<td>2.84**</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Network Size × Firm Size</td>
<td>.110 (.06)</td>
<td>1.84†</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Network Size × Tie Strength</td>
<td>.380 (.19)</td>
<td>1.98*</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>Knowledge Quality × Network Size</td>
<td>.032 (.02)</td>
<td>1.60</td>
<td></td>
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<tr>
<td>Knowledge Quality × Tie Strength</td>
<td>–.995 (.38)</td>
<td>–2.59**</td>
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<tr>
<td>Knowledge Quality × Age</td>
<td>–.018 (.01)</td>
<td>–1.49</td>
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<tr>
<td>Number of observations</td>
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</tr>
<tr>
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<td>367</td>
<td></td>
<td>367</td>
<td></td>
<td>367</td>
<td></td>
</tr>
<tr>
<td>F test</td>
<td>8.98**</td>
<td></td>
<td>49.64**</td>
<td></td>
<td>36.70**</td>
<td></td>
</tr>
<tr>
<td>VIF of the error (mean)</td>
<td>1.085 (2.45)</td>
<td></td>
<td>1.398 (2.38)</td>
<td></td>
<td>1.498 (4.13)</td>
<td></td>
</tr>
<tr>
<td>Adjusted R^2 (%)</td>
<td>8.52</td>
<td></td>
<td>15.32</td>
<td></td>
<td>33.28</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Year dummy variables were included but not reported in the model. Unstandardized coefficients are reported; standard errors are in parentheses. All dependent variables are lagged for one year. The Huber-White sandwich method robust regression with gvkey cluster was used for regressions to construct heteroscedasticity robust standard errors for unbiased estimators (Peterson, 2009). Variation inflation factors (VIF for multicollinearity test) for all variables are smaller than 10.

†p < .10. *p < .05. **p < .01.
Discussion

Despite the abundance of network-based studies in the existing literature, the study of networks with firms’ networking behavior as the dependent variable has received scant
attention (Hoang & Antoncic, 2003). In this study, we build on network management capability (Ford & McDowell, 1999; Hakansson & Ford, 2002; Kale et al., 2001), network inertia (Kim et al., 2006), and prominence (Rosenkopf & Padula, 2008) perspectives to systematically examine how a firm’s networks evolve over time. From this standpoint our study is among the few that investigates network dynamics in a longitudinal fashion. Our study reveals that network dynamics are rooted in certain characteristics of the firm and the
### Table 3: Effects of Tie-Specific Variables on Change in Network Diversity

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 4</th>
<th></th>
<th></th>
<th></th>
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<tr>
<td></td>
<td>Coefficient (SE)</td>
<td>t-stat</td>
<td>Coefficient (SE)</td>
<td>t-stat</td>
<td>Coefficient (SE)</td>
<td>t-stat</td>
</tr>
<tr>
<td>Intercept</td>
<td>.654 (.23)</td>
<td>2.84**</td>
<td>.385 (.08)</td>
<td>4.75**</td>
<td>.226 (.04)</td>
<td>5.52**</td>
</tr>
<tr>
<td>Firm size</td>
<td>.06 (.02)</td>
<td>2.98**</td>
<td>.059 (.02)</td>
<td>3.10**</td>
<td>.029 (.01)</td>
<td>2.37*</td>
</tr>
<tr>
<td>Firm age</td>
<td>.001 (.00)</td>
<td>.89</td>
<td>.005 (.00)</td>
<td>1.37</td>
<td>-.004 (.00)</td>
<td>-.263**</td>
</tr>
<tr>
<td>Firm profitability</td>
<td>-.003 (.00)</td>
<td>-1.23</td>
<td>-.004 (.00)</td>
<td>-1.43</td>
<td>-.011 (.00)</td>
<td>-3.58**</td>
</tr>
<tr>
<td>Firm R&amp;D Intensity × 10^6</td>
<td>-9.430 (.00)</td>
<td>-24</td>
<td>-8.440 (.00)</td>
<td>-21</td>
<td>1.752 (.00)</td>
<td>.84</td>
</tr>
<tr>
<td>Firm liquidity</td>
<td>-.000 (.00)</td>
<td>-.78</td>
<td>-.000 (.00)</td>
<td>-.50</td>
<td>-.000 (.00)</td>
<td>-3.11**</td>
</tr>
<tr>
<td>Inverse Mill’s Ratio</td>
<td>-.12 (.05)</td>
<td>2.32*</td>
<td>-.123 (.05)</td>
<td>-2.44*</td>
<td>-.007 (.00)</td>
<td>-1.72†</td>
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<tr>
<td>Network size</td>
<td>.001 (.00)</td>
<td>2.23*</td>
<td>.015 (.00)</td>
<td>7.73**</td>
<td>.056 (.01)</td>
<td>9.76**</td>
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<tr>
<td>Tie strength</td>
<td>-.059 (.02)</td>
<td>-2.47*</td>
<td>-.544 (.04)</td>
<td>-13.87**</td>
<td>.014 (.02)</td>
<td>7.33**</td>
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<tr>
<td>Knowledge quality</td>
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<td>3.01**</td>
<td>.056 (.01)</td>
<td>9.76**</td>
<td>.014 (.02)</td>
<td>7.33**</td>
</tr>
<tr>
<td>Knowledge Quality × Network Size</td>
<td>-.011 (.01)</td>
<td>-2.00*</td>
<td>-.070 (.01)</td>
<td>-7.19**</td>
<td>.000 (.00)</td>
<td>.27</td>
</tr>
<tr>
<td>Knowledge Quality × Tie Strength</td>
<td>-.011 (.01)</td>
<td>-2.00*</td>
<td>-.070 (.01)</td>
<td>-7.19**</td>
<td>.000 (.00)</td>
<td>.27</td>
</tr>
<tr>
<td>Knowledge Quality × Age</td>
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<td>.27</td>
<td>.000 (.00)</td>
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<tr>
<td>F test</td>
<td>16.05**</td>
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<td>52.94**</td>
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<td>64.01**</td>
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<td>VIF of the error (mean VIF of all)</td>
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<td></td>
<td>1.539 (2.38)</td>
<td></td>
<td>1.690 (3.78)</td>
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<tr>
<td>Adjusted R^2 (%)</td>
<td>11.21</td>
<td>35.04</td>
<td>40.85</td>
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</table>

**Notes:** Year dummy variables were included but not reported in the model. Unstandardized coefficients are reported; standard errors are in parentheses. All dependent variables are lagged for one year. The Huber-White sandwich method robust regression with gvykey cluster was used for regressions to construct heteroscedasticity robust standard errors for unbiased estimators (Peterson, 2009). Variation inflation factors (VIF for multicollinearity test) for all variables are smaller than 10.

†p < .10. *p < .05. **p < .01.

Firms’ existing network structure. We contribute to the literature by highlighting the importance of examining the structural characteristics of the firms’ existing network and its productivity in time t in order to understand the structure of the firm’s network in time t + 1 and beyond.

First, our findings support the role of firms’ existing network size in determining their future network structure. The results are consistent with the current literature on network management in that the management issues in a network context can be exceedingly complicated due to the embedded and reciprocal character of relationships (Ford & McDowell, 1999; Hakansson & Ford, 2002). The negative relationship between network size and network growth reveals that firms are cognizant of the costs and limits involved in managing a network and manage these by slowing network growth as the size of the firm’s network increases (Maurer & Ebers, 2006).
The network management capability perspective receives further support when firms’ management resources and capabilities are taken into account. The study of boundary conditions on the network size argument suggests that network size is more negatively associated with network growth for smaller and younger firms. This finding also suggests that large firms, as well as older ones, are better able to pursue the benefits of managing new
relationships because of their resources and experience. For such firms network management capabilities appear to extend the upper bounds of the network they believe they can efficiently manage encouraging them to grow their network.

Consistent with our expectations, we found that having a larger network initiates a change in network structure. While paying attention to a “manageable network size,” firms also need to introduce diversity to their existing networks to acquire the capabilities demanded by their changing environment and search for novel ideas and combinations. By doing so, they overcome the threat of becoming increasingly alike through imitation and being less effective at generating new knowledge (Dyer & Nobeoka, 2000). Our results also indicate that as new opportunities arise the biotechnology firm will look to add novel ties to replace redundant ties. Our findings lead to the conclusion that over time larger networks become more diverse, though the firm’s pursuit of new capabilities is tempered by the recognition of the limits of network growth.

Our findings also reveal the importance of the relationships between members of the network. Our findings with respect to the influence of tie strength were the strongest and most consistent in our study. Our findings suggest that building relational attachment with members of their network directly hinders further change in their network in terms of both network growth and diversity and also moderates the impacts of network size and knowledge quality on growth and diversity. Our results support previous literature, which posits that network ties of longer duration (i.e., strong ties) constitute partner-specific routines and structures that reduce uncertainty, which is important in the context of the biotechnology industry but also result in network inertia (Kim et al., 2006).
Perhaps the most interesting findings in our study are the findings surrounding knowledge quality. The consistent significance of the knowledge quality variables in both Tables 2 and 3 suggests considering the content quality of network ties, namely, what is produced through these networks, as a significant variable in explaining the change in firms’ network structure. Contrary to the inertia arguments, but in support of the prominence perspective, knowledge quality is positively related to network change in both dimensions. These findings support the literature on prominence (Rosenkopf & Padula, 2008), suggesting that the success of the network enables further change in the network by improving the biotechnology firm’s position in the market for collaboration partners. Quality production from their network increases the firm’s visibility creating additional opportunities for the firm that overcomes the natural tendency to maintain a network that is productive.

Interestingly, our findings underscore the interplay between the powers of inertia and powers of prominence in shaping a firm’s future network. We show that in a context where trust and mutual understanding is important, the impact of prominence is deterred by the inertial forces of tie strength. The risk of cutting and discontinuing ties, as well as the risks and costs of bringing on new members deters the firm from fully capitalizing on its new found prominence. Model 3 and Model 6 are consistent in showing the role of strong ties in creating a lock-in within a firm’s existing network even when new opportunities for change stemming from prominence are available.

Overall, our findings contribute to our understanding of network dynamics. Our basic contribution is to link the firm’s prior network configuration (network size and network tie strength) and the productivity of the firm’s network in time \( t \) to the evolutionary path of the firm’s network in time \( t + 1 \) and beyond. Our study provides strong empirical evidence of the importance of network dynamics and the need for the study of networks to move to longitudinal studies in order to further our knowledge. Our results make it clear that firm age and size significantly impact the firm’s ability to initiate a change in their network. Firm age and size also provide firms the skills and resources necessary to manage larger and more diverse networks and adapt their networks to their changing needs.

More importantly, our findings provide a nuanced perspective of the relationship between the network inertia perspective and the prominence perspective. Our results indicate that in accordance with the prominence perspective, success creates new opportunities in the market for partners that lead to growth in network members and increased diversity in the firm’s network. However, inertia also clearly exists and tempers the firm’s ability or willingness to make changes in its network even when these new found opportunities arise. Strong inertial forces within networks stemming from the lock-in properties of strong ties negatively moderate the evolution of the firm’s network in response to these new found opportunities arise. This nuanced exploration of the interplay of network management capabilities, inertia, and prominence is the most important contribution of this research. Networks are complex social structures that evolve and change in response to the needs and limitations of the firms involved as well as the opportunities that present themselves to the firm as its position changes over time. No single perspective provides the answers the field needs to move our understanding of the dynamics of networks forward. These perspectives must be unified in an inclusive theory of network dynamics that provides greater guidance to researchers seeking to understand the evolution of
networks over time. Our research provides empirical results that help to point the way forward in the development of this unified theory of network dynamics.

Limitations and Future Research

It is important to report that our findings are limited by the type of network we studied, a scientific network based on co-authorships. Networks of other business entities may behave differently. For example, we need to find out if sales or finance-based networks might be characterized by different evolutionary dynamics.

As in the case of most single industry studies, our study might suffer from the issue of generalizability. This research relies upon the networks of a sample of firms drawn from a single industry with its distinctive characteristics. Our results are still generalizable to the industries that have similar characteristics to the biotechnology industry.

Our study assumes the existence of firms’ networks in order to investigate network change. Future studies might look into the specific characteristics of the firm that lead a certain network to be created and how these founding conditions influence the evolution of networks over time. Our study has also been focused on the focal firm to exclusion of the partner firms. This leads to a need to study how the characteristics of the partners that are added or dropped influence the evolution and performance of the firm’s network. Also, in this study we do not evaluate whether, when, how, and under what conditions the firm benefits from changing the structure of its network. It is a critical next step to look into the performance impacts of changing network structures in a future study.

Conclusion

Numerous studies have noted the disaggregation of the value chain across many industries, and especially those drawing strongly on science and technology. As a result, companies tend to rely on scientific networks as a central component of their innovation strategies. Most studies have used network analysis tools to explore how a firm’s position in the network at a specific point in time impacts a given firm’s innovative performance. Our paper is novel in that it explores how characteristics of the firm and its network impact the evolution of the firm’s network over time. Our paper makes several contributions, for example that more experienced or older and larger firms have the capacity to manage larger networks and as a result are associated with more dynamic network management patterns, but that tie strength mitigates this ability. The paper also finds that a form of “signaling” exists within the biotechnology industry, in that firms associated within important findings, seen through publications in prominent journals, attract new partners. This finding is an important contribution because it provides a counterbalance to the inertial models of network evolution. Our results argue for a more holistic view of network evolution in which at any given time the firm is facing both inertial forces that limit change in its network and opportunity driven forces that drive change in its network. In certain conditions, such as a highly visible success, existence of larger networks and strong ties shift the balance toward the inertial forces and maintaining the status quo. Clearly, more research into the determinants of these forces,
their impact on firm performance, and the appropriate balance between them needs to be undertaken.

First, we find that firms’ existing tie-specific characteristics, in the form of a firm’s existing network size, tie strength, and the knowledge quality, constitute significant determinants of network evolution. Second, we contribute to the literature by showing empirically how organizations involved in networks choose to create or grow certain linkages with one another. Our longitudinal research design enables us to show certain patterns in network evolution. This paper joins the few in the literature examining networks dynamics over time (Koka et al., 2006; Zaheer & Soda, 2009). It pushes the frontier by directly testing the effects of certain characteristics of the firm’s existing network that would lead a change in its network structure. Our paper directs attention to the issue of network management capability by showing that network evolution dynamics might change whenever firms have such a managerial capability. It directs attention to the inertial perspective by highlighting how network size and tie strength temper network change. It also directs attention to the importance of prominence and its ability to open up opportunities for firms to expand their network over time. Lastly, we demonstrate the necessity of more longitudinal studies of networks by providing empirical evidence that we cannot predict today’s network structure without seriously considering yesterday’s network structure and productivity.

Notes

1. We also used number of employees as a measure of firm size. Average number of employees is 282.
2. We thank an anonymous reviewer for pointing this issue.

References


