Exploring the Evolution of Scientific Networks of Biotechnology Firms

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ABSTRACT

Despite decades of network research, the crucial question, "How do networks evolve?" has not been sufficiently explored. We explore this question by analyzing the co-authorship networks in the U.S. biotechnology firms. Specifically, from network management and network inertia perspectives, we argue that structural changes in the firms' co-authorship networks are dependent on the specific characteristics of firms' initial networks. Longitudinal analysis of the U.S. biotechnology firms over a span of seventeen years largely supports our arguments. Overall, we find that firms' existing tie-specific characteristics in the form of a firm's existing network size, tie strength, and the knowledge quality carried through these ties constitute significant determinants of network evolution.

Keywords: Network dynamics; Network evolution; Co-authorship networks; Biotechnology industry; Longitudinal analysis.

INTRODUCTION

Research on innovation has long recognized the need to build external networks in order to access new knowledge. As such, external networks are viewed as an important mechanism for organizations to accomplish activities such as gathering information, and accessing complimentary assets and resources. Networks have been shown to 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 and Reese 1993; Gulati 1998). Prior research supports the value of inter-firm networking by showing that the establishment of networks leads to increased performance (Baum et al. 2000; Rothaermel 2001). In addition,Vanhaverbeke et al. (2009) recently showed that a firm's network affect its ability to create new technologies in its technology core areas and/or non-core areas.

Despite the abundance of research on inter-firm networks and the network form of organization, the evolution of networks over time remains an underexplored (Parkhe et al. 2006; White 2005; Agterberg et al. 2010; Kijkuit and Van den Ende 2010). Prior research on firm networks has mainly focused on the impact networks on firms rather than an understanding of the nature and evolution of networks. There is a dearth of researching that attempts to explain why certain ties are established while others are destroyed, or how these networks change voer time. We still very little about *how a particular firms 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 the literature on networks by studying how the characteristics of the firms and the firms' network influences the development of the structure of the firms network in the future (Elfring and Hulsink 2007; Kijkuit and Van den Ende 2010).

Addressing the research questions above suggests the need to examine the additions to and subtractions from firms' networks over time. This dynamic view of how changes in the firms' relationships in one period affect the structure of the firms' networks in subsequent periods is critical in developing a better understanding of how such networks are organized (Salancik 1995), how firms manage their relationships and for our understanding of networks to move from static network analysis to a dynamic and fully drawn theory of organizations and networks (McDermott 2007; Toms and Filatotchev 2004).

Firms' initial network ties are intrinsically subject to change over time which makes attributions of causality in network evolution difficult using longitudinal data. This suggests that causality is still an open question in for most of the current network studies (Parkhe et al. 2006). Much of the current research is limited by its focuc on the dyadic level leaving changes in the firm's broader network beyond the scope of these studies. Network studies have also been limited by considering only changes in entry and exit without taking into account the whole structure of the network (Hennart, Kim and Zeng 1998). One of the few studies that look into the antecedents of changes in firms' networks (Hite and Hesterly,2001) argues that the resource needs of firms might evolve and such evolving needs might necessitate a shift in the organization's networks, but they are unable to empirically test of this proposition.

To develop a framework through which we can study network evolution requires an in-depth analysis of the dynamics of the relationships among the members of the network, and the network itself over time (Isett and Provan 2002). Therefore, we argue that while it could initially be some of the unique characteristics and resources of the firms that lead the firms to form a specific network (Powell et al. 1996), network change is also driven by *network tie specific* characteristics (Kim et al. 2006: 706, emphasis added), such as the size of the network, the strength of the ties in the network and the quality of the joint product of the network.. In other words, in order to predict how firms' networks change it is important to consider the characteristics of firms' current relationships that influences the evolution of their networks in subsequent periods. Firms seeking additional resources via their network are likely to begin with their existing network ties and adapt those network ties, based on their current network ties' ability to provide the required resources. If they cannot acquire what they need through their existing network ties, they will attempt to add new ties to access the required resources.

This paper seeks to address 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 (Walker et al. 1997; Gulati and Gargiulo 1999). 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 processes that constrain transformation in the network over time and mostly ignore potential influence of the characteristics of the existing network, such as size, tie strength and quality of the joint product, that might lead to changes to the network in the future. With a few exceptions (Gulati 1995; Ebers 1999), 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 researchers in general only examine firms that form totally new network ties or that successfully dissolves their old network ties without ever looking into the firm's pre-existing network of embedded relationships (Kim et al. 2006). Recently network dynamics, which is the view of networks as dynamic processes that are formed, dissolved, and reformed on a continuous basis, has begun to gain appeal among researchers leading to calls for an examination of the dynamic processes which initiate change in firms' networks across time (Powell et al. 2005; Koka et al. 2006). Taking such a dynamic approach, we view changes in firms' networks as a continuous process of termination and reformation of existing ties, and the creation of new ties over time. In order to address the question of "what causes such a dynamism?" we examine the specific characteristics of firms' existing network ties and how they impact the configuration of the firms network ties over time.

Tie-Specific Determinants of the Network Dynamics

Theoretically it is well accepted that firms need to adjust the configuration of their network ties in order to accommodate changing demands from their internal and external task environments (Ebers 1999). Over time, gaps between the firms' needs and what is available from their network ties are likely to occur. Therefore, 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 firms' relative attractiveness in the market for partners is also likely to change based on the firms prior activities, successes, and failures. Successes are likely to expand the pool of potential networks members and create new opportunities for the firm to engage in beneficial collaborations. This basic dynamic process in response to the changing needs of the firm requires an in-depth look at the characteristics of the firms' existing networks. When creating a change in their networks, firms are likely to consider the benefits that they have received from their existing network relationships. Benefits that accrue to a focal firm from an existing network tie are likely to lead to the persistence of that tie (Kim et al. 2006), unproductive ties may be culled and lead to a contraction of the network. Moreover, particular features of firms' existing network ties might lead to differences in the configuration of its future ties. In this paper, we address specific features of the firms' existing networks that influence change in the network ties in subsequent periods, such as the size of firms' existing networks, the strength of ties, and the quality of joint product of these ties. We also explore the boundary conditions of what is offered as the determinants of a network change and develop hypotheses based on the interactions between the firm characteristics and network tie-specific constraints as the main antecedents of network evolution.

Network tie size

Large networks, networks with more ties, provide firms access to more information and knowledge, which facilitates the generation of novel ideas. 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, et. al (1999) found that resource flows into the firm increased with the size of their alliance network. Similarly, Demirkan et al. (2007) found that biotechnology firms' innovative performance increases with the size of their co-authorship networks. There are potential limits to the returns to network size and several articles have documented declining marginal returns to alliance networks (Deeds & Hill 1996, Rothaermel, 2001). However, overall 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 coming from different organizations in the network; having large networks, no matter how successful it is, might impose significant management costs on the focal firm (Ford and McDowell 1999; Hakansson and Ford 2002). Considering the potential costs and the limits to managerial attentions, managers eventually 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 the potential costs faced by firms with large existing networks managers of these firms are likely to be cautious about adding additional ties to their network leading to substantially more inertia in large networks. Therefore, from a network management perspective, considerations of the ability of the firms to successfully manage large networks might make further changes in network ties particularly difficult. Due to such considerations, we argue that having large networks will discourage firms from adding new members to the network and increasing the rate of network growth. And thus:

Hypothesis 1(a): Existing network size will be negatively associated with network change in terms of the inclusion of new members to the network

Hypothesis 1(b): Existing network size will be negatively associated with network change in terms of the rate of growth in the network.

The overall composition of the network in terms of the similarity or diversity of firms in the network will be subject to change as the firm's network evolves. As firms develop their networks in response to opportunities they are likely to create redundancy in their networks. Emerging opportunities present significant ambiguity and uncertainty about the knowledge and skills needed and the quality of potential partners under these conditions, firms are likely to engage in redundant ties. With limited diversity in the network, especially within a large and growing network, there is a danger that as firms in the network become increasingly alike and needs evolve, the network will become less effective at generating new knowledge (Dyer and Nobeoka 2000). The lack of diversity will force the firm to either expand the network to seek new knowledge ro to change the composition of the network while restraining the size of the network. As noted above, firm's will evaluate the performance of their 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 in order to create room in the network to access the new knowledge and skills it requires. Redundant network ties are likely to have limited performance benefit, for the focal firm, since redundant relationships suffer from a similarity of ideas, skills and knowledge. In managing their networks we expect firms to cull redundant ties that are unproductive first, since they provide few benefits and the firm retains access to the knowledge in this tie via other more productive 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 of a firm's network and increase the diversity of the firm's network. 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 large networks will include a greater diversity of ties. Accordingly, we suggest that firms' existing network size will be positively associated with diversity in their networks when considering a further change. Therefore:

Hypothesis 1(c): Existing network size will be positively associated with network change in terms of the diverse composition of the network.

Management issues in a network context can be exceedingly complex due to the embedded and reciprocal character of network relationships (Ford and McDowell 1999; Hakansson and Ford 2002). They also add to firms' organizational costs by yielding an expensive and inefficient management structure (Goerzen 2005). These issues might become even more complicated when a change in the network is geared towards the inclusion of new members and network growth. Prior research has noted that young or new firms face particular difficulties due to immature routines and unstable relationships with respect to the simple task of learning how to work efficiently together, or put simply due to the liability of newness (Stinchcombe 1965). Similarly, past literature has shown that an increase in firm size increases the probability of the accumulation of specific firm-level competencies (Rosenberg 1976). Larger firms are more likely to set up knowledge management policies such as promoting a culture of sharing information and knowledge as well as knowledge management rules (Kremp and Mariesse 2004). The literature also suggests that in contrast to larger firms, small firms are more characterized by resource dependency rather than the resource sufficiency (Calof 1993).

This suggests that for large and established firms, constraints induced firms in terms of the management of their networks might not be as critical as they are within small and newly established firms. If firms have already built their bureaucratic structures to manage their networks, a change in network in terms of inclusion of new members and inducing further growth in the network should not be as much of a challenge. For such firms, larger networks might mean larger associated benefits and a change towards more new members and growth could be expected.

Hypothesis 2(a): The relationship between the network size and network change in terms of the inclusion of new members will be positively moderated by firm age

Hypothesis 2(b) The relationship between the network size and network change in terms of the inclusion of new members will be positively moderated by firm size.

Hypothesis 3 (a:) The relationship between the network size and network change in terms of the rate of growth in the network will be positively moderated by firm age

Hypothesis 3(b) The relationship between the network size and network change in terms of the rate of growth in the network 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 and Hebert 1991). For example, Parkhe (1993) found out that in a strategic alliance, the level of perception of opportunistic behavior between the alliance partners is negatively related to the history of cooperation between them. This suggests that the stronger and more repeated the relationships, the better the cooperative performance between partners.

Moreover, repeated, strong ties are suggested to enhance both relational and cognitive lock-in (Gargiulo and Benassi 1999). Firms who are entrenched in strong ties might at the same time 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, strong ties might also be considered as a constraint against further change in the network. In other words, firms' network ties which are characterized by strong and long lasting network relationships will not be further motivated to include new ties and expand their networks. Overall, because attachment and commitment in a relationship can affect the members' attitudes (Salancik 1995), firms who are characterized by such commitments will find it difficult to initiate a change in their networks towards both including new members and growing network ties.

Network diversity, on the other hand, reflects the variety of backgrounds and knowledge bases of the members in the network (Ruef et al. 2003). While bringing in further diversity to the existing network ties will enhance the richness and the quality of information exchanged (McPherson et al. 2001), diversity of ties will also mean more complex and more difficult relationships to manage. There are significant costs associated with greater diversification within the network. Kim et al. (2006) point out that network ties of longer duration (i.e. strong ties) constitute partner-specific routines and structures in the network that would further result in network inertia. In networks that are characterized by strong ties, members institutionalize an understanding of the specific styles of their existing ties (Doz et al. 2000). They establish a common understanding of each other that would further strengthen the nature of relationships. In such cases changing network ties towards more diversity might mean a complete abandonment of the existing set of routines and structures in the network, which will eventually hurt the current success of the network ties. Accordingly;

Hypothesis 4(a): Network tie strength within firms' networks will be negatively associated with network change in terms of the inclusion of new members to the network

Hypothesis 4(b) Network tie strength within firms' networks will be negatively associated with network change in terms of the rate of growth in the network

Hypothesis 4 (c) Network tie strength within firms' networks will be negatively associated with network change in terms of the diverse composition of the network.

From a rational actor point of view, the potential purposes and functions of network ties are more important than the structure of the ties themselves. Such a perspective considers the expected economic benefits of current and future actions that are derived from firms' networks. Accordingly, we suggest that even with the existence of strong network ties firms still prioritize the benefits that they receive from their existing networks. While a successful collaboration with existing network members feeds on itself and further maintains its legitimacy, collaborations, which do not produce successful outcomes will lead to a search for new ties. While as noted above strong ties are an inertial factor in network evolution, strong ties ability to deter change is likely to be influenced by the productivity of the network. In cases where the network is unsuccessful in generating useful output, the focal firm is more likely to initiate a change to increase the productivity of its network. The need to initiate change is likely to spur the firm to diversify the knowledge and skills in its network by bringing more diversity to the network. A preference for diversity in the network suggests a search for novelty, inclination to move in different communities and interact with heterogeneous partners (Powell et al. 2005).

Therefore:

Hypothesis 5: The relationship between the network ties strength and network change in terms of the diverse composition of the network will be negatively moderated by the knowledge quality.

Knowledge quality

The prevailing assumption in our theory of network change is that firms will be more likely to initiate a change in their networks when they can no longer benefit from their existing networks. That is, the quality of what is carried within the network ties might be a significant measure of the success of the network and how firms can benefit from it.

By the quality of knowledge we refer to the value of knowledge output created within firms' networks. Looking at the knowledge quality might enable us to understand whether firms are successfully benefiting from their existing networks. From a network inertia perspective (Kim et al. 2006), firms that successfully benefit from their existing networks will not necessarily initiate a change in their networks. When firms' knowledge quality, which is generated through the use of their networks, are regarded as unique and novel, there will not be a strong tendency for the firms to change their networks through either addition of new members or inducing further growth in the network. As firms build network relationships for a variety of resources, they develop a network profile or portfolio of ties over time. These ties are reinforced if they are accompanied by high quality knowledge output. This embedded action may cause the firms to be constrained to a narrower set of relationships that perpetuates itself over time. In such cases, quality of knowledge might become a constraining factor for further network change. From such an "inertia"- based perspective (Kim et al. 2006; Hannan and Freeman 1984), success in existing networks is reflected through the quality of knowledge created within the network of the firm and would also inhibit a further variety of knowledge, know-how, and expertise coming into a firm's network.

Hypothesis 6(a): Knowledge quality within a firm's network will be negatively associated with network change in terms of the inclusion of new members to the network

Hypothesis 6(b) Knowledge quality within a firm's network will be negatively associated with network change in terms of the rate of growth in the network

Hypothesis 6(c) Knowledge quality within a firm's network will be negatively associated with network change in terms of the diverse composition of the network.

DATA AND METHODOLOGY

Data

In order to test the hypotheses above, we chose the U.S. biotechnology industry as our research setting. We collected inter-firm network data based on the scientific research collaborations of the focal firm (Acedo et al. 2006). In biotechnology industry, studies based on research collaborations at the co-authorship and scientist level are quite extensive (Oliver and Liebeskind, 1998; Zucker et al. 2002; Oliver 2004, Lam 2007). These studies established the importance of the scientific networks in the biotechnology industry by finding that firms whose researchers engaged in joint research and publishing (i.e. forming research collaboration networks) with other institutions are more effective at sourcing new scientific information. Similarly, Zucker et al. (1993) have found that the researchers (star scientists) mostly make up the technology of the firm and contribute to firm performance through defining discoveries and providing intellectual capital.

Locus of innovation is argued to be found within the networks of inter-firm relationships, which is also an evolving community (Powell et al. 1996; Kogut 2000). Felin and Hesterly (2007) study argue that the final explanations of inter-firm networks may actually be nested within the firm and a priori firm-level heterogeneity may determine network structure. It is also argued that 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 and Liebeskind 1998), and that studies of the biotechnology industry can demonstrate how informal collaboration norms contribute to the scientific growth of organizations (Oliver 2004). Therefore, we look into the researcher level collaboration within the biotechnology industry to determine the appropriate level of networking.

Accordingly, we identified a sample of publicly-traded biotechnology firms that are listed in Recombinant Capital (ReCap), because complete financial data are needed to validate their performance indices. BioScan and ReCap are the two most comprehensive databases that document the variety of activities in the global biotechnology industry and both sources are fairly consistent (Hoang and Rothaermel 2005).

We developed our co-authorship network based on these firms. Specifically, we studied the scientific networks of the biotechnology firms in our sample. Each network consisted of a focal biotechnology firm and a set of alters, i.e., research institutions, universities, or pharmaceutical firms, connected to the focal firm by the coauthorship of a research paper (Wasserman and Faust 1994). 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). Therefore, we observed the changes in the co-authorship networks of these firms over the specified years longitudinally.

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 independent variables, an observation number of 3,056 remained in the sample with 367 firms. 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 three network structure variables as our dependent variables: the new network members, rate of growth in the network, and the level of diversity (heterogeneity) in the firm's network. 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 and Gargiulo, 2004).

New network members are operationalized as the ratio of new ties within a given year *t* to the overall network size in the same year. *New network members* are considered to be "new" if they had not appeared in the firm's network within the past three years.

Growth in biotechnology firm's network, *network growth*, is proxied as the percentage change in a firm's organizational ties from one year to the next. In order to measure this we first determined the number of old network ties and new network ties for a given year. *Old network ties* are defined as the ties that a firm had within the past three years. A firm's network growth is measured by dividing the difference between the new network ties and old network ties by the new network ties that a firm has in year *t*.

In measuring the diversity in the network, *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 $NDij = [1-\Sigma_{ij}(PC_{ij})^2]/TC_i$ 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 and Gargiulo 2004). For example, if for year *t* the firm's researchers had collaborated with researchers from 10 organizations, then the network size of that specific firm is coded as 10, which is a count variable.

In order to measure the *network tie strength* between the network partners we looked into the partners that firms had collaborated with for each year. 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.

Another important variable to be controlled is that of the *R&D intensity*. It is shown that R&D expenditures are a significant determinant of firm innovativeness (Ahuja 2000). 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 is 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 or longitudinal data have observations on cross-section units i = 1, 2,..,368 of firms, over time periods t = 1990, 1991, …, 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; Woolridge 1995; Beugelsdijk 2008). We first estimated a probit model of the likelihood of 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 the 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 firms' having an initial network. For this stage, we used variables that are not in direct control of the firm for further network creation. That is, these variables are the ones that lead 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 and 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 ten largest that shows significant level of biotech activity. Studies of technology clusters, such as biotechnology, have yielded explanations that focus on the development of social networks (Almeida and 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).

Table I reports the means, standard deviations, and correlations for the variables in the first stage probit model.

********** Insert Table I about here**********

We generated the Inverse Mill Ratio (IMR) from the first stage probit model and used it as a control variable in the second stage regressions to avoid potential sample selection bias that may exist in our sample due to the effects of unobserved factors such as the existence of its prior (or initial) level of established relationships on firm's current network structure. This method eventually yields unbiased estimators of the predictors of the second model (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 III reports the means, standard deviations, and correlations for the variables in the second stage models.

********** Insert Table III about here**********

RESULTS

Tables I and III report the means, standard deviations, and correlations for the variables in the first and second stage models consecutively. Network formation in Table I is a dummy variable indicating whether a firm has an initial network or not. Firms that start with networks have the value of 1 for the existence of an inter-firm network, and 0 otherwise. Network formation has the mean of 0.53 with the standard deviation of 0.5, meaning that 53% of our sample firms have prior networks, this is quite normal for the biotechnology industry. Firm size is measured by the natural logarithm of total assets and mean value is 1.520, which is the size of the average companies[†]. On average, the age of our sample firms is 9.54 which is an indication how young the firms are in the biotechnology industry. We specifically followed Ahuja (2000: pp.437) in our data collection and operationalization of the issued patents variable. In collecting our data, we used the application dates of granted patents. Number of patents granted per year is an innovation measure and on average our sample firms have 3.20 patents per year. The correlations for the year dummy variables are not presented here to save space. Accordingly, Table II reports the first stage model results.

********** Insert Table II about here**********

As expected, both firm size and firm age are positively associated with initial network formation at $p<.001$ and $p<.01$ consecutively. In accordance with the past literature, firm location is also a significant determinant of initial network formation since nine of the eleven location variables are significant.

[†] We also used number of employees as a measure of firm size. Average number of employees is 282.

Table III reports the means, standard deviations, and correlations for the variables in the second stage models. New members is a dummy variable that takes the value of 1 if there is an inclusion of new members to the network and 0 otherwise. Table III shows that on average, 23% of the firms have at least one new member in their network. On average there is a 1% decline in network growth in our sample. 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. Firm profitability is captured by the return on equity variable which is the ratio of net income to total equity in a year. On average our firms have negative profitability with the value of 34% which is common for the biotechnology industry. Other firm characteristic variable is R&D intensity that has the mean of 9.96. This statistic shows that on average firms invest in R&D approximately 9.96 times of their total sales within a year. Our final firm characteristic variable is the liquidity which is proxied by current ratio. 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 i.e. 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 i.e. there are approximately 11 organizations on average within the scientific network of the firm. Relational strength is measured by the percentage of times that the focal firm collaborated with the partners which are in the firm's network for three consecutive years relative to others. Our sample firms collaborated on average 24% times in three consecutive years. Knowledge quality is the total number of firm's partners' excluding the focal firm, highest-ranking publications. Our firms' partners have on average 2.01 highest ranked publications per year.

Table IV reports the results of the second stage regression variables, which shows the effects of tie specific variables on network change in new members.

********** Insert Table IV about here**********

Above mentioned control variables such as Firm Age, Firm Size, Firm Profitability, Firm R&D, Firm Liquidity and IMR are entered in the equation first (Models 1, 4, and 7), then independent variables such as Network Size, Relational Strength and Knowledge Quality are entered second in the regression models (Models 2, 5, and 8). Lastly, we entered the interaction variables to our full models (Models 3, 6, and 9).

According to Model 2, Hypotheses 1(a) and 4(a) are both supported at the .5% level. While the relation between the knowledge quality and the change in new members is positive and significant at 5% level in Model 2, our Hypothesis 6(a) is not supported since we had hypothesized a negative relationship between these two variables.

Model 3 presents the interaction effects between network size and firm age, and between network size and firm size. According to the interaction variables in Model 3 Hypothesis 2(a) and 2(b) are supported at the 5% level. These interaction effects are both depicted in Figures 1 and 2.

********** Insert Figures 1 and 2 about here**********

We test Hypotheses 1(b), 4(b) and 6(b) in Model 5, in Table V. In this model the direct effects of network size and relational strength on the change of growth in the network are supported at the 10% and 1% levels respectively. That is, Hypotheses 1(b) and 4(b) are supported, whereas Hypothesis 6(b) is not supported. This as well as Hypothesis 6(a) requires further explanation.

********** Insert Table V about here**********

In Hypotheses 3(a) and 3(b) we predicted a moderating effect of firm size and firm age on the relationship between the network size and the change of growth in the network. These hypotheses are tested in Model 6. Our results reveal that interaction effect between the network size and firm size, Hypothesis 3(a) and 3(b), are supported at .001 levels.

********** Insert Figures 3 and 4 about here**********

Model 8 in Table VI show the regression results for Hypotheses 1(c), 4(c), and 6(c). In other words, we test the direct effects of network size, relational strength, and knowledge quality on the change of network diversity. The positive association between the network size and the change of network diversity is supported at the 5% level. Similarly, the negative direct effect of relational strength and the change in network diversity also received strong support. Contrary to our expectations, knowledge quality is found to be positively associated with the change in network diversity; Hypothesis 6(c) is not supported.

********** Insert Table VI about here**********

Finally, in Hypothesis 5 we predicted a moderating effect of knowledge quality between the network tie strength and network change in terms of the diverse composition of the network will be moderated by the knowledge quality. We show in our Model 9 that this hypothesis has received support at the 1% level.

********** Insert Figure 5 about here**********

DISCUSSION

Despite the abundance of network-based studies in the existing literature, the study of networks and firms' networking behavior as the dependent variable has received scant attention (Hoang and Antoncic 2003). In this study, we take network management (Ford and McDowell 1999; Hakansson and Ford 2002) and network inertia (Kim et al. 2006) perspectives to systematically examine how a firm's network change over time. From this standpoint our study is among the few that investigates the network dynamics in a longitudinal fashion (for a few example, see Toms and Filatotchev (2004)). Our study reveals that network dynamics are rooted in certain characteristics of firms' existing network structure. In other words, we contribute to the literature by showing the need to look into the characteristics of the firms' existing networks in understanding what initiates the change.

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 and McDowell 1999; Hakansson and Ford 2002). The negative relationship between network size and network change in terms of the inclusion of new members as well as the change in the growth of the network reveals that firms are cognizant of the costs and limits involved in managing a network and achieve this by limiting the entry of new members into their network and slowing the networks rate of growth as the size of the firm's network increases (Maurer and Ebers 2006).

This management perspective on network dynamics receives further support when firms' management 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 change in terms of the inclusion of new members 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. With these findings we show that when it comes to inter-firm networks firms need to consider the time and resources going into the management of such relationships and hence maintain an efficient level of inter-firm relationships in order to benefit from networking in terms of innovation.

While we observe a similar relationship for network change in terms of the growth of the network, our findings show that in the case of larger and older firms, network size may further enhance network growth. For such firms network management capabilities appear toe xtend the upper bounds of the network they believe they can efficiently manage encouraging them to grow their networks and add new members.

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 cabailities demanded by their evolving situations and the demands from their environment and in a 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 and Nobeoka 2000).

Our findings also reveal the importance of the relationships between members of the network by supporting our hypotheses on the characteristics of the network ties in terms of relational strength. Our findings suggest that in time firms might build relational attachment with members within their network, and that this hinders further change in their network not only in terms of adding new members to the network and network growth, but also in terms of changing the composition of the network. However contrary to our hypothesized relationship between tie strength and network growth we find that strong ties are actually positively related to network growth once the interactions between network size and firm age and size are considered. This is an intriguing finding and may indicate that strong ties require less managerial attention and therefore free the firm to grow its network. However the lack of consistent results across all three measures of network dynamic indicates that the relationship between tie strength and network dynamics is complex and merits further attention.

Perhaps the most interesting findings in our study is the unexpected findings surrounding knowledge quality. The consistent significance of the knowledge quality variable suggests considering the content quality of network ties, i.e. what is carried through these networks, as a significant variable in explaining the change in firms' network structure. However, contrary to our expectations, knowledge quality created within these ties is positively related to network change in all three dimensions. These findings suggest that the success of the network enables further change in the network by improving the firm's position in the market for partners. In fact success of their network improves the firm's visiblity to new and diverse partners creating additional opportunities for the firm which overcomes the natural tendency to maintain a network that is productive. This point becomes clearer for firms with weaker levels of relational strength. For such firms we found that knowledge quality is more positively related to network change in terms of diversity; firms that are less attached to their existing partners face less inertia become more attractive to others opening up new opportunities for partners which initiates a further change in their network.

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 relational strength, to the evolutionary path of the firm's network. While theorized in prior research our study provides strong empirical evidence to support this position on network evolution. In addition, our results make it is clear that firm age and size, which we believe to be a proxy for a firm's network management capability, as well as the quality of the product of the firm's network significantly impacts the evolution of firm networks, Firms which are able to manage their network and have successful network relationships are able to initiate significant changes in their network.

Our findings provide a counterbalance to the theoretical arguments on network inertia, where firms that successfully benefit from their existing networks will not necessarily initiate a change in their networks. Our results indicate that there are strong inertial forces within networks that slow the growth and the introduction of new members, but the improvement of the firm's position in the market for partners creates new opportunities that lead to new members, network growth and increased diversity in the firm's network. Firms face opposing forces in managing their network the inertial forces mitigating changes in the network and the opportunity driven forces seeking to add new and more diverse members to the network. Our results seem to indicate that the balance shifts from inertia to opportunity when the network produces high quality, visible outputs that improve the firm's position in the market for partners.

Limitations and Future Research

It is important to report that our findings are limited by the type of network we studied, a research collaboration network. 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 share similar characteristics with the biotechnology industry.

This study mainly examines the tie-specific characteristics of firms' existing networks in considering the network dynamics. 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. Also, in this study we do not evaluate whether the firm benefits from such an evolving network structure; it is worthwhile to look into the benefits of changing network structures as 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. Numerous studies have used network analysis tools to map the structure of R&D networks and explore how the structure of these networks, and the position of companies within them, impact a given firm's innovative performance. Our paper is novel in that it explores how firm characteristics and the characteristics of the firm's network impact the evolution of the firm's network over time. Drawing on a study of scientific networks involving publicly traded U.S. biotechnology firms between 1990 and 2006, 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. 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 counter-balance to the inertial models of network evolution. In fact, taken as a whole are results argue for a more wholisitic view of network evolution in which at any given time the firms is facing both inertial forces that limit change in its network and opportunity driven forces that drive change in its network and that certain conditions, such as a highly, visible success, shift the balance towards the opportunity driven forces, while others, such as increasing network size and tie strength, shift the balance towards 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.

Overall, we first show that firms' existing tie-specific characteristics in the form of a firm's exiting network tie size, tie strength, and the knowledge quality carried through these ties 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. Given the paucity of network evolution research, this paper joins the few exceptions in the literature (Powell et al. 2005; Koka et al. 2006), pushing 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. Lastly, we demonstrate the necessity of more empirical studies by providing empirical support for an opportunity driven theory of network dynamics that counter-balances the current dominate inertial theory of network dynamics.

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TABLE I
Descriptive Statistics and Correlation Matrices for Heckman First Stage Variables

No	Variable	Obs	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Network Formation	8194	0.53	0.5														
2	Firm Size	4380	1.52	0.77	.19													
3	Firm Age	7417	9.54	9.07	.22	.22*												
4	Issued patents	8194	3.20	23.42	.10	.19*	.09*											
5	Loc1	8194	0.15	0.36	.02	.12*	-.11*	.06*										
6	Loc2	8194	0.14	0.34	-.01	.03	.00	.01	-.02*									
7	Loc3	8194	0.10	0.30	.02	-.00	.00	.00	-.14*	-.13*								
8	Loc4	8194	0.13	0.34	.01	-.07*	.00	-.02	-.17*	-.16*	-.13*							
9	Loc5	8194	0.01	0.12	.04*	-.04	.01	-.00	-.05*	-.05*	-.04*	-.05*						
10	Loc6	8194	0.04	0.18	-.04*	.05*	-.01	-.01	-.08*	-.07*	-.06*	-.07*	-.02					
11	Loc7	8194	0.01	0.11	.05*	.06*	.04*	.02	-.05*	-.05*	-.04*	-.04*	-.01	-.02				
12	Loc8	8194	0.02	0.14	-.02*	-.00	-.04*	-.00	-.06*	-.06*	-.05*	-.06*	-.02	-.03	-.02			
13	Loc9	8194	0.03	0.17	.03	-.06*	.04*	-.01	-.07	-.07*	-.06*	-.07*	-.02	-.03	-.01	-.03		
14	Loc10	8194	0.04	0.19	.00	.00	-.02	.02	-.08*	-.08*	-.07*	-.08*	-.02	-.04*	-.02	-.03	-.03	
15	Loc11	8194	0.17	0.37	.02	-.08*	-.04*	-.02	-.19	-.17	-.15	-.17	-.06*	-.09*	-.05*	-.09*	-.06*	-.08*

Notes: *indicates statistically significant at 1% level (one-tailed test).

TABLE II
Results of Probit Analysis for the First-Stage Heckman Network Model

Variables	**Network Formation**	
	Coeff. (SE)	z-stat
Intercept	-1.396(.24)***	-5.93
Firm Size	.475 (.07)***	7.19
Firm Age	.013 (.00)**	2.43
Issued patents	.080 (.01)***	7.12
Loc1	.649 (.20)***	3.18
Loc2	.546 (.28)*	1.95
Loc3	.626 (.22)**	2.91
Loc4	.094 (.23)	.42
Loc5	1.163 (.36)***	3.25
Loc6	.360 (.25)	1.47
Loc7	.964 (.32)***	2.94
Loc8	.663 (.45)	1.49
Loc9	1.143 (.26)***	4.38
Loc10	.663 (.28)**	2.34
Loc11	1.164 (.18)***	6.34
No. of . Obs.	4,160	
No. of. Clusters	437	
Log- likelihood	-1683.08	
Wald $\chi 2$	383.90***	

Notes: ***,**, and * indicates statistically significant at 1%, 5%, and 10% respectively. 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.
Location Variables: Location variables are based on the 10 largest that shows significant level of biotech activity. Loc1 is dummy variable that takes the value of 1 for San Francisco, Loc2 for Boston, Loc3 for San Diego, Loc4 for Tristate (NY, NJ and CT), Loc5 for DC area includes MD, Loc6 for Philadelphia, Loc7 for Los Angeles, Loc8 for North Carolina, Loc9 for Texas, Loc 10 for Seattle and Loc11 for none of the above clusters, and zero otherwise.

TABLE III
Descriptive Statistics and Correlation Matrices for Heckman Second Stage Variables

No.	Variable	Obs	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1	New Members	7174	0.23	0.32											
2	Network Growth	7174	-0.01	0.75											
3	Network Diversity	7174	0.33	0.37											
4	Firm Size	4380	1.52	0.77	.07*	-.08*	.27								
5	Firm Age	7417	9.54	9.07	.12*	-.01	.24*	.23*							
6	Firm Profitability	8193	-0.34	1.65	-.03	-.00	-.01	.37*	-.00						
7	Firm R&D	8194	9.96	130.35	.02	.00	.03	-.01	.01	-.03					
8	Firm Liquidity	4360	2.01	10.2	-.03	.00	-.03	-.06*	-.00	-.04*	-.00				
9	IMR	4160	0.45	0.36	-.15*	.01	-.35*	-.62*	-.35*	-.21*	.00	.06*			
10	Network Size	7174	10.72	34.2	.08*	-.17*	.35*	.35*	.13*	.02	-.00	-.00	-.21*		
11	Relational Strength	7174	0.24	0.33	.17*	-.35*	.69*	.32*	.24*	.00	.03	-.03	-.34*	.42*	
12	Knowledge Quality	8105	2.01	2.97	.42*	-.06*	.62*	.24*	.17*	-.00	.01	-.02	-.22	.66*	.56*

Notes: *indicates statistically significant at 1% level (one-tailed test).

TABLE IV
Effects of Tie Specific Variables on Change in New Members

Variables	**Model 1**		**Model 2**		**Model 3**	
	Coeff.(SE)	t-stat	Coeff.(SE)	t-stat	Coeff.(SE)	t-stat
Intercept	.725 (.06)	12.08***	.181	2.10**	.168 (.09)	1.79*
Firm Size	.009 (.02)	.62	.015 (.02)	-.74	.014(.02)	.63
Firm Age	.012 (.00)	3.48***	.010 (.00)	2.28**	.011 (.00)	2.38**
Firm Profitability	.004 (.00)	.67	.001 (.00)	.39	.002 (.00)	0.45
Firm R&D Intensity x 10^6	-4.601 (.00)	1.02	-4.032 (.00)	-.09	-3.552 (.00)	-0.08
Firm Liquidity	.002 (.00)	1.23	.000 (.00)	.33	.001 (.00)	0.32
IMR	-.014 (.05)	.26	-.218 (.05)	-.33	-.010 (.06)	-0.17
Network Size			-.001 (.00)	-2.45**	-.002 (.00)	-2.73***
Relational Strength			-.063 (.02)	-2.45**	-.063 (.02)	-2.42**
Knowledge Quality			.006 (.00)	2.37**	.006 (.00)	2.38**
Network Size × Firm Age					.000 (.00)	2.02**
Network Size × Firm Size					.001 (.00)	2.00**
No. of observations	3,056		3056		3056	
No. of clusters	367		367		367	
F-test	2.43*		2.66***		2.47***	
Adjusted R-square (%)	8.52%		15.32		22.29	

Notes: ***,**, and * indicates statistically significant at 1%, 5%, and 10% respectively. Year dummy variables were included, but not reported in the model. Unstandardized coefficients are reported; standard errors are in parentheses.

TABLE V
Effects of Tie Specific Variables on Change in Growth Rate

Variables	Model 4		Model 5		Model 6	
	Coeff.(SE)	t-stat	Coeff.(SE)	t-stat	Coeff.(SE)	t-stat
Intercept	.012 (.00)	2.73***	.007	.32	.086	.33
Firm Size	-.145 (.05)	2.9***	-.140 (.06)	-2.50**	-.163 (.06)	-2.76***
Firm Age	.012(.01)	1.20	.018 (.01)	1.55	.017 (.01)	1.33
Firm Profitability	.003 (.00)	.79	.006 (.01)	.67	.006 (.01)	.70
Firm R&D Intensity x 10^3	-.004 (.00)	-.84	-.003 (.00)	-.27	-.003 (.00)	-0.26
Firm Liquidity	-.001 (.00)	-.65	-.000 (.00)	-.22	-.000 (.00)	-0.24
IMR	-.012 (.14)	-0.57	-.092 (.15)	-.62	-.137 (.16)	-0.86
Network Size			-.002 (.00)	-1.88*	-.003 (.00)	-1.39
Relational Strength			-.205 (-.07)	-2.87***	.160 (.07)	2.23**
Knowledge Quality			.017 (.01)	2.36**	.017 (.01)	2.39**
Network Size × Firm Age					.001 (.00)	2.76***
Network Size × Firm Size					.004 (.00)	3.22***
No. of observations	3,056		3,056		3,056	
No. of clusters	367		367		367	
F-test	2.23**		2.89***		3.13***	
Adjusted R-square(%)	12.23		20.79		25.78	

Notes: ***,**, and * indicates statistically significant at 1%, 5%, and 10% respectively. Year dummy variables were included, but not reported in the model. Unstandardized coefficients are reported; standard errors are in parentheses.

TABLE VI

Effects of Tie Specific Variables on Change in Network Diversity

Variables	Model 7		Model 8		Model 9	
	Coeff.(SE)	t-stat	Coeff.(SE)	t-stat	Coeff.(SE)	t-stat
Intercept	.654 (.23)	2.84***	.385 (.08)	4.75***	.362 (.08)	4.41***
Firm Size	.06 (.02)	2.98***	.059 (.02)	3.10***	.061 (.02)	3.20***
Firm Age	.001 (.00)	.89	.005 (.00)	1.37	.006 (.00)	1.54
Firm Profitability	-.003 (.00)	-1.23	-.004 (.00)	-1.43	-.004 (.00)	-1.38
Firm R&D Intensity x 10^6	-9.430 (.00)	-0.24	-8.440 (.00)	-.21	-8.371 (.00)	-0.21
Firm Liquidity	-.000 (.00)	-0.78	-.000 (.00)	-.50	-.000 (.00)	-0.48
IMR	-.12 (.05)	2.32**	-.123 (.05)	-2.44**	-.113 (.05)	-2.23**
Network Size			.001 (.00)	2.23**	.001 (.00)	2.39**
Relational Strength			-.059 (.02)	-2.47**	-.092 (.03)	-2.91***
Knowledge Quality			.007 (.00)	3.01***	.007 (.00)	2.00**
Knowledge Quality × Relational Strength					-.011 (.00)	4.41***
No. of observations	3,056		3,056		3,056	
No. of clusters	367		367		367	
F-test	5.67***		8.83***		8.21***	
Adjusted R-square(%)	32.17		46.89		51.92	

Notes: ***,**, and * indicates statistically significant at 1%, 5%, and 10% respectively. Year dummy variables were included, but not reported in the model. Unstandardized coefficients are reported; standard errors are in parentheses.

FIGURE 1

Interaction Effects of Network Size and Firm Size on Change in New Members

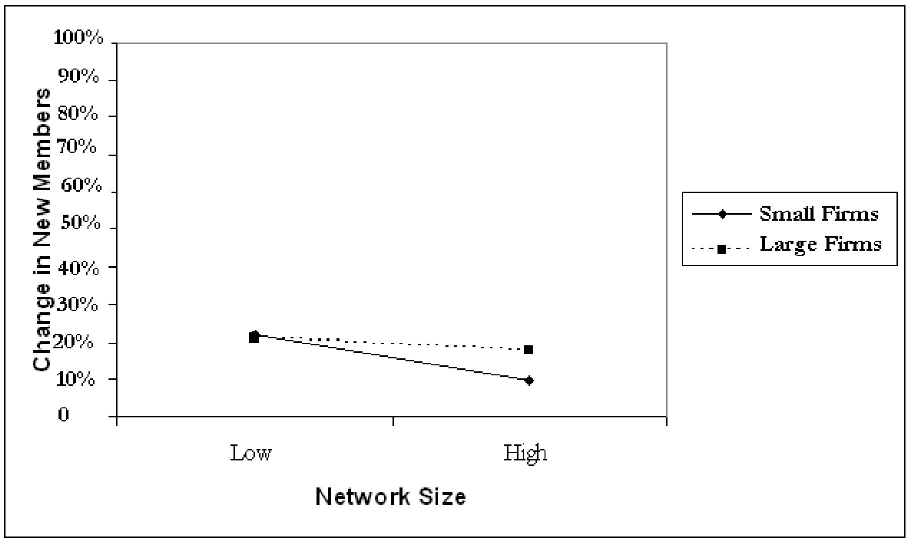

FIGURE 2

Interaction Effects of Network Size and Firm Age on Change in New Members

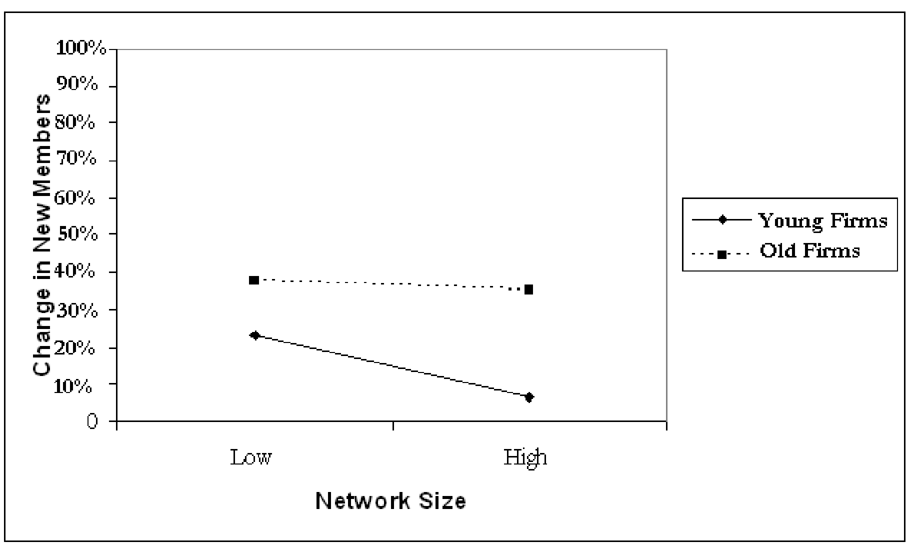

FIGURE 3

Interaction Effects of Network Size and Firm Size on Change in Growth Rate

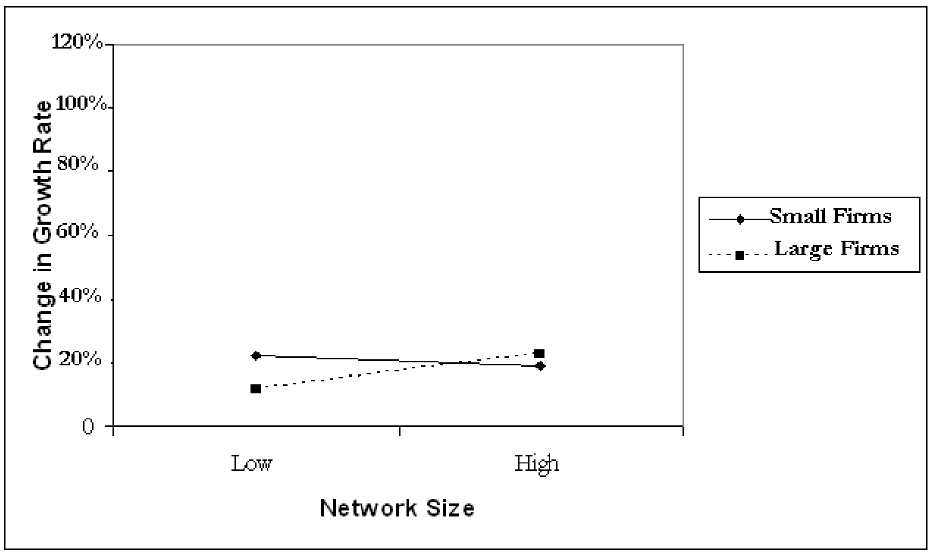

FIGURE 4

Interaction Effects of Network Size and Firm Age on Change in Growth Rate

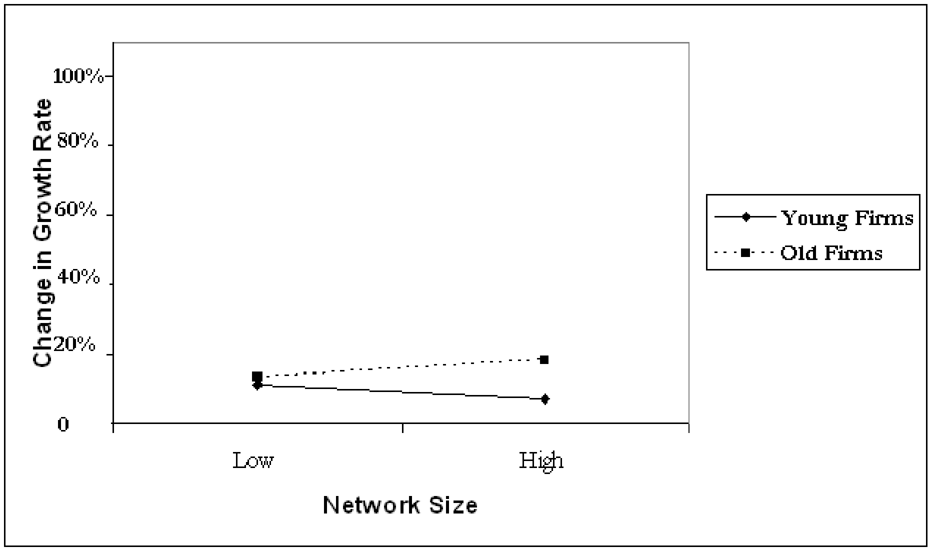

FIGURE 5

Interaction Effects of Knowledge Quality and Relational Strength on Change in Network Diversity