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Maureen McKelvey
Bastian Rake

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Friedrich Schiller University Jena
Carl-Zeiss-Str. 3
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www.uni-jena.de

Max Planck Institute of Economics
Kahlaische Str. 10
D-07745 Jena
www.econ.mpg.de

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Research Network Position and Innovative Performance: Evidence from the Pharmaceutical Industry *

Maureen McKelvey† and Bastian Rake‡

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Abstract

This paper explores how and why collaboration with different types of partners and the position within a research network can affect firms' innovative performance in terms of product innovations. A detailed empirical analysis is carried out in the biotechnology and pharmaceutical industry. This industry is characterized by a rapidly developing, complex, and dispersed knowledge base, where one would expect positive benefits from collaboration and the position within a network for innovative output. The paper uses a unique dataset in pharmaceutical cancer research based on scientific co-publications and new drug approvals. We apply social network analysis and count data regressions. We observe that collaboration with a diverse set of partners from academia and the network position in terms of eigenvector centrality is positively related to product innovation. However, we do not find a general positive association between collaboration, particularly with biotechnology companies, and product innovation or between central network positions and product innovation. Therefore, these results require a re-assessment of the role of scientific collaboration and biotechnology companies in the development of the pharmaceutical industry.

Keywords: Research Networks, Research Collaboration, Innovative Performance, Pharmaceuticals
JEL Classification: L25, O31

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†University of Gothenburg, Institute for Innovation and Entrepreneurship, School of Business, Economics and Law, SE-40530 Gothenburg, Sweden, phone: +46-(0)31-786-1442, e-mail: maureen.mckelvey@handels.gu.se

‡Friedrich Schiller University Jena, Graduate College "The Economics of Innovative Change" (DFG-GK-1411), Carl-Zeiss-Strasse 3, D-07743 Jena, Germany, phone: +49-(0)3641-943-274, e-mail: bastian.rake@uni-jena.de

1 Introduction

A well-established stream of literature suggests that a firm's position within a research network influences its innovative output, particularly in industries in which the knowledge base is rapidly developing, complex, and widely dispersed (e.g., Owen-Smith and Powell, 2004; Powell et al., 1999). Under these conditions, the structure of the entire network and the actors' position within it determine access to the relevant knowledge sources and, therefore, the actors' innovative activities and performance (Kogut et al., 1992). Collaboration networks are important primarily because hardly any single actor, e.g., a firm or academic institution, can keep abreast of the progress in all knowledge areas necessary for successful innovative activities (Nooteboom, 2009, 1999). Consequently, research is increasingly conducted in collaboration with different partners. Hence, collaboration networks are a means to pool, exchange, and develop new knowledge, and the locus of innovation is no longer the individual actor, but the entire network (Powell and Grodal, 2005; Powell et al., 1996; Powell and Brantley, 1992). These networks are created by heterogeneous actors who are linked through a web of different types of relations (McKelvey et al., 2004a).

In this rich stream of literature, papers commonly use patents as a proxy for innovation outputs (e.g., Ahuja, 2000). Few previous papers have been able to explore in detail the direct effects of collaboration and network position on offerings to the market. Therefore, this paper explores how and why collaboration with different types of partners and the position within a research network can affect firms' innovative performance in terms of product innovations.

The paper focuses on the biotechnology and pharmaceutical industry. In this industry, networks of collaborative relations emerged as a response to a rapidly developing, complex, and widely dispersed knowledge base (McKelvey et al., 2004a,b). Given the importance of scientific knowledge, its publication, and collaboration, it is interesting to focus on research networks and the link between firms' positions in the network and their innovative performance. Moreover, in this industry, firms have relied on "block-buster drugs", and product approval is a major step for selling in the market. Using data on co-publications and new drug approvals, a detailed empirical analysis is conducted based

on the specific characteristics of the industry. Additionally, the study employs social network analysis and Poisson regressions.

With its novel empirical material, the paper can contribute to the literature in four ways. First, in contrast to the majority of studies on research networks at the firm level, we use co-publications instead of inter-organizational agreements to account for scientific collaboration. Research networks are constructed using pharmaceutical publication data in the area of cancer research obtained from the Web of Science databases for the years 1998 to 2008. With these data, we can directly observe joint knowledge generation. Moreover, co-publications might also account for more informal types of scientific collaboration based on personal relations. Second, we use drug approvals as a measure for innovative output, whereas most related studies rely on patent data. Innovation is proxied by the number of new pharmaceuticals on the firm level, and this information is obtained from the Drugs@FDA database provided by the U.S. Food and Drug Administration (FDA). The use of drug approval data circumvents the problem that nearly all therapeutically promising compounds are patented before their therapeutic potential is fully examined. Hence, other papers based on the number of patents likely overestimate the actual number of new medications introduced to the market. Third, we use detailed company level data. Fourth, we concentrate on a specific area of firms' research activities, namely, pharmaceutical cancer research. With this focus, compared with studies on the industry level, we can establish a closer link between scientific collaboration and innovative performance.

We chose cancer research for our study because of its worldwide prevalence and the importance of pharmaceuticals for its treatment. Cancer is a leading cause of death worldwide. Thus, the disease area represents an important market for pharmaceutical companies and is associated with considerable expenditures for medical care. More than 12 million individuals are newly affected, and approximately 7.5 million people die of cancer each year (IARC, 2008). Both numbers are expected to increase considerably until 2030. Nevertheless, the introduction of new pharmaceuticals has considerably increased the number of individuals surviving specific types of cancer. Moreover, advances in molecular biology have provided promising avenues for future drug development (IARC, 2008).

The paper proceeds as follows. Section 2 presents the related literature. In Section 3, the empirical strategy and the data are presented. Subsequently, we present a description of the research network in pharmaceutical cancer research in Section 4. The results of our empirical analysis are presented in Section 5. Finally, Section 6 concludes.

2 Related Literature

2.1 Collaboration in the Pharmaceutical Industry

Collaboration has been found to be an increasingly important mode of knowledge generation. Teams are increasingly more common than single authors and inventors across different scientific disciplines (Wuchty et al., 2007). However, the phenomenon of intensified collaboration is not restricted to the scientific domain. Since the 1980s, the number of R&D collaborations among firms has increased considerably (Hagedoorn, 2002). These developments that indicate growing collaborative relations have been particularly pronounced in the pharmaceutical industry. Innovative activities in this industry have been found to be organized as collaboration networks based on interactions of different types of actors. Among these actors, universities and research institutes dedicated to basic science play a key role. The emergence of these networks can be viewed as a response to the rapidly developing, complex, and widely dispersed knowledge base used in the industry's R&D process (Orsenigo et al., 2001; McKelvey, 1996; Arora and Gambardella, 1994).

The most important drivers leading to the emergence of collaboration networks have been changes in the industry's knowledge base and its R&D process. Advances in biomedical knowledge led to a gradual change in the industry's predominant R&D approach from "random screening" to a more rational and science-based drug discovery and development process (Henderson et al., 1999). The importance of interactions among different types of partners increased further after the emergence of modern biotechnology in the mid-1970s and its introduction to the industry's R&D process. Collaborative relations can provide access to knowledge and other resources that complement an organization's own knowledge base and R&D activities (Arora and Gambardella, 1994).

Because the industry's R&D process is based on scientific knowledge, collaborations be-

tween firms and academic institutions have been crucial for successful innovative activities (Cockburn and Henderson, 1998). This collaboration is not restricted to co-patenting, licensing or other forms of contractual agreements and alliances. In the biotechnology and pharmaceutical industry, companies engage actively in the collaborative production of scientific knowledge and its publication. Participating in the scientific community is valuable for firms to attract capable researchers, to build up absorptive capacity and to generate the required knowledge for successful innovation (e.g., Zucker and Darby, 1997; Hicks, 1995; Gambardella, 1992).

Scientific advances in biotechnology have frequently been commercialized by specialized new ventures. These companies had access to the latest scientific knowledge and research techniques but lacked the competencies and resources for the clinical development, approval, and marketing of new drugs. These elements have become accessible through collaboration with established pharmaceutical companies (McKelvey et al., 2004b; Malerba and Orsenigo, 1996). Incumbents faced the opposite problem and have been interested in collaborating with biotechnology companies to gain access to and experience with the new techniques that have created opportunities for the development of new pharmaceuticals (McKelvey et al., 2004a; Malerba and Orsenigo, 1996). Consequently, collaboration can be regarded as one way to incorporate entrants' knowledge and competencies into incumbents' value chains (Rothaermel, 2000).

2.2 Collaboration and Innovative Performance

Based on growing collaborative R&D activities, many scholars have analyzed the effects of intensified collaboration on the (innovative) performance of the involved firms. Becker and Dietz (2004) find that R&D collaboration and the number of partners involved in the collaboration increase the probability of developing new products. In line with these results, Graf and Krüger (2011) provide evidence for a positive relation between the number of linkages and innovative performance in terms of patent counts. Additional evidence suggests that innovative activities, i.e., bio-pharmaceutical patents, can be explained by the number of biotechnology startups' collaboration agreements (Shan et al., 1994). Collaborative relations provide not only access to the knowledge and experience of direct partners but also to their partners' expertise (Gulati and Gargiulo, 1999). In addition

to direct interactions, Ahuja (2000) demonstrates the relevance of indirect linkages for innovative activities, i.e., firms' number of patents.

However, not only the number of partners might influence firm performance. The extent to which partners can profit from collaboration might be influenced by the partners' characteristics and knowledge bases. Stuart (2000) shows that in addition to granting access to technological resources and knowledge transfer from innovative partners, collaboration with well-known partners might improve reputation. Moreover, collaboration might serve as a quality signal for future collaborative partners, customers, and investors. Additionally, the type of R&D partners might influence firms' innovative performance. Particularly, collaboration with universities and public research institutions enhances the sales growth of products and services new to the market (Belderbos et al., 2004).

The pharmaceutical industry has been characterized by tremendous growth of R&D and other forms of collaboration among different types of actors (Roijakkers and Hagedoorn, 2006; Powell et al., 2005). Because the industry's knowledge base builds on scientific advances, collaboration with academic institutions, such as universities and public research institutes, has been found to be crucial for firms' innovative activities. Empirical evidence suggests that links to academic institutions through co-authorship of scientific papers increase research productivity in terms of pharmaceutical companies' patents granted in at least two of the three most important markets (Cockburn and Henderson, 1998). Biotechnology companies collaborating with universities simultaneously have lower R&D expenditures and higher innovative outputs in terms of patents, marketed products, and products under development. However, the companies' financial performance is ultimately not superior to their counterparts without university linkages (George et al., 2002). These results support earlier findings indicating that collaboration with academic partners when firms are established is positively related to biotechnology startups' innovative performance measured as patents and growth in R&D employment and spending (Baum et al., 2000).

As stated earlier, the emergence of biotechnology and its incorporation into the industry's R&D process has led to increasing collaborations between newly established biotechnol-

ogy firms and pharmaceutical companies. A major driver of these collaborations is the complementarity of the companies' key resources and competencies (e.g., McKelvey, 1996; Gambardella, 1995; Powell and Brantley, 1992). Consequently, collaboration between incumbents and biotechnology companies as providers of new technologies is positively related to the number of new product developments by incumbents (Rothaermel, 2001a). The development of new products itself might then support incumbents' financial performance.

2.3 Network Position and Innovative Performance

In addition to the influence of the number of collaboration partners on firms' innovative performance, the literature has analyzed the relation between firms' network positions and their performance. However, the empirical evidence provided thus far is rather ambiguous, which might be a consequence of the different measures used as proxies for innovative performance. Tsai (2001) argues that central network positions provide better access to knowledge generated outside a business unit. Hence, units that occupy central network positions should be able to outperform their counterparts particularly with respect to innovative activities. In his empirical analysis, Tsai (2001) shows that degree centrality in the intra-organizational network significantly enhances business units' innovative performance proxied by the number of new products divided by the target number of new products. Analyzing local networks of wine producers in Italy and Chile, Giuliani (2007) finds that degree centrality in knowledge exchange networks is positively related to wine quality. Soh (2003) argues that high closeness centrality is beneficial for efficient information dissemination, which increases the performance of new products as indicated by the number of new product awards obtained. Although these studies suggest a positive relationship between central network position and innovative performance, Graf and Krüger (2011) find contradictory evidence. Focusing on regional innovator networks, the authors find a negative association between betweenness centrality and the number of patent applications.

Using an extensive dataset on human biotechnology firms, Powell et al. (1999) find evidence that central network positions increase firm performance. This finding applies to a broad variety of performance measures, such as sales, employment growth, the number of

patents and internally funded R&D expenditures. These results are partly supported by earlier findings in the same industry suggesting that degree centrality positively predicts increases in the number of employees, whereas the results for closeness centrality are not significant (Powell et al., 1996). With respect to the biotechnology industry near Boston, Owen-Smith and Powell (2004) find that the relation between betweenness centrality and innovative activities can change as the network develops over time. More precisely, the authors find a negative relation between central network positions and successful patent applications in the early years of the network. As the network becomes more mature, centrality is positively associated with innovation. This changing importance of centrality is connected to the increasing importance of for-profit organizations, such as biotechnology companies and venture capitalists, in the local network (Owen-Smith and Powell, 2004).

3 Data and Empirical Strategy

3.1 Empirical Strategy

To analyze the collaborative relations of firms in pharmaceutical cancer research, we use social network analysis based on scientific co-publications. With this method, we follow the growing literature addressing relational data in the analysis of innovation networks and innovation systems (e.g., Cantner and Rake, 2011; Graf, 2011; Breschi and Catalini, 2010). Social network analysis focuses on relationships among interacting units and thus provides the appropriate framework for our study. Consequently, a network is defined as a finite set of actors and their relations among one another (Wasserman and Faust, 1994). In our study, we refer to organizations, i.e., firms, universities, non-academic medical care providers and other public and private organizations, as actors in the network.

Relations among organizations are represented by co-publication links. The underlying assumption is that authors of a scientific publication have collaborated in its production. This collaboration implies that they have engaged in the joint generation of new knowledge and certain types of knowledge transfer. Using the reported author affiliations, we can assign the publication to the organizations for which the authors have been working at the time of publication. We construct the co-publication network based on these relations among organizations and calculate different network measures to assess the position

of each organization within the network. These measures are included in the econometric analysis. In the regression analysis, we focus on firms, their relations, and positions within the co-publication network.

We use the number of new pharmaceuticals approved by the FDA as a proxy for firms' innovative success with product innovations. Hence, the dependent variable determines the use of count data regression models with the Poisson model as the benchmark model for the empirical analysis. In the ordinary Poisson regression model, the dependent variable follows a Poisson distribution that yields the probability mass function $Pr[Y = y] = e^{-\mu}\mu^y/y!$ (Cameron and Trivedi, 2005). The Poisson regression model parameterizes the relation between the mean parameter μ and a vector of covariates x_i through

$$\mu = \exp(x_i'\beta) \text{ with } i = 1, \ldots, N \tag{1}$$

In (1), β denotes a vector of regression parameters. The covariates are assumed to be linearly independent and usually include a constant.

An important property of the Poisson regression framework is equidispersion, i.e., the variance is equal to the mean. However, in many practical applications, this assumption is violated. Using a regression-based test as proposed by Cameron and Trivedi (1990), we do not find significant overdispersion in all model specifications. However, we account for possible overdispersion by using Huber-White robust standard errors.[1] Because the approval of new pharmaceuticals is a rather rare event, the number of observed zeros might be much higher than the Poisson model predicts. We apply the Vuong test to test for zero-inflation (see Vuong, 1989). The test indicates that the ordinary Poisson model is most suitable for the data and should be preferred over its zero-inflated version.

3.2 Data

Our empirical analysis is based on data from different sources. To collect data on scientific co-publication, the BioPharmInsight database is used to compile a list of 30 medical

[1] We also compute negative binominal regressions. However, these models do not converge in every specification. In the models that converge, the goodness of fit statistics and the coefficients and their significance are very similar to those of the Poisson model.

indications in the therapeutic area of cancer.[2] Each indication describes a medical condition or disease that allows for the development of a pharmaceutical therapy. We use these medical indications to conduct a keyword search in the Web of Science databases (WoS) to gather data on scientific publications. We include in our datset all publications that contain at least one of the respective medical indications in their title. We further restrict the publication data to areas related to pharmaceutical research, i.e., they have been assigned to the WoS categories "Biochemistry & Molecular Biology", "Biotechnology & Applied Microbiology", "Chemistry, Applied", "Chemistry, Medicinal", "Medicine, Research & Experimental", "Pharmacology & Pharmacy" or "Toxicology".[3] Moreover, we exclude all publications that are not classified as journal articles. To construct collaboration networks based on co-publication, we distinguish two sub periods, 1998 to 2002 and 2004 to 2008. To create periods periods of equal length and to distinguish clearly between the two sub periods, we do not use articles published in 2003. In total, the sample consists of 17,317 journal articles for which we could identify author affiliations. These affiliations are used to assign publications to the organizations from which they originated.

As a proxy for successful product innovation, data on new drug pharmaceuticals are obtained from the U.S. Food and Drug Administration's (FDA) Drugs@FDA database.[4] The database contains information on the trade name of new drugs, their generic names, the components providing pharmacological activity, the approval date and a classification of the newness of a drug formulation. We match the medical indications with data on new drug approvals based on their pharmacological active ingredients. To match these elements, we follow Cerda (2007) in consulting the 19th edition of the Drug Information Handbook published by Lexi-Comp and the American Pharmaceutical Association (Lacy et al., 2010). The handbook provides a list of the drugs' active ingredients, the medical indications the respective drug is used for and further information, such as adverse effects. We consider only those medical conditions that can be found on the FDA approved label. Hence, unlabeled and investigational uses are not considered. We match the data on new drugs to the organizations in our publication data based on the name of

[2] http://www.biopharminsight.com/index.html. A list of the respective medical indications can be found in Table 5 in Appendix A.1.

[3] A description of the categories can be found at http://scientific.thomsonreuters.com/mjl/.

[4] http://www.fda.gov/Drugs/InformationOnDrugs/ucm135821.htm

the organization that applied for approval of the respective drug. The U.S. drug market is one of the largest in the world, and many new drugs introduced in the U.S. are marketed worldwide. Therefore, we strongly believe that the number of new drugs in the U.S. is to a large extent representative of the world market.

The raw data obtained from the WoS and the FDA have various shortcomings concerning the reported names of organizations. Therefore, we manually standardize organization names and addresses. We account for changes in organizational boundaries, e.g., due to mergers and acquisitions, by assigning each institution to its highest order independent entity by 2008. Specifically, all subsidiaries are assigned to the parent company if the latter holds more than 50% of the shares. Following this rule, we assign government agencies and laboratories to the responsible institution. Research institutes are assigned to their respective umbrella organizations. Because the decision of whether to place a university hospital or a respective medical department as an affiliation seems rather arbitrary, we consider university hospitals as part of the university with which they are affiliated. The same process applies to other university departments or institutes.

We consulted different databases to obtain financial information for the companies in our sample. The Amadeus database was used to obtain information on companies based in Europe. We supplement these data for firms headquartered outside Europe with data obtained from their financial reports provided by Company.info and the U. S. Securities and Exchange Commission (SEC). Financial data are converted to U.S. dollars using the exchange rate at the end of the respective years. Most companies for which we have financial information are publicly quoted. However, the rather high number of companies listed on the stock market might not bias our sample in terms of firm size, firm age, and innovativeness. Because many small and young firms go public in the bio-pharmaceutical industry, our sample seems to be quite representative. Overall, 771 firms have been identified in at least one publication during our two sub-periods of observation and are therefore included in our dataset. In the first period, 325 firms could be assigned to at least one article, whereas 562 firms published during the second period.

4 Description and Visualizations of Cancer Research Networks

In this section, we use social network analysis to illustrate collaboration patterns between different types of organizations in the field of pharmaceutical cancer research in the periods 1998 to 2002 and 2004 to 2008. We use the igraph package for the statistical software R by Csardi and Nepusz (2006) to visualize the collaboration networks applying the algorithm proposed by Fruchterman and Reingold (1991) with 1000 replications. A detailed description concerning the computation of the different network measures can be found in Cantner and Rake (2011).

The descriptive network statistics in Table 1 reveal that the cancer research network expands over time. The number of organizations involved in at least one publication increases considerably from almost 2000 in the first period to nearly 3200 in the second period. This result accounts for an increase of approximately 60%. Most actors are part of the largest component, i.e., the largest connected part of the network. Both the absolute number and the share of actors participating in the largest component increase from the first to the second period. The absolute number of isolated organizations that do not collaborate with others increases slightly. However, the share of isolated organizations declines due to the growing number of actors.

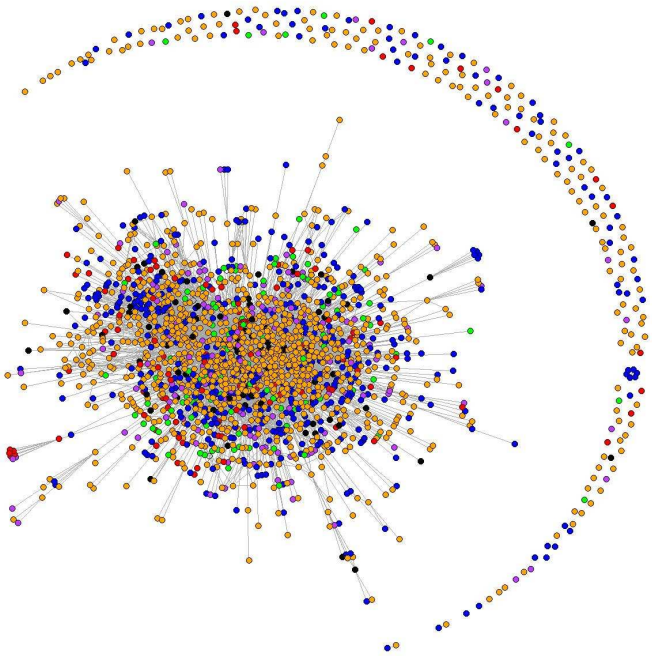
Period	Number of Actors	Number of Components	Abs. Size Largest Component	Rel. Size Largest Component	Abs. Number of Isolates	Rel. Number of Isolates	Density	Mean Degree	Degree Centralization	Betweenness Centralization	Average Path Length	Clustering Coefficient
1	1996	186	1755	0.879	147	0.074	0.004	8.288	0.089	0.086	3.591	0.185
2	3197	189	2960	0.926	151	0.047	0.003	9.600	0.092	0.107	3.588	0.170

Table 1: Descriptive Statistics of the Cancer Research Network

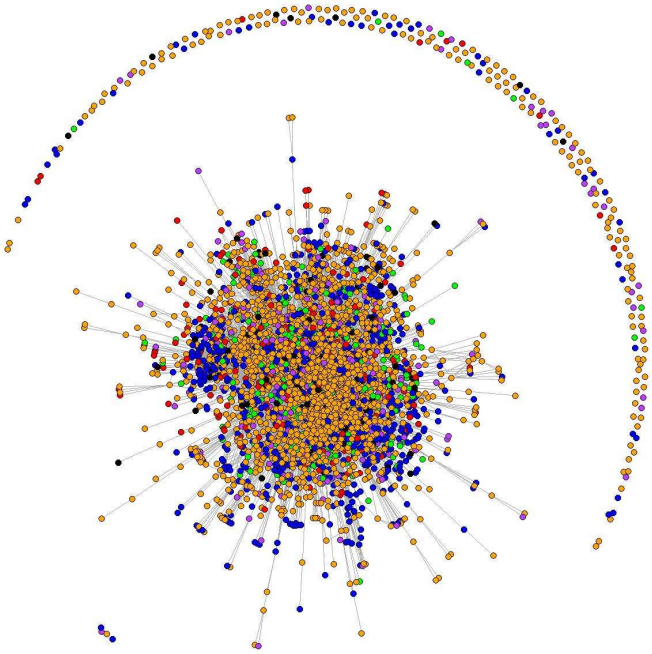
The density of the network, i.e., the amount of realized linkages divided by the number of possible linkages, decreases form the first to the second period. In both periods, the number is rather close to the minimum value of zero. A decreasing density indicates that the number of actors grows faster than the number of linkages among them. Nevertheless, as indicated by the mean degree, the average number of partners with which an actor is connected increases from approximately 8.3 in the first period to 9.6 in the second period. The degree centralization and betweenness centralization measures are rather close to zero, which indicates that the number of partners and the betweenness centrality scores of the actors are rather similar. The dissimilarities in these measures increase slightly from the first to the second period. The average path length remains rather stable above 3.5. The clustering coefficient is decreasing, indicating that the network becomes slightly less coherent over time. The latter finding might again be driven by the rapid expansion of the number of actors from the first to the second period.

Visualizations of the research networks in Figure 1 illustrate the growth of the research network from the first to the second period. In both periods, many different types of organizations collaborate in pharmaceutical cancer research. Hence, not only academic institutions are located in the center of the network. Several pharmaceutical and biotechnology companies occupy central positions in the network. Even some companies whose main business is not pharmaceuticals but the production of diagnostic devices or drug compounds occupy central network positions. The same finding applies to non-academic medical care providers and other organizations. The latter organizations are often government laboratories, foundations or other NGOs specializing in research and treatment of specific cancer types.

The general trend of a growing and diverse set of organizations as being part of the network and an increasing but less rapidly growing connectivity among them can also be observed in several robustness checks. In these robustness checks, we restrict our sample to basic research and biotechnology publications because the collaboration patterns in these fields might differ from more applied clinical research. We restrict the sample to journals included in the WoS prior to 1998 according to the CHI classification of journals to ensure that our results are not driven by a growing number of journals in the dataset.



(a) 1998-2002



(b) 2004-2008

Figure 1: Cancer Research Networks on the Organizational Level

Organization types: academic institutions (orange), pharmaceutical firms (black), biotechnology companies (green), other companies (red), non-academic medical care providers (blue), other organizations (violet)

5 Regression Results

5.1 Variables and Descriptives

In our regression analysis, we concentrate on firms', their collaboration partners, network positions, and new products. We use the number of new drug approvals in period t (NDA_t) as a dependent variable. This variable encompasses all new molecular entities, i.e., active ingredients that have never been marketed before in the U.S., new chemicals derived from marketed active ingredients, new formulations and dosages of marketed ingredients, and new combinations of marketed ingredients approved by the FDA in period t, i.e., the second period from 2004 to 2008. In the 30 medical indications considered, 71 new drugs have been approved during the two periods of analysis.[5] Thirty-four of these drugs have been classified as new molecular entities. Further descriptive statistics can be found in Table 2.[6] Although a new drug might serve as therapy for multiple diseases, we count it as a single innovation. Otherwise, we would overstate the actual number of new drug approvals in the therapeutic area of cancer.

Our explanatory variables are constructed using social network analysis. To account for the number of collaboration partners, we use the degree of firms within the cancer co-publication network. Specifically, $Degree_{t-1}$ refers to the number of direct linkages to other actors in the network in $t-1$. We further distinguish the number of collaboration partners by considering different types of partners. $AcademicPartner_{t-1}$ is defined as the number of academic partners, i.e., universities and research institutes, in $t-1$. These partners include also university hospitals because we are not able to distinguish between university hospitals and medical departments in a meaningful way. $BiotechPartner_{t-1}$ represents the number of collaboration partners in $t-1$ that are classified as biotechnology companies according to the definition of the OECD (2005).

In addition to the count of different collaboration partners, we calculate the total number of collaborations with different types of actors. $Collaborations_{t-1}$ denotes the total amount of collaborations in $t-1$, $CollaborationsAcademia_{t-1}$ refers to the number of col-

[5] Table 5 in Appendix A.1 provides a list of the medical indications taken into account.

[6] Table 6 in Appendix A.2 provides an overview of the variables used in the empirical analysis.

laborations with partners from academia, and $CollaborationsBiotech_{t-1}$ is the number of collaborations with biotechnology companies lagged by one period. Additionally, we account for the total number of organizations to which firms are indirectly linked in $t-1$ ($IndirectTies_{t-1}$). Specifically, we compute the number of organizations to which a firm is linked at path length 2. Hence, a firm is connected to these organizations through its direct collaboration partners. Similarly, we calculate the number of indirect ties to academia ($IndirectAcademicTies_{t-1}$) and biotechnology companies ($IndirectBiotechTies_{t-1}$).

We apply three measures of centrality accounting for the positions of firms within the co-publication network as a whole. The first variable, weighted degree centrality, combines the number of different collaboration partners with the interaction intensity (Opsahl et al., 2010):

$$DegreeCentrality_i^w = d_i^{1-\alpha} * \left(\sum_j^N w_{i,j} \right)^{\alpha} \tag{2}$$

In (2), N refers to the total number of actors, and d_i is the degree of actor i. $w_{i,j}$ is a weight representing the collaboration intensity between two actors i and j. The parameter α represents the relative importance of the number of partners and the number of collaborations. We set α to 0.5, assuming equal importance of both factors. For the interpretation of $DegreeCentrality_i^w$, we refer to the definition of prominence by Knoke and Burt (1983). Following this concept, we define actors with a high level of centrality as those among the most visible in the network, directly connected or adjacent to many others. Actors with low degrees occupy peripheral positions and can be viewed as less active in the relational process and the information flows.

$BetweennessCentrality_{t-1}$ incorporates the idea that interactions between non-neighboring actors within a network depend on other actors lying on a path between the two. The latter actors might be highly valuable for the entire network because they might play a controlling or intermediary role. The concept of betweenness centrality captures this idea by measuring the extent to which an actor can be regarded as a gatekeeper or broker in the network. Following Freeman (1977), we can express a standardized betweenness centrality index as

$$BetweennessCentrality_i = \frac{2 * \sum_{j<k} \frac{g_{jk}(a_i)}{g_{jk}}}{(N-1)(N-2)} * 100 \tag{3}$$

With i being distinct from j and k, $g_{jk}(a_i)$ denotes the total number of shortest paths linking actors j and k containing actor i. The probability that two actors, j and k, are linked by a distinct actor i is provided by $g_{jk}(a_i)/g_{jk}$.

We calculate actors' eigenvector centrality scores, $EigenvectorCentrality_{t-1}$, as a third measure of centrality. Eigenvector centrality considers not only the connectivity of a specific actor but also the connectivity of its collaboration partners. Stated differently, an actor's eigenvector centrality can be defined as the sum of connections to other actors, weighted by their centrality scores (Bonacich, 2007, 1987, 1972):

$$EigenvectorCentrality_i = \frac{\sum_{j=1}^{N} c_{i,j} EigenvectorCentrality_j}{\lambda} * 100 \qquad (4)$$

Equation (4) is solved using the eigenvectors and eigenvalues of the adjacency matrix (Bonacich, 1987, 1972). In (4) N refers to the total number of actors. $c_{i,j}$ is a binary indication of whether two actors i and j are connected. λ denotes the largest eigenvalue of the adjacency matrix. Actors with high eigenvector centrality scores are connected to many other actors who are well connected themselves.

We introduce several control variables in our empirical analysis. $LargestComponent_{t-1}$ is a dummy equaling 1 if a firm is a member of the largest component, i.e., the largest connected part of the network, in $t-1$. The underlying assumption for this variable is that knowledge is exchanged within the connected part of the network. Being part of the largest component should then influence the degree to which firms can profit from the ongoing knowledge exchange. Moreover, we account for firm size ($Employees_{t-1}$) by using the log of the average number of employees lagged by one period. We add further dummies indicating whether a company's headquarters is located either in Asia or Oceania ($Asia$) or in Europe ($Europe$).[7] The dummy variable $PharmaFirm$ equals one if a firm is active in the development or manufacturing of pharmaceuticals and its main activities do not fulfill the biotechnology definition of the OECD (2005).

As shown in Table 7, many of our variables that account for the collaboration partners and the network positions of firms are rather highly correlated. The main reasons for the

[7] There are no companies headquartered in Africa or Latin America in our dataset.

considerable correlation are that the variables are related through the underlying research network and that some variables are more specific subsets of others. Therefore, we introduce each of the respective variables separately with the control variables in the regression models. The correlations of the latter with the variables of interest are acceptable.

	Observations	Mean	Std. Dev.	Min	Max
NDA_t	771	0.029	0.214	0	3
$Degree_{t-1}$	325	4.532	7.970	0	73
$Collaborations_{t-1}$	325	461.391	1581.647	0	14636
$IndirectTies_{t-1}$	298	110.926	118.042	1	701
$AcademicPartner_{t-1}$	325	2.963	5.266	0	50
$CollaborationsAcademia_{t-1}$	325	213.966	804.584	0	9118
$IndirectAcademicTies_{t-1}$	298	79.866	80.318	1	440
$BiotechPartner_{t-1}$	325	0.117	0.375	0	3
$CollaborationsBiotech_{t-1}$	325	16.338	65.475	0	516
$IndirectBiotechTies_{t-1}$	298	4.091	6.739	0	45
$DegreeCentrality^{w}_{t-1}$	325	38.321	107.536	0	1033.648
$BetweennessCentrality_{t-1}$	325	0.027	0.126	0	1.319
$EigenvectorCentrality_{t-1}$	325	2.522	4.744	0.000	41.333
$LargestComponent_{t-1}$	325	0.926	0.262	0	1
$Employees_{t-1}$	247	6.902	2.764	1.609	13.007
$Asia$	771	0.233	0.423	0	1
$Europe$	771	0.281	0.450	0	1
$PharmaFirm$	677	0.195	0.396	0	1

Table 2: Descriptive Statistics for the Firm Sample

5.2 Results Concerning Collaboration Partners

In Table 3, we present our estimations including different types of collaboration partners. We begin by analyzing the relation between the firms' total number of different collaboration partners and their innovative performance in model (1). We find a positive but not significant coefficient for $Degree_{t-1}$. The total number of collaborations ($Collaborations_{t-1}$) in our empirical analysis is not significantly related to the firms' number of new drug approvals. The number of indirect ties, $IndirectTies_{t-1}$, is not significantly associated with the innovation measure.

In the subsequent regression models, we distinguish among different partner types. The number of academic partners ($AcademicPartner_{t-1}$) is positively and significantly related to the number of newly approved pharmaceuticals. Collaboration with universities and

public research institutes might be beneficial for pharmaceutical innovation in several ways. Co-publication with these types of partners might help firms to build up absorptive capacity and to incorporate recent scientific advances in their in-house knowledge base. Moreover, academic institutions and particularly university hospitals and pharmacy departments might provide knowledge, medical equipment, and patients needed during the clinical phases of the drug development process. Consequently, a high number of academic partners might improve firms' access to basic and clinical knowledge, which are both crucial in the drug development process.

The reputation of academic institutions might be another reason for collaboration. Co-publications with well-known academic partners might support the drug approval process. We consider this reason for collaboration and concentrate on basic research publications in one of our robustness checks. In this robustness check, the coefficient for $AcademicPartner_{t-1}$ is positive but not significant. Hence, we cannot completely rule out the reputation of academic partners as a reason for collaboration. Because Lim (2004) suggests a strong relation between basic research and pharmaceutical innovation, we conclude that access and the joint generation of new knowledge are the main reasons for collaboration between firms and academic institutions.

In models (5) and (6), our results for the total number of collaborations with academic institutions ($CollaborationsAcademia_{t-1}$) and the number of indirect ties to academic institutions ($IndirectAcademicTies_{t-1}$) indicate no significant association with the number of firms' new drug approvals. With respect to another type of collaboration partners, namely, biotechnology companies ($BiotechPartner_{t-1}$), we do not find a significant relation to the firms' innovative performance. The same result applies to the total number of collaborations with biotechnology companies ($CollaborationsBiotech_{t-1}$).

Firms might substitute collaboration with biotechnology companies with other types of partners, e.g., academic ones. These alternative partners might be more willing to share both knowledge and research results. This argument is supported by the positive and significant relation between the number of indirect linkages to biotechnology companies ($IndirectBiotechTies_{t-1}$) and firms' innovative performance. Although the access to sci-

entific knowledge generated in academic institutions is most valuable for firms' innovative activities, biotechnology companies engage in the commercialization of such knowledge. Firms might choose to collaborate directly with an academic institution and are thus only indirectly linked to the biotechnology companies. Finally, because our co-publication data were obtained through a keyword search of disease names, we might not be able to fully account for publications on research methods and the discovery of new compounds.

Membership in the largest component of the network ($LargestComponent_{t-1}$) is positively and significantly related to the number of new drug approvals. This finding supports the argument that a firm must be linked to the largest connected part of the network to profit from the knowledge flows within it. Firm size ($Employees_{t-1}$) is positively related to the number of new drug approvals, suggesting that predominantly large companies are successful innovators in this area of pharmaceutical research. We find a positive and strongly significant relation between $PharmaFirm$ and the number of new drug approvals. This result suggests that the vast majority of biotechnology companies has not yet managed to become a fully integrated drug producer. Hence, it is the incumbent pharmaceutical firms that introduce new pharmaceuticals to the market.

To examine the robustness of our results, we restrict our sample to articles classified as biotechnology research by the WoS, basic research articles according to the CHI classification of journals (Hamilton, 2003), and articles published in journals included in the WoS prior to 1998. Additionally, we use the average amount of the firms' total assets in $t-1$ as size control. We further control for R&D intensity, firm age, and the number of new drug approvals lagged by one period. These analyses yield similar results compared with the original estimations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: NDA_t									
$Degree_{t-1}$	0.0161								
$Collaborations_{t-1}$		0.0000							
$IndirectTies_{t-1}$			0.0016						
$AcademicPartner_{t-1}$				0.0295**					
$CollaborationsAcademia_{t-1}$					0.0001				
$IndirectAcademicTies_{t-1}$						0.0021			
$BiotechPartner_{t-1}$							0.1346		
$CollaborationsBiotech_{t-1}$								-0.0012	
$IndirectBiotechTies_{t-1}$									0.0339**
$LargestComponent_{t-1}$	13.2886***	13.9286***		13.1865***	14.0257***		14.1090***	12.8762***	
$Employees_{t-1}$	0.5119**	0.5909**	0.5053**	0.4898**	0.5709**	0.5285**	0.6053**	0.6651***	0.4654**
$Asia$	0.0807	0.0397	0.0478	0.0678	0.0450	0.0538	0.0522	-0.0191	0.1224
$Europe$	-0.4512	-0.2442	-0.4720	-0.5304	-0.2534	-0.3964	-0.2118	-0.1021	-0.4754
$PharmaFirm$	3.0418***	3.2190***	2.9673***	2.9677***	3.1840***	3.0212***	3.2555***	3.3380***	2.9270***
$Constant$	-22.4419***	-23.8598***	-9.1834***	-22.1030***	-23.7485***	-9.4131***	-24.2171***	-23.5434***	-8.7658***
N	167	167	153	167	167	153	167	167	153
Log pseudolikelihood	-36.047	-36.556	-36.168	-35.685	-36.398	-36.344	-36.582	-36.486	-35.434

o * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

$Employees_{t-1}$ is included in logarithmic form in the analysis.

Because all firms that have indirect linkages are connected to the largest component, we exclude this control variable in the respective models.

Although 325 firms published in $t-1$, we have employment and firm type information for only 167 of these firms. 153 firms have indirect partners.

Table 3: Collaboration and Innovative Performance

5.3 Results Concerning Network Position

Table 4 presents the results concerning the firms' network positions and their innovative performance. We begin our empirical analysis by employing the weighted degree centrality ($DegreeCentrality^{w}_{t-1}$) as a measure of network position. Our results indicate that the firms' weighted degree centrality is positively but not significantly related to their number of new drug approvals. We use betweenness centrality as a different concept to account for the position of firms in the network of scientific collaboration in pharmaceutical cancer research. The coefficient of $BetweennessCentrality_{t-1}$ is positive but also not significant.

Eigenvector centrality ($EigenvectorCentrality_{t-1}$) as a third centrality concept is positively and significantly related to the number of new drug approvals. This result indicates that firms can only profit from high connectivity if their collaboration partners are also connected to a diverse set of organizations. Academic institutions might particularly be collaboration partners that are highly connected themselves. Nevertheless, the use of eigenvector centrality provides additional insights because it considers the connectivity of the partners and the connectivity of a firm itself. Highly connected organizations might be among the scientifically leading institutions in this field of research. Hence, firms can profit from collaboration with these organizations in several ways. Highly connected collaboration partners might provide access to leading edge scientific knowledge originating in their own organizations and in partnering organizations. Moreover, firms might build up contacts with researchers from highly connected and possibly scientifically leading institutions. These contacts might enable firms to attract well trained R&D personnel for their own R&D laboratories, which might enhance the firms' innovative output in terms of new products.

Our results for the control variables are similar to those presented in Table 3. We obtain qualitatively similar results for all three centrality measures when we restrict our analysis to articles classified as biotechnology research, basic research articles, and articles published in journals included in the WoS prior to 1998. We use the average amount of total assets as an alternative control variable of firm size and conduct robustness checks controlling for R&D intensity, firm age, and the number of drug approvals in $t-1$.

Overall, our results for the relationship between central network positions and firms' innovative performance offer ambiguous evidence. Although we find a positive relation between eigenvector centrality and the number of new drug approvals, our results do not show significant coefficients for degree and betweenness centrality.

	(1)	(2)	(3)
Dependent Variable: NDA_t			
$DegreeCentrality^{w}_{t-1}$	0.0008		
$BetweennessCentrality_{t-1}$		0.6161	
$EigenvectorCentrality_{t-1}$			0.0368**
$LargestComponent_{t-1}$	14.2067***	13.7149***	12.9960***
$Employees_{t-1}$	0.5542**	0.5576**	0.4775**
$Asia$	0.0538	0.0381	0.1128
$Europe$	-0.3493	-0.3480	-0.5907
$PharmaFirm$	3.1463***	3.1388***	2.9593***
$Constant$	-23.7598***	-23.2735***	-21.8028***
N	167	167	167
Log pseudolikelihood	-36.326	-36.286	-35.685

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$
$Employees_{t-1}$ is included in logarithmic form in the analysis.

Table 4: Network Position and Innovative Performance

6 Conclusion

This paper has explored how and why collaboration with different types of partners and the position within a research network can affect firms' innovation performance in product innovations. Our main results can be interpreted conceptually. In the biotechnology and pharmaceutical industry, the network position of a firm in terms of eigenvector centrality and the access to scientific opportunities through collaboration with a diverse set of academic partners is positively related to product innovation. However, we do not find a general positive association between collaboration, particularly with biotechnology companies, and product innovation or between central network positions and product innovation. Therefore, these results require a re-assessment of the role of scientific collaboration and biotechnology companies in the development of the pharmaceutical industry.

Collaboration with academic partners emerges as important. We find evidence that the number of academic collaboration partners is positively related to firms' innovative per-

formance. This results makes sense given that research collaboration with a diverse set of academic partners might provide the necessary knowledge and expertise for the successful development of new drugs (e.g., Lim, 2004; Cockburn and Henderson, 1998). Developing new drugs depends on multiple bodies of knowledge, and collaborations with (multiple) academic partners can provide access to specialized and diverse knowledge. This knowledge might help pharmaceutical firms to exploit scientific and technological opportunities.

However, we do not find a significant relation between the total number of collaborations with academic partners or the number of indirect links to academic institutions and the number of new pharmaceuticals. These results indicate that firms cannot compensate for missing links with academic institutions by intensified collaboration with their existing academic partners and indirect connections.

Furthermore, the total number of collaborators is not significant. Stated differently, firms do not profit from collaborations per se, and being connected to many organizations might not be sufficient to increase firms' innovative performance. Hence, our results suggest that firms must be connected to those partners that provide valuable knowledge corresponding to the firms' own competencies. Except for indirect linkages to biotechnology companies, we do not find a significantly positive association between the number of indirect links and firms' innovative performance. Hence, our results contradict earlier contributions indicating the importance of direct and indirect collaborations for successful innovation (e.g., Ahuja, 2000).

Surprisingly, collaboration with biotechnology firms does not appear to be important to product innovation. In contrast to the many studies that indicate the importance of biotechnology for pharmaceutical innovation (e.g., Rothaermel, 2001a), we do not find a significant association between the number of biotechnology companies that firms collaborate with, the total amount of collaborations with these companies, and the firms' number of new drug approvals. The descriptive statistics reveal that collaboration with biotechnology firms is not frequent in our dataset. The maximum number of biotechnology partners is 3, and the average is 0.117. One explanation for this rather low level of scientific co-publication with biotechnology companies might be that collaborative research

with biotechnology companies is not as important for the development of new drugs as the literature frequently claims. Pharmaceutical firms might prefer other forms of knowledge transfer, such as licensing, to joint research projects with biotechnology companies (cf., Brink et al., 2004). Biotechnology companies might serve primarily as suppliers of research methods and promising compounds for new pharmaceuticals along the industry's knowledge supply chain (Nightingale and Mahdi, 2006). Moreover, our dataset might not capture other parts of biotechnology, such as scientific advances related to research methods and the development of new therapeutic active compounds.

One interesting result is related to the position of firms within the research network. We account for this position through the application of different centrality measures. Our findings reveal that the firms' eigenvector centrality is positively related to their number of newly approved drugs. Weighted degree centrality is not significantly related to the firms' innovative performance. Consequently, these results suggest that firms can only profit from high connectivity if their collaboration partners are also highly connected. The firms' betweenness centrality is not significantly associated with their innovative performance. The latter result indicates that firms cannot profit from a gatekeeper or knowledge broker position within the network. Our results are consistent with previous research suggesting a positive relation between eigenvector centrality and innovative performance (see Powell et al., 1999). However, the empirical evidence contradicts earlier studies indicating a positive relation between degree or betweenness centrality and firms' innovative performance (e.g., Giuliani, 2007; Owen-Smith and Powell, 2004; Tsai, 2001).

Our detailed database of organizations involved in research and in new product development in the field of cancer might explain why several of our results differ from those of previous research. Four key improvements have been made, which might explain to some extent our different results compared with previous literature. First, we examine actual co-publications of scientific articles, rather than collaborative agreements in general. Second, we examine product innovation (FDA approvals) rather than patents. Because the vast majority of therapeutically promising compounds are patented before their therapeutic potential is fully examined, the number of patents might be a misleading indicator of the actual number of new drugs. Third, extensive company level data have been obtained

for those firms active in the therapeutic area. The fourth improvement is that we limit the analysis to cancer to account more specifically for relationships between collaboration and networks with innovative performance in product innovations. Although our data have limitations as well, compared with the proxies generally used, these data provide a more direct indication of the relationships studied both for "innovation" and for "industry".

Our research includes several shortcomings and opportunities for future research. First, a very important question involves the relationship with health care providers, especially hospitals. In our data, we cannot systematically distinguish between universities and university hospitals because we have observed that many individual researchers often use multiple affiliations or different affiliations in different papers. Therefore, for further research, an interesting topic is to separately analyze the role of university hospitals, other university departments and the role of non-academic medical care providers. Second, the number of observations in our study is relatively small, and product innovations in new pharmaceuticals are a rare event. Future research might be able to analyze the relationship between firms' network positions and their innovative performance on a larger scale, perhaps by analyzing multiple therapeutic areas. A higher number of observations could also help to test whether the relationship between firms' network positions and their innovative performance is curvilinear in nature as suggested by several authors (e.g., Gilsing et al., 2008; Rothaermel, 2001b; Deeds and Hill, 1996). Because the number of new drug approvals per firm is rather limited, we cannot test a curvilinear relationship in a meaningful way. Third, our results are restricted to the biotechnology and pharmaceutical industry. Therefore, future research should address the relationship between network position and innovative performance in other industries.

A Appendix

A.1 Medical Indications

Angiogenesis	Liver Cancer
Bladder Cancer	Lung Cancer
Bone Cancer	Lymphoma
Brain Cancer	Melanoma
Breast Cancer	Metastasis
Cervical Cancer	Mouth or Throat Cancer
Chemotherapy Related	Mucositis
Colon Cancer	Multiple Myeloma
Endometrial Cancer	Non Hodgkins Lymphoma
Gastrointestinal Cancer	Ovarian Cancer
Head and Neck Cancer	Pancreatic Cancer
Hematological Cancer	Prostate Cancer
Kaposi Sarcoma	Radiation Related
Kidney Cancer	Soft Tissue Sarcoma
Leukemia	Solid Tumors

Table 5: List of Medical Indications

A.2 Variables and Correlations

Dependent Variable	
NDA_t	Number of new drug approvals in period t
Independent Variables	
$Degree_{t-1}$	Total number of direct linkages, i.e., collaboration partners, in $t-1$
$Collaborations_{t-1}$	Total number of collaborations in $t-1$
$IndirectTies_{t-1}$	Total number of indirect linkages in $t-1$
$AcademicPartner_{t-1}$	Number of collaboration partners from academia in $t-1$
$CollaborationsAcademia_{t-1}$	Number of collaborations with academia in $t-1$
$IndirectAcademicTies_{t-1}$	Number of indirect linkages to academia in $t-1$
$BiotechPartner_{t-1}$	Number of collaboration partners classified as biotechnology companies in $t-1$
$CollaborationsBiotech_{t-1}$	Number of collaborations with biotechnology comapnies in $t-1$
$IndirectBiotechTies_{t-1}$	Number of indirect linkages to biotechnology companies in $t-1$
$DegreeCentrality^{w}_{t-1}$	Weighted degree centrality of a firm in $t-1$
$BetweennessCentrality_{t-1}$	Betweenness centrality of a firm in $t-1$
$EigenvectorCentrality_{t-1}$	Eigenvector centrality of a firm in $t-1$
$LargestComponent_{t-1}$	Dummy for membership in the largest component in $t-1$
$Employees_{t-1}$	Log of the average number of employees in in $t-1$
Asia	Dummy equaling 1 if firm headquarter is in Asia or Oceania
Europe	Dummy equaling 1 if firm headquarter is in Europe
$PharmaFirm$	Dummy equaling 1 if the firm is classified as pharmaceutical company

Table 6: Description of Variables

	(1)	(2)	(3)	(4)	(5)	(6)
(1) $Degree_{t-1}$	1					
(2) $Collaborations_{t-1}$	0.8678***	1				
(3) $IndirectTies_{t-1}$	0.7857***	0.6342***	1			
(4) $AcademicPartner_{t-1}$	0.9196***	0.6892***	0.8016***	1		
(5) $CollaborationsAcademia_{t-1}$	0.8271***	0.7922***	0.6596***	0.8648***	1	
(6) $IndirectAcademicTies_{t-1}$	0.7584***	0.6215***	0.9955***	0.7632***	0.6248***	1
(7) $BiotechPartner_{t-1}$	0.5203***	0.5692***	0.3516***	0.3414***	0.3265***	0.3514***
(8) $CollaborationsBiotech_{t-1}$	0.5895***	0.8052***	0.4131***	0.3317***	0.3887***	0.4245***
(9) $IndirectBiotechTies_{t-1}$	0.6930***	0.5004***	0.8917***	0.7656***	0.6410***	0.8697***
(10) $DegreeCentrality^{\lceil}_{t-1}w$	0.9513***	0.9746***	0.7191***	0.8138***	0.8448***	0.6991***
(11) $BetweennessCentrality_{t-1}$	0.8430***	0.6338***	0.6127***	0.8351***	0.7183***	0.5716***
(12) $EigenvectorCentrality_{t-1}$	0.9451***	0.7962***	0.9116***	0.9320***	0.8322***	0.8898***
(13) $LargestComponent_{t-1}$	0.1475**	0.0823	0.0000	0.1435**	0.0750	0.0000
(14) $Employees_{t-1}$	0.4158***	0.3379***	0.3807***	0.3860***	0.3308***	0.3727***
(15) $Asia$	-0.0866	-0.0951	-0.1028	-0.0532	-0.0857	-0.1230*
(16) $Europe$	0.1081	0.0582	0.0076	0.1417*	0.0928	0.0051
(17) $PharmaFirm$	0.3082***	0.1969***	0.2527***	0.3330***	0.2193***	0.2408***

	(7)	(8)	(9)	(10)	(11)	(12)
(7) $BiotechPartner_{t-1}$	1					
(8) $CollaborationsBiotech_{t-1}$	0.7320***	1				
(9) $IndirectBiotechTies_{t-1}$	0.2301***	0.2381***	1			
(10) $DegreeCentrality^{\lceil}_{t-1}w$	0.5659***	0.7282***	0.5996***	1		
(11) $BetweennessCentrality_{t-1}$	0.3594***	0.3476***	0.6279***	0.7457***	1	
(12) $EigenvectorCentrality_{t-1}$	0.4379***	0.4947***	0.8427***	0.8880***	0.7981***	1
(13) $LargestComponent_{t-1}$	0.0882	0.0706	0.0000	0.0994	0.0601	0.1504**
(14) $Employees_{t-1}$	0.3053***	0.2951***	0.3320***	0.3794***	0.3203***	0.3602***
(15) $Asia$	-0.0680	-0.0810	-0.1397*	-0.0948	-0.0708	-0.1415*
(16) $Europe$	0.0271	0.0003	-0.0084	0.0859	0.1230*	0.0827
(17) $PharmaFirm$	0.1009	0.1189*	0.1880**	0.2445***	0.2858***	0.2745***

	(13)	(14)	(15)	(16)	(17)
(13) $LargestComponent_{t-1}$	1				
(14) $Employees_{t-1}$	0.0365	1			
(15) $Asia$	0.0173	0.2493***	1		
(16) $Europe$	0.0433	-0.0193	-0.3454***	1	
(17) $PharmaFirm$	0.1162*	0.1688**	0.1206**	0.0904*	1

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

$Employees_{t-1}$ enters in logarithmic form into the analysis.

Table 7: Correlations for the Firm Sample

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