GEOGRAPHICAL CLUSTERS, ALLIANCE NETWORK STRUCTURE, AND INNOVATION IN THE US BIOPHARMACEUTICAL INDUSTRY

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Abstract

I examine the effects of firms' cluster membership on their alliance network structure, and how firms' absorptive capacity moderates the relationship between alliance network structure and innovation. Little is known regarding the inter-relationship between cluster membership, network structure and innovation. This study bridges this gap by first establishing the endogenous nature of network structure with respect to cluster membership and then by studying the moderating effect of absorptive capacity for the alliance network structure and innovation relationship.

I contribute to the strategic management literature in several important ways. First, I clarify the implications of cluster membership on network structure by including two competing explanations: complementary and substitution mechanisms. Contrary to the popular belief that cluster membership does not matter, I find that it does matter in the study of the US biopharmaceutical industry. My findings show that firms' location within a cluster area does not

substitute for their strategic choices specifically for their alliance strategies. Second, I theoretically argue and then empirically demonstrate that network structure is an endogenous phenomenon with respect to cluster membership. Third, I demonstrate that when controlled for endogeneity with respect to cluster membership, alliance network structure and innovation relationship is positively moderated by firms' absorptive capacity. In contrast to prior literature, I find that the main effect of firms' structural holes on innovation is not significant when controlled for endogeneity. This finding is important given the mixed findings for structural holes and innovation relationship in previous studies. Finally, to the best of my knowledge, in the strategic management literature this study is the first study to introduce an exponential regression model with Generalized Methods of Moments (GMM) estimation that accounts for both the endogenous nature of independent variables and the count nature of dependent variable.

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DEDICATION

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1.0 INTRODUCTION

1.1 OVERVIEW

A central premise of studies involving geographical clusters is that cluster membership influences firms' strategic choices such as alliance network structure. Particularly, firms located within geographical clusters are purported to have advantages both as an initiator and as a target of alliance activities compared to firms that are located outside geographical clusters due to economic, cultural, and social benefits associated with cluster membership[1] (Saxenian, 1994; Porter, 1998; Bagchi-Sen, 2004; Scott, 2004). Yet approximately 53% of the US firms in the biopharmaceutical industry are headquartered outside a biopharmaceutical cluster and they do not appear to be significantly disadvantaged. On average, out-cluster firms are more productive than in-cluster firms (approximate sales per employee for out-cluster firms is 0.3 MM vs. 0.2 MM). I explore these conflicting conjectures as it relates to the relationship between cluster membership, research and development alliance network structure, the moderating role of absorptive capacity, and innovation.

My reasoning is that strategic choices involving the design of an alliance network structure are not random decisions. Firm attributes affect firms' alliance choices regarding with

[1] Throughout the paper, the terms cluster membership, in-cluster, and location within a cluster are used interchangeably.

whom to form alliance with, leading to an endogenous nature of alliance network structure (Gulati and Gargiulo, 1999). These strategic choices are based on firm specific attributes such as cluster membership because firms' strategic choices are influenced and constrained by their geographic location (Birkinshaw, Braunerhjelm, Holm, and Terjesen, 2006; Scott, 2004; Sorenson and Baum, 2003; Porter, 1998). I study one such strategic choice, alliance network structure because firms' positions in their alliance network structure affect firms' innovation (Owen-Smith and Powell, 2004; Ahuja, 2000; Walker, Kogut and Shan, 1997). Therefore, taking the endogenous nature of alliance network structure with respect to cluster membership into account changes both the theoretical and empirical lens for examining the alliance network structure and innovation relationship.

While both cluster membership defined as geographic location within a cluster area and alliance network structure have significant innovation outcomes (Audretsch & Feldman, 1996; Jaffe & Trajtenberg, 1999; Chacar & Lieberman, 2003; Ahuja, 2000; Owen-Smith and Powell, 2004), studying the influence of cluster membership on alliance network structure and accounting for its endogenous impact on network structure, absorptive capacity, and innovation relationship has important theoretical and empirical consequences. If firms' strategic choices are endogenous with respect to a certain firm attribute such as cluster membership then theoretical models and empirical methods should mirror these influences and constraints. Thus, I propose that firms' alliance network structure is an endogenous phenomenon with respect to firms' cluster membership and the endogenous network structure with respect to cluster membership influences firms' innovation based on firm's absorptive capacity.

I test my theoretical model by using a longitudinal dataset consisting of a sample of US biopharmaceutical firms (SIC 2834) from 1998 to 2004. The results of this study, first, indicate

that contrary to the popular belief that cluster membership does not matter due to advanced communication technologies, I find that it does matter in the context of US biopharmaceutical industry. My findings also show that firms' location within a cluster area does not substitute for their strategic choices specifically for their alliance strategies. Second, my results show that alliance network structure is an endogenous phenomenon with respect to cluster membership. Third, I find that when controlled for endogeneity with respect to cluster membership, alliance network structure and innovation relationship is positively moderated by firms' absorptive capacity. In contrast to prior literature, additional analysis reveals that the main effect of firms' structural holes on innovation is not significant when controlled for endogeneity. This finding is important given the mixed findings for structural holes and innovation relationship in previous studies.

1.2 RESEARCH QUESTIONS

In this dissertation my objective is to address the following research questions.

1) What is the effect of cluster membership on firms' alliance network structure?

    1a) what is the effect of cluster membership on firms' centrality in their alliance networks?

    1b) what is the effect of cluster membership on firms' structural holes?

2) How does firms' absorptive capacity moderate the relationship for endogenous alliance network structure and innovation?

1.3 THEORETICAL PERSPECTIVES AND MOTIVATION

My research is motivated by the following observations from both scholarly research and practice. First, biases arising from endogeneity in business research has been studied from a methodological perspective while ignoring substantive theoretical questions (e.g. Douglas, 2006; Hamilton and Nickerson, 2003; Shaver, 1999). Demonstrating that empirical results may change when endogeneity is addressed by using appropriate econometric techniques is different from developing theoretical arguments that establish endogeneity in a model. That is, theoretical reasons as to why a given strategic choice is endogenous should also be addressed before embarking on using econometric techniques to account for endogeneity in empirical models.

Second, the economic geography literature has two intellectual streams: place and space arguments (Sorenson & Baum, 2003). Place arguments state that the strategic actions of firms are influenced and constrained by the characteristics of their physical location, such as availability of research institutions and scientists (e.g. Furman, 2003). In contrast, space arguments suggest that firms' strategic actions are influenced by availability of knowledge spillovers in a geographical area (e.g. Flyer and Shaver, 2003). Based on place perspective, or as I call it the complementary[2] view, cluster characteristics may augment the alliance network structure of firms by providing access to cluster resources. For example, availability of cluster resources makes a cluster member an attractive alliance partner for out-cluster firms.

Alternately, the geography of space, or as I call it the substitution view, suggests that knowledge spillovers among firms located in a cluster lessen the need to develop an alliance

[2] For clarity, in the literature complementary is also used to denote interaction of two variables. Here, I use the word 'complementary' simply to represent something that completes one thing or to fill out (Webster, Collegiate Dictionary).

network structure. For example, knowledge spillovers in a geographically bounded area motivate innovation by increasing firm's patents (Jaffe, Trajtenberg, & Henderson, 1993; Jaffe & Trajtenberg, 1999). Based on these perspectives, one might argue that cluster membership has a dual effect on firms' alliance network structure. On the one hand, there is a complementary effect that cluster membership promotes and contributes to firms' alliance network structure. On the other hand, there is a substitution effect that cluster membership holds back the development or replaces firms' alliance network structure. Clarifying the complementary versus substitution effect of cluster membership on alliance network structure is important for our understanding of cluster membership benefits (or costs) because the design of alliance network is a strategic choice with innovation consequences.

Third, the alliance literature is based on the assumption that alliance network structure offers information and control benefits (Koka and Prescott, 2002) and that these are exploited by firms (for an exception, see McEvily & Yao, 2005). Further, according to the absorptive capacity literature, firms that have the capabilities to acquire, assimilate, transform, and exploit external information innovate and have competitive advantage (Cohen & Levinthal, 1990; Zahra & George, 2002; Lane, Koka, and Pathak, 2006). Therefore, I suggest that firms' alliance network structure affects innovation contingent upon their absorptive capacity. Put differently, alliance network structure is a necessary but not sufficient condition for firms' innovation.

Finally, geographic clusters and alliance networks have gained a growing importance across industries. A recent survey conducted by Deloitte Research (2005) demonstrated that geographic location of an alliance partner is one of the drivers of alliance formation. This raises a natural question: what factors or firm attributes affect firms' strategic alliance network

structure? Thus, the impact of cluster membership on firms' strategic choices, such as on strategic alliances, should be further explored.

Building on these observations, I advance the theoretical as well as the empirical understanding of the endogenous nature of firms' network structure with respect to their cluster membership and in turn implications for innovation. Simply put, I suggest that cluster membership affects firms' R&D alliance network structure leading to an endogenous alliance network structure with respect to cluster membership. The impact of the endogenous alliance network structure on innovation is contingent on firms' absorptive capacity.

I draw on economic geography and inter-organizational networks literatures. The economic geography literature suggests that cluster membership has significant innovation outcomes (Audretsch & Feldman, 1996; Porter, 1998; Jaffe & Trajtenberg, 1999; Chacar & Lieberman, 2003). Specifically, it argues that cluster membership affects innovation by providing access to resources available in a cluster area or by benefits from knowledge spillovers due to co-location. For the purposes of this study, cluster membership is defined as a geographic location of a biopharmaceutical firm's headquarters (HQ) or R&D-Laboratory in a cluster area. Clusters are geographically enclosed areas that include a group of co-located firms tied together by economic interdependencies as well as complex social interaction due to proximity which also contribute to knowledge sharing (Porter, 1998a; Tallman et al. 2005).

Similar to prior research, I focus on two aspects of alliance network structure: degree centrality and structural holes. Degree centrality indicates how active a firm is in its alliance network structure by examining the number of its alliances. Structural holes (Burt, 1992) represent the lack of connections among a focal firm's partners. A focal firm spans many structural holes if its partners do not have alliances with each other. In order to have a better

understanding of firms' network position in their R&D alliance networks I include firms' entire set of alliances with both in-cluster and out-cluster firms.

1.4 RESEARCH DESIGN

1.4.1 Research Context and Data

In order to test the hypotheses developed in this dissertation I use a panel dataset of 147 US biopharmaceutical firms. My dataset includes information on firms' geographical location, R&D alliance network structure, absorptive capacity, firm size and age, and innovation-patents granted for the period from 1998 to 2004. I collected data from multiple sources. First, using the Mergent Online, Compustat, and Thomson databases I identified public companies that designate their primary business as pharmaceutical preparations (SIC 2834). Second, I relied on Mergent online, Compustat, Edgar database, and company websites in order to gather geographic location data that includes both headquarters and R&D facilities location. Since geographical clusters are identified based on metropolitan statistical areas (MSAs) and MSAs are defined to include counties, I also had to identify counties that firms in my sample are located. County and MSA information were obtained from the US Census bureau. Third, data on R&D alliances were obtained from Recombinant Capital (Recap), a private database that tracks and analyzes alliances including biopharmaceutical firms. Validity of alliance data has also been checked against Thomson Financial Security Data Company's alliance database (SDC).

My study focuses on the biopharmaceutical industry (SIC 2834) because both clustering and alliance networks have been shown to influence firms' innovation in this sector (Arora and

Gambardella, 1990; Audretsch and Feldman, 1996; Powell, et al., 1999; McKelvey et al., 2003; Owen-Smith & Powell, 2004). The complexity of biopharmaceutical products contributes to rising financial costs and an increase in time spent on development. These two factors have led to increased dependency on R&D alliances. The number of alliances, particularly R&D alliances, has grown tremendously over the last five years in the biopharmaceutical sector. According to the Deloitte Research on alliance formation the total value of new alliances including only pharmaceutical and biotech companies has grown from $6 billion in 1999 to $11 billion in 2004. In addition, this sector is among the fastest growing industries in the US, the inflation adjusted biopharmaceutical industry output is expected to increase from $69.2 billion in 2004 to $128.3 billion in 2014 (Milken Institute Fact Sheet, 2004).

1.4.2 Econometric Analysis

I tested my hypotheses by using multiple econometric techniques. My analysis includes two stages. In the first stage, I test the theoretical relationship between cluster membership, centrality and structural holes variables (Hypotheses 1 and 2) by a random effects negative binomial model. I test hypothesis 2 (cluster membership-structural holes relationship) by using random effects generalized least squares (GLS) regression.

In the second stage, to test the moderating effect of absorptive capacity for the centrality-innovation and structural holes innovation hypotheses (hypotheses 3 and 4) I employ an exponential instrumental variable regression due to the endogenous nature of my independent variables. Particularly, I use a fixed effects model with General Method of Moments (GMM) estimation. I use the fixed effects model in an exponential form because my dependent variable (patent) is a count variable (Cincera, 1997).

1.4.3 Results

The findings of this study show support for the overall research model. In hypotheses 1a-b, I propose competing predictions for the effect of firms' in-cluster location on their central position in their alliance network structure. The results of analysis support hypothesis 1a that firms' in-cluster location when measured by HQ location is positively associated with being more central in their R&D alliance network structure compared to firms located elsewhere. That is, in-cluster location complements firms' central position in their alliance networks structure. Similar to hypothesis 1, hypotheses 2a-b also proposed competing explanations for the in-cluster location and structural holes relationship. The results support hypothesis 2a, that in-cluster firms span more structural holes in their R&D alliance networks than firms located elsewhere. Similar to hypothesis 1a, in-cluster location complements firms' structural holes in their alliance network structures. The significant findings for Hypothesis 2 (cluster membership and structural holes relationship) indicate that having a headquarters (or at least one R&D-Lab) within a cluster leads to higher structural holes compared to firms that do not have headquarters (or at least one R&D-Lab) within cluster. Similar to arguments in hypothesis 1, in-cluster firms have structural holes advantage, which brings in information diversity.

The second stage of the analysis includes results of hypotheses 3 and 4. In hypothesis 3, I predict that firms' absorptive capacity positively moderates the centrality and innovation relationship. Coefficient of the interaction variable (0.001), centrality X absorptive capacity provides support for hypothesis 3, that the interaction between firms' absorptive capacity and centrality is positive and significant. This indicates that based on firms' absorptive capacity central firms innovate more than other firms when endogeneity of centrality is controlled with HQ location. In support of hypothesis 4, which predicts that firms' absorptive capacity

positively moderates the relationship between firms' structural holes and innovation, the results of fixed effects model with GMM estimation indicate a significant relationship. Thus, hypothesis 4 is supported when I account for endogeneity by HQ location variable.

1.5 CONTRIBUTION

According to the inter-organizational networks literature, several aspects of alliance network structure such as centrality and structural holes influence firm innovation. For the centrality and innovation relationship prior research has shown both a direct relationship and a contingent relationship based on cluster membership. Ahuja (2000) and Walker, Kogut, and Shan (1997) found that there is a direct positive relationship between centrality and the innovation output due to high level of information sharing and complimentary skills among partners. Based on the contingency perspective, Owen-Smith & Powell, 2004 found that centrality in a geographically bounded network has no effect while centrality in a dispersed network has positive effect on innovation.

As for the effect of structural holes on innovation, the outcome of research has been mixed. On the one hand, a negative relationship has been presented because structural holes inhibit development of trust among partners leading to moral hazard problems. This hinders knowledge sharing among partners, affecting innovation negatively (Ahuja, 2000). On the other hand, a positive relationship between structural holes and innovation has been presented by Hargadon and Sutton (1997). Their study showed that firms exploit their positions as a spanner of structural holes in order to innovate.

My conception of the relationship between cluster membership, inter-organizational alliance networks and innovation differs in several ways from prior research. First, in contrast to previous studies (Shan, Walker, & Kogut, 1994; Ahuja, 2000; Owen-Smith & Powell, 2004; Bell, 2005) by identifying cluster membership as an antecedent to firms' alliance network structure, my framework explicitly incorporates alliance network structure as an endogenous phenomenon. Both theoretical and empirical model specifications have limited prior studies' ability to account for the endogenous nature of alliance network structure in an inclusive model that also incorporates innovation implications. This follows the approach in the strategy literature where a performance variable is regressed on a strategic choice variable. However, this empirical approach does not account for endogenous nature of strategic choice and the estimated coefficients may not reveal valid relationship between independent and dependent variables (Shaver, 1998). Similarly, previous research on clusters includes the resources and resource mix associated with clusters but do not focus on how firms' location within clusters affects their alliance networks thereby firms' innovation (Porter, 1998; Porter, 2003; Saxenian, 1994). By incorporating an inclusive theoretical and an empirical model that examines cluster membership, alliance network structure, and innovation, I provide new insights for understanding the theoretical arguments as well as empirical reasons behind the endogenous nature of alliance network structure with respect to firm attribute.

Second, my approach is not limited to one geographic location or a cluster. I include the top 12 cluster areas identified as biopharmaceutical clusters in the US. Including, the top 12 clusters allows for regional diversity which may affect firms' network structure. By regional diversity I mean variation in resources associated with clusters. These include resources associated with both place (such as existence of other firms, research institutions) and space (such as knowledge

spillovers). Third, in contrast to prior studies in which only alliances among firms in the same industry are taken into consideration (Ahuja, 2000) I take the complete alliance network structure of biopharmaceutical firms. Put differently, my alliance network is not limited to a single industry network but rather it includes the entire set of alliances a biopharmaceutical firm has established. These may include, but are not limited to, alliances among firms in the same industry. This approach provides a better understanding of a firm's position in the entire alliance network structure. That is, my alliance network includes not only the direct ties but also the indirect ties a firm has in its entire network. This is important because both direct and indirect network ties act as conduits of information among network actors (Owen-Smith and Powell, 2004).

2.0 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 BACKGROUND

My framework has two main arguments. First, I argue that cluster membership defined as firms' geographic location within a cluster area affect alliance network structure by means of two mechanisms: a complementary mechanism and a substitution mechanism. As shown in the cluster membership- innovation relationship in Figure 1, I theoretically establish the endogenous nature of alliance network structure with respect to firms' cluster membership. Second, given the endogenous nature of alliance network structure with respect to firm's cluster membership I examine the implications of alliance network structure for innovation contingent on firms' absorptive capacity. Following prior literature I suggest a contingent view on alliance network structure and innovation relationship. Similar to Tsai (2001) I suggest absorptive capacity moderates the effect of alliance network structure on firms' innovation because if firms have not developed the capabilities for acquisition, assimilation, transformation, and commercialization of new information they are unlikely to translate alliance network structure benefits into innovation.

Cluster membership defined as the geographic location of firms' within a cluster area is important, because the geographical location of firms affects their strategic choices. In particular, proximity of firms to key customers, suppliers and other research institutions provide strategic benefits (Birkinshaw et. al., 2006). Extending the social network theory to inter-

organizational network framework one may argue that the proximity of top executives to key customers or suppliers may promote strong interpersonal relationships which in turn influence firms' performance (Granovetter, 1973). Although scholars from economic geography and inter-organizational network literature have long studied the relationship between cluster membership and innovation, as well as alliance network structure and innovation respectively, most research in this tradition has largely focused on cluster membership or alliance network structure as independent predictors of innovation. The economic geography literature suggests that cluster membership is a predictor of innovation in two ways. First, firms located in clusters that provide complementary inputs realize greater innovative productivity (Feldman, 2000). Second, innovation as measured in R&D expenditures, number of R&D-Laboratories in a cluster, or number of R&D employees is an outcome of knowledge spillovers in a cluster area (Feldman, 1994, 2002; Aharonson, Baum, and Feldman, 2004). However, the economic geography literature does not focus on how the endogenous alliance network structure with respect to firm attributes affects firms' innovation.

Noting alliance network structure and innovation relationship as demonstrated in Figure 1, the inter-organizational networks literature presents alliance network structure as a predictor of innovation (Shan, Walker, and Kogut, 1994; Owen-Smith and Powell, 2004). This research has focused on using a network approach in explaining innovation generation (Ahuja, 2000). Nevertheless, it does not examine the endogenous nature of alliance network structure with respect to firm attributes, particularly cluster membership. This conceptionalization of the role of cluster membership or alliance network structure on innovation raises two issues.

First, the literature on how cluster membership is linked to innovation has provided competing explanations. One view suggests that in-cluster firms innovate because they have

access to tangible cluster resources such as labor pool, and financial resources (Saxenian, 1994). This suggests that cluster resources augments firms' strategic choices such as inter-firm alliances and thus in-cluster firms are more innovative. I call this view the complementary view. An alternate view suggests that in-cluster firms are more innovative because there are free knowledge spillovers and firms take advantage of spillovers (Jaffe, 1989; Feldman, 1994b). These spillovers are substitutes for firms' strategic choices such as alliance formation that might lead to innovation. I call this view the substitution view.

Second, both the theoretical and empirical study of alliance network structure and innovation relationship is based on the assumption that alliance network structure as a strategic choice is not constrained by firm attributes. Yet, strategic choices are constrained as they are based on firm attributes and external conditions (Shaver, 1998). Thus, the empirical implication of alliance network structure on innovation changes, once the endogenous nature of network structure with respect to firm attributes is accounted for both theoretically and empirically. This may result in a change in the size and direction of coefficients in an empirical model that includes innovation as a dependent variable.

The issues raised above have several important implications for my framework linking cluster membership, alliance network structure, and innovation. First, my theoretical arguments include alternate explanations regarding the impact of cluster membership on alliance network structure. Second, I establish endogenous nature of alliance networks structure with respect to firm attribute of cluster membership by recognizing the impact of cluster membership on alliance network structure. Finally, I posit that firms must have developed necessary capabilities in place in order to exploit benefits brought in by their positions in alliance network structure.

Differently put, firms' absorptive capacity moderates the relationship between endogenous alliance network structure with respect to cluster membership and innovation.

Based on prior literature I identify two aspects of network structure that are explained by complementary and substitution mechanisms in connection with cluster membership. (1) Centrality: The numbers of alliances firms have in their alliance networks, and (2) structural holes: the lack of connections between focal firm's partners. Degree centrality is relevant for the context of this study because it provides information volume benefits for innovation. Structural holes provide information diversity benefits, which are also associated with firm innovation in the literature (Hargadon and Sutton, 1997; Ahuja, 2000). Simply put, I argue that cluster membership affects the centrality of firms and structural holes they span in their alliance network structure by means of two alternate mechanisms: a complementary mechanism and a substitution mechanism. Alliance network structure, in turn, influences innovation performance contingent on firms' absorptive capacity. A summary of hypothesized relationships in the study is provided in Table 1.

2.2 THEORY AND HYPOTHESES DEVELOPMENT

2.2.1 Cluster Membership and Alliance Network Structure

2.2.1.1 Cluster membership and centrality

Firms are more central in their alliance networks when they are involved in a large number of alliances with other organizations (Wasserman and Faust, 1994). There are two main theoretical perspectives that provide alternative explanations for the relationship between cluster

membership and centrality: complementary view and substitution view. Based on the complementary view, firms located within a cluster area become more central in their alliance networks while substitution view suggests that in-cluster firms have less of a need to be central in their alliance networks.

According to the complementary view, a firm's in-cluster location affects its number of alliances thereby its centrality by means of three mechanisms: (1) in-cluster firms form alliances with other in-cluster organizations due to reduced transaction and communication costs associated with proximate alliance partners (transaction costs); (2) in-cluster firms serve as attractive alliance partners for out-cluster firms who need access to cluster resources (resource complementarities); and (3) the social networks within a cluster reduce the moral hazard problem associated with alliance partners (embeddedness).

Firms enter into agreements in which the transaction costs are at a minimum (Williamson, 1975). Physical proximity facilitates inter-firm cooperation (Dyer, 1996; Enright, 1995). Naturally, for in-cluster firms it is less costly to form alliances with other in-cluster organizations because of the absence of long distance search, monitoring and formal communication costs. Moreover, firms utilize their local advantages in a manner to maximize the performance benefits. Saxenian (1994) states that Hewlett Packard and other physically proximate firms have improved performance by setting up alliances with other firms in the Silicon Valley technology cluster. McKelvey et al. (2003) found that firms are more likely to collaborate with co-located organizations than with international ones in the Swedish biopharmaceutical sector when they are involved in research and development. Anecdotal evidence also suggests that geographical proximity is important in alliance relationships. For example, an executive from a medical device manufacturing company states that "*it is a lot*

easier to drive across town and visit a supplier than it is to pick up the phone and try to talk through some complicated issue" (WSJ, October 26, 2006).

In-cluster firms have more alliances than out-cluster firms because in-cluster firms are attractive alliance partners for out-cluster firms. First, in-cluster firms have access to cluster resources. For example, factor endowments such as production inputs are localized (Feldman, 2000). Second, clusters provide various opportunities for collaboration among universities, research-intensive biotechnology firms and large pharmaceutical corporations located within a cluster. Indeed, Arora and Gambardella (1990) state that there are systematic linkages among universities, biotechnology firms, and large pharmaceutical corporations. Kogut et al (1994) suggest that firms within a region share both tradable and un-tradable resources such as knowledge. This provides the motive for out- cluster firms to enter into alliances with in-cluster firms in order to benefit from these un-tradable resources within clusters. Aharonson et al. (2004) provides evidence that R&D alliances are a complement to in-cluster location. Bagchi-Sen (2004) shows that in-cluster firms also initiate alliances with out-cluster firms[3]. Third, knowledge transfer among in-cluster firms happen in the form of component knowledge transfer (Tallman et. al., 2004). Firms might enter into alliances with other in-cluster firm in order to benefit from others' component knowledge. Component knowledge in the biopharmaceutical industry might include knowledge of drug manufacturing, clinical trials, and new medications for certain diseases. For example, a pharmaceutical company located in a cluster might form an alliance with a small biotech company in order to market and sell a new preparation by the biotech company.

[3] In-cluster firms might enter into alliances from two directions: as initiator of alliance activity and as a target of alliance activity.

Clusters provide the necessary condition for the development of social networks among employees of firms located in one location. For example, employees working in the cluster areas often socialize in the same clubs, their children attend the same schools, and they attend the same local events. Employees' social networks in a cluster also affect in-cluster firms forming alliances with other firms in the same cluster. Firms entering into alliances face moral hazard problems due to uncertainty and the likely costs of opportunistic behavior by partners (Das and Teng, 1998). Social networks help in becoming aware of such moral hazard problems associated with partners (Gulati, 1999). This enables firms to establish alliances with organizations they already know from employees' social networks. Similarly, Inkpen and Tsang (2005) argue that social ties among employees in an industrial district serve as a foundation for formal connections among firms in these areas. Giuliani (2005) argues that business interactions which include any business related interactions (e.g. participating in fairs, vertical, horizontal trade of goods, etc.) among in-cluster firms and knowledge flows among these firms are not highly co-occurring phenomena. In other words, social interaction among individuals within a cluster area does not substitute for formal alliances. Therefore, firms' in-cluster location affects the number of alliances they form leading to more central positions in their alliance network.

In contrast, according to the substitution perspective one might expect that in-cluster location and having access to resources in a cluster are substitutes for entering into alliances. This reasoning paves the way for the spillover mechanism in explaining the relationship between in-cluster location and firm centrality. Spillover arguments suggest that firms benefit from one another due to their proximity because resources such as knowledge spillover to other parties and there are geographic boundaries to spillovers (Jaffe, 1989; Jaffe et al. 1993; Krugman, 1991; Audretsch and Feldman, 1996; Jaffe & Trajtenberg, 1999). Firms located within a

geographically close group of firms, institutions, suppliers, and service providers have different benefits than firms located elsewhere. For example, clusters tend to have social networks due to both intentional and unintentional frequent interaction among employees working for different in-cluster firms.

Information flows from its source through social networks in a cluster and therefore spillovers are localized. This enables in-cluster firms to benefit from spillover effects. Thus, if there are spillovers then firms might not form inter-firm alliances because the need to form alliances is already satisfied by the spillover effects. This leads to in-cluster firms forming fewer alliances thereby being less central in their alliance networks. Owen-Smith and Powell (2004) show that membership in a cluster provides access to information and other resources through informal channels in the region. This suggests that in-cluster firms need not form alliances with other in-cluster firms because centrality in their local network will not bring any unique benefits to in-cluster firms. In summary, spillover effects and social networks in a cluster substitute for formal alliances.

The contradictory effects of complementary and substitution mechanisms thus prompt two competing predictions with respect to the relationship between cluster membership and centrality. From the complementary view, cluster membership promotes or adds to the alliance network structure and hence, increases firms' centrality. Conversely, cluster membership substitutes for the alliance network structure leading to less centrality in the alliance network structure.

Hypothesis 1a: *In-cluster firms are* ***more central*** *in their alliance network than firms located elsewhere.*

***Hypothesis 1b**: In-cluster firms are **less central** in their alliance network than firms located elsewhere.*

2.2.1.2 Cluster membership and structural holes

Firms span structural holes in their networks when they connect firms that are not otherwise connected to each other. The concept of structural holes is important because it illustrates that firms that have many alliances actually have access to diverse information if their alliance partners are not connected to each other (Burt, 1992; Koka and Prescott, 2002). Consider a pharmaceutical company having alliances with two biotech companies which do not have an alliance with each other. The pharmaceutical company may benefit by controlling information coming from both biotech companies. In other words, the pharmaceutical company spans a structural hole between these two biotech firms. Then, it is more likely that the pharmaceutical firm is aware of biopharmaceutical research conducted in two biotech companies. In case of a novel research at the biotech company, the pharmaceutical company might be the one that benefits by forming a new alliance with the biotech firm, which might lead to development and marketing of a new pharmaceutical product. However, if two biotech companies have an alliance with each other then it is also likely that they might share the novel research and proceed with a new drug development without the pharmaceutical company. This means that the pharmaceutical company loses control over novel research (or is constrained) in its network because its alliance partners are also connected to each other.

Similar to the cluster membership and centrality arguments, I use the complementary and substitution perspectives as underlying rationales for explaining cluster membership and structural holes relationship. The reasoning is straight forward: Based on the complementary

view firms located within cluster areas span more structural holes, while according to substitution perspective in-cluster firms span less structural holes in their alliance networks.

According to the complementary view I argue that brokerage or *tertius gaudens* and information exchange due to cultural differences are two main mechanisms that explain the hypothesized relationship. The idea of *tertius gaudens* or that "it is the third who benefits" is based on benefiting from a conflict between two parties (Simmel, 1950; Burt, 1992). Based on the brokerage mechanism one argues that in-cluster firms act as a broker between two out-cluster firms who enter into an alliance with the same in-cluster firm (Burt, 1992). As I discussed earlier, the need to access cluster resources motivates out-cluster firms in establishing partnerships with in-cluster firms due to scientific, technical, and engineering knowledge that clusters provide (Tallman et al. 2004). Then, it is more likely that the same in-cluster firm establishes alliances with more out-cluster firms. This implies that in-cluster firms may span more structural holes due to their location than out-cluster firms. Put differently, in cluster firms act as brokers between two out-cluster firms thereby acquiring information benefits that come with brokerage. Similarly, based on *tertius gaudens* arguments an in-cluster firm might also gain by acting as a *tertius* (Simmel, 1950). For example, an in-cluster firm might be the licensor (or seller) of a novel pharmaceutical product to out-cluster firms.

Information exchange is another mechanism that explains structural holes and innovation relationship. Cultural differences across regions promote information exchange among firms. For example, Saxenian (1994) states that clusters have their own cultures. Inkpen and Tsang (2005) further elaborate that cultural differences among partners motivate information exchange. Similarly, cluster specific knowledge includes component knowledge that is related to parts rather than the whole and it is available to all cluster members (Tallman et al. 2004). Based on

the complementary mechanism, this also motivates out-cluster firms to form alliances with in-cluster firms. Thus, derived from the above evidence, I posit that in-cluster firms span more structural holes because they provide access to cluster resources as brokers of alliance relationship, they act as a tertius among out-cluster firms, and exchange cluster specific information with out-of-cluster firms .

According to the alternate substitution view, however, firms' in-cluster location might affect the degree of connectivity of in-cluster firms' alliance partners. The network closure rationale by Coleman (1988), serves as my underlying mechanism in the following hypothesized relationship. Since social ties among in-cluster firms facilitate alliance formation with one another, then it is more likely that in-cluster firms' partners located within the same cluster have alliances with each other as well. Similarly, individuals working in close proximity develop a shared identity and become closer. The social interaction among employees motivates alliance formation among their employers. This means that in-cluster firms' networks are more constrained, in other words, in-cluster firms have fewer structural holes in their ego networks. Gulati (1998) states that many alliance opportunities are presented to firms through their existing partners. Therefore, if a firm has in-cluster partners it is more likely that this firm enters into alliances with other in-cluster firms more frequently due to reduced transaction and communication costs associated with proximity. The same logic applies to alliances between in-cluster firms' partners as well. According to the above view, interconnectivity among focal firms' alliance partners might lead to a cohesive network (Coleman, 1988) that lacks structural holes. This implies that an in-cluster firm's alliance partners that are located in the same cluster are more likely to establish alliances with each other because of proximity. Thus, an in-cluster firm is more constrained in its alliance network because its alliance partners are connected to one

another. Put differently, according to the substitution and thereby network closure reasoning the part of a firm's network structure with other in-cluster firms will be more constrained compared to an out-cluster firm's overall network.

Based on the competing arguments stated above I suggest following hypotheses for the relationship between cluster membership and structural holes.

***Hypothesis 2a**: In-cluster firms span **more structural holes** in their alliance network than firms located elsewhere.*

***Hypothesis 2b**: In-cluster firms span **fewer structural holes** in their alliance networks than firms located elsewhere.*

2.2.2 The endogenous alliance network structure with respect to cluster membership and innovation relationship: Absorptive capacity as a moderator

So far, I have argued that firms' alliance network structure is endogenous with respect to cluster membership. The endogeneity of alliance network structure is developed by means of two mechanisms. First, according to complementary mechanism, cluster membership augments firms' alliance network structure by providing necessary conditions such as reduced transaction costs associated with forming alliances. Second, according to substitution mechanism, cluster membership replaces or holds back firms' alliance network structure by providing access to free knowledge spillovers within geographical clusters.

Thus, having theoretically established the endogenous nature of two network structure attributes- centrality and structural holes, in this part I develop theoretical arguments for the network structure and innovation relationship given the endogenous nature of network structure with respect to cluster membership. This is important because prior work has established the

relationship between alliance network structure and innovation based on the strict exogeneity of alliance network structure. However, the relationship between network structure and innovation can be subject to various firm specific factors such as cluster membership (i.e. geographic location within a cluster). Therefore, in building the theoretical relationship for alliance network structure and innovation I also include the influence of cluster membership.

Research examining the effects of network structure on innovation has supported a contingency view without considering the endogenous nature of network structure in theoretical and empirical models. For instance, Owen-Smith and Powell (2004) argued and found that centrality in a geographically bounded network has no effect on innovation while centrality in a geographically dispersed network has a positive effect on innovation. In other studies in which the geographic boundary of the network has not been contemplated as a contingency, the relationship between firms' centrality and innovation has been positive (Ahuja, 2000; Shan et al. 1994). For example, Ahuja (2000) found that centrality, defined as a number of direct ties a firm has, positively affects innovation in global chemical companies. Similarly, Shan et al (1994) found that the number of alliances of biotechnology start-ups positively influences their innovation.

The link between structural holes and innovation has also been studied as a contingency or a direct relationship. From the contingency view, McEvily and Yao (2004) found that firms' structural holes positively moderate the relationship between absorptive capacity and innovation. Studying the effect of structural holes and innovation relationship without contingency factors, Ahuja (2000) found that increasing structural holes has a negative effect on firms' innovation in the international chemicals industry. Nonetheless, prior work has assumed that firms have the

capabilities necessary to exploit volume of information accessed due to centrality or diversity of information accessed due to spanning structural holes.

In addition to the above contingency view in the literature, I suggest that firms' absorptive capacity is another contingency factor that influences the relationship among centrality, structural holes and innovation. While firms' centrality and structural holes influenced by firms cluster membership provide access to information volume and diverse information respectively, absorptive capacity determines how efficient and effective this information will be utilized towards innovation. Recent research suggests that firms innovate to the extent that they have absorptive capacity (Cohen & Levinthal, 1990).

Absorptive capacity is the ability to acquire, assimilate, transform, and exploit external information for firm advantage (Lane, Koka, and Pathak, 2006; Zahra & George, 2002; Cohen & Levinthal, 1990). Firms may have access to large amounts of diverse information due to their centrality and structural holes they span in their network structure, which is influenced by their cluster membership. However, their innovation will not be positively affected unless they exploit this information. I suggest that the effect of firms' centrality and structural holes influenced by cluster membership on their innovation depends upon their absorptive capacity. Thus, centrality and structural holes might be necessary but not sufficient conditions for innovation given the effect of cluster membership on firms' centrality and structural holes.

2.2.2.1 Centrality and absorptive capacity

I draw on the social capital argument to explain the relationship between firms' centrality and innovation. I build on the arguments that alliance network structure provides information resources that are defined as social capital (Bourdieu and Wacquant, 1992). Performance implication of social capital has been previously explored in the literature. For example, Koka

and Prescott (2002) theoretically argued and empirically demonstrated that information resources firms acquire due to their alliances are social capital and this is contingently related to firm performance in the steel industry. Therefore, I suggest that central firms have more social capital in terms of information volume. Yet, social capital by itself does not suffice to explain centrality and innovation relationship in a comprehensive way. Thus, I complement this view with a contingency argument by looking at the moderating effect of absorptive capacity for the relationship between centrality and innovation, given the endogenous nature of firms' centrality.

Based on this reasoning I suggest that although firms' centrality in their alliances provides information volume the use of this information is likely to be contingent on firms' absorptive capacity. That is, firms that have the ability to acquire, assimilate, transform and commercialize information are likely to have greater innovation benefits from their central position in their alliance networks. The process through which absorptive capacity is developed provides support for this line of reasoning. For example, centrality provides access to and in turn acquisition of information but this does not necessarily mean that information will be productive in terms of innovation. Firms need to have capabilities to comprehend, interpret (Lane & Lubatkin, 1998); to internalize and convert information into usable form (Kim, 1998) and finally to commercialize it (Cohen & Levinthal, 1990). In other words, if firms have access to information but do not have the sufficient level of capabilities to convert this information into a usable form then it is likely that they will not receive positive benefits. Tsai's (2001) study supports this reasoning; he found that the interaction between centrality and absorptive capacity has a positive significant effect on firms' innovation in the context of intra-firm networks. Extending his arguments to alliance networks I suggest that absorptive capacity will positively

influence the relationship between firms' centrality in their alliance networks and their innovation.

Hypothesis 3: *Given the endogeneity of firms' centrality in their alliance network structure with respect to their cluster membership, firms' absorptive capacity positively moderates the relationship between firms' centrality in their alliance networks and innovation.*

2.2.2.2 Structural holes and absorptive capacity

Firms span structural holes when their partners are not connected to each other (Burt, 1992). From a structural holes perspective, firms have access to diverse information when they span structural holes in their network. As stated previously, prior literature suggests two competing views for the relationship between structural holes and innovation (Ahuja, 2000) without considering the endogenous nature of structural holes. According to resource sharing view, disconnections among firms' alliance network hinders information sharing and therefore, structural holes are negatively related to innovation. According to information diversity view, however, if firms' network includes too many disconnections then firms have access to diverse information which increases firm innovation. Reconciling these two competing views, I suggest a contingency argument to include firm's absorptive capacity as a moderator for the relationship between structural holes and innovation based on two mechanisms.

First, according to structural holes argument, disconnections in firms' alliance networks provide diverse information (Burt, 1992; Koka and Prescott, 2002). However, efficient and effective use of this diverse information depends on the level of absorptive capacity a firm has. Although Ahuja (2000) found that the number of structural holes spanned by a firm is negatively related with its innovation in international chemicals industry, I suggest a positive moderating effect of absorptive capacity in the structural holes and innovation relationship. Even if the

range of diverse information is large due to the presence of structural holes in their alliance network, firms are more likely to build on their existing capabilities because absorptive capacity is path dependent (Zahra & George, 2002). Put differently, subsequent information acquisition depends on prior information acquired. This suggests that it is more likely that firms build on similar information rather than diverse information.

Second, drawing from the bounded rationality reasoning (Simon, 1997), similar to individuals, firms do not have infinite capabilities to acquire, assimilate and exploit information. Due to both financial and physical limitations firms can only pursue certain line of research (Ahuja, 2000). This is apparent in the biopharmaceutical sector where many small biotech companies work on only one therapeutic area. Drug development is a long process and usually it takes on average 15 years to develop and market a final drug. Naturally, firms are more likely to build on their existing research rather than starting over with a diverse information base. Therefore, even if firms have access to diverse information due to structural holes in their network, they are more likely to build on their existing information base. Similarly, McEvily and Yao (2005) suggest that even if firms have diverse information, they are only able to make connections with their existing information base due to their absorptive capacity. Therefore, based on structural holes and bounded rationality reasoning I suggest that firms' absorptive capacity positively affects the relationship between structural holes firms span and their innovation given the endogenous nature of structural holes.

Hypothesis 4: *Given the endogeneity of firms' structural holes in their alliance network structure with respect to their cluster membership, firms' absorptive capacity positively moderates the relationship between firms' structural holes in their alliance networks and innovation.*

3.0 METHODS

3.1 RESEARCH CONTEXT AND DATA COLLECTION

The context for this research is the US biopharmaceutical sector. Both clustering and alliance networks have been shown to influence firms' innovation in this sector (Arora and Gambardella, 1990; Audretsch and Feldman, 1996; Powell, et al., 1999; McKelvey et al., 2003; Owen-Smith & Powell, 2004). The complexity of biopharmaceutical products contributes to rising financial costs and an increase in time spent on development[4]. These two factors have led to increased dependency on R&D alliances. The number of alliances, particularly R&D alliances, has grown tremendously over the last five years in the biopharmaceutical sector. According to the Deloitte Research on alliance formation the total value of new alliances including only pharmaceutical and biotech companies has grown from $6 billion in 1999 to $11 billion in 2004. In addition, this sector is among the fastest growing industries in the US, the inflation adjusted biopharmaceutical industry output is expected to increase from $69.2 billion in 2004 to $128.3 billion in 2014 (Milken Institute Fact Sheet, 2004). As people age and economies grow, consumers will demand more and better medical care. These developments increase the

[4] For example, the development cost for a new drug is over $800 million, and it takes on average 15 years to develop a drug.

importance of biopharmaceutical sector in the future. Therefore, understanding this sector is indispensable for scientific research.

Data used to test the hypotheses in this study were obtained from several sources. First, using the Mergent Online, Compustat, and Thomson databases I identified 215 public companies that designate their primary business as pharmaceutical preparations (SIC 2834). However, due to missing data on several variables for multiple years I lose 68 firms. My final sample consisted of 147 biopharmaceutical firms from 1998 to 2004. In summary, I have 847 observations for 147 firms in my final longitudinal dataset.

Second, I relied on Mergent online, Compustat, Edgar database, and company websites in order to gather geographic location data that includes both headquarters and R&D facilities location. In order to identify firms' geographic location I obtained company addresses from Mergent online. Since clusters are identified based on metropolitan statistical areas (MSAs) and MSAs are defined to include counties, I also had to identify counties that firms in my sample are located. County and MSA information were obtained from the US Census bureau. Financial information including, assets, sales, R&D expenditures, and number of employees data were also obtained from the same sources and supplemented from Worldscope.

Third, data on R&D alliances were obtained from Recombinant Capital (Recap), a private database that tracks and analyzes alliances including biopharmaceutical firms. The Recap database has been extensively used in prior studies (Lane & Lubatkin, 1998; McEvily & Yao, 2005). Validity of alliance data has also been checked against Thomson Financial Security Data Company's alliance database (SDC). The Recap database has the most comprehensive alliance data as it includes all the alliances of biopharmaceutical firms with other firms as well as other organizations such as government institutions, and universities. In this study, I focus on R&D

alliances which include all research and development activities pertaining to discovery and development of a pharmaceutical end product. I collected cumulative alliance data for the period between 1995 and 2004. Given the judgment in my cutoff point (1995) in the data collection, left censoring might be an issue. However, this may not affect the validity of results of this study for several reasons.

First, the biopharmaceutical industry is relatively new industry when excluding the big pharmaceutical firms. For example, the average age of companies in my sample is nineteen years. Second, the alliance activity in this sector picked up in 1990s. The number of new alliances formed increased from 341 in 1990 to more than 2,000 new alliances in 2000 (Recap Inc). Third, I restricted the analysis for the period between 1998 and 2004; this confirms that alliances formed between 1995 and 1997 were completely represented in the cumulative alliance network of 1998. Finally, my alliance database includes 5,367 alliances (including 3,086 organizations) since 1995. Since I focus only on R&D alliance my dataset represents 40% of the entire alliance data Recap Inc has in the biopharmaceutical sector since 1973. Thus, I believe that that my alliance dataset is representative of alliance activity in the biopharmaceutical sector and left censoring of data is not an issue in my analysis.

Finally, I gathered patent data to measure innovation from the US Patents- Granted Collection on Delphion. Delphion's database includes information on all patents granted by the US Patent and Trademark Office (USPTO) since 1971. Since my study includes US companies I limited my search to the patents granted to US companies by the US patent Office. Delphion has also been used in prior studies (Chacar and Lieberman, 2003; Furman et al., 2005).

3.2 CLUSTER IDENTIFICATION

I identify the US clusters based on the Milken Institute's America's Biotech and Life sciences Clusters, 2004 Study (see Figure 2). The Milken Institute (2004) has identified 12 metropolitan statistical areas (MSA) in the US as biopharmaceutical clusters. These clusters have shown the greatest *concentration* and *specialization* of biopharmaceutical firms (for a more detailed description, see Milken Institute, 2004, America's biotech and life sciences clusters). A few studies identified clusters based on calculating the relative distance among individual firms across a geographic area (Aharonson, Baum, and Feldman, 2004), or based on an economic area identified by the Bureau of Economic Analysis (Porter, 2003). Others have used MSA to identify geographic units or clusters (Jaffe et al. 1993; Feldman, 1994).

In order to validate my use of Milken study in cluster identification in the biopharmaceutical industry I compared clusters I employed in this study to the biopharmaceutical clusters identified by the Cluster Mapping Project (2002) at the Institute for Strategy and Competitiveness, Harvard Business School. The results of the comparison show that clusters that are identified by the Milken Study were also identified as biopharmaceutical clusters by the Cluster Mapping Project. However, the Milken study is a more comprehensive study on biopharmaceutical clusters in the US than the Cluster Mapping Project because Milken's cluster identification process takes into consideration innovation, industry concentration, the availability of financial resources, local talent pool, and occupational strengths associated with clusters. The Cluster Mapping Project approach is based on the employment levels of biopharmaceutical industry firms and its suppliers and buyers in supporting industries. Thus, I believe that Milken Study's cluster identification is the most appropriate way to operationalize my independent variable, cluster membership.

3.3 MEASURES

3.3.1 Independent variable

3.3.1.1 Cluster membership

Previous studies identified cluster membership based on firms' headquarters location in a cluster area (Bell, 2005; DeCarolis and Deeds, 1999; Aharonson et. al., 2004; Owen-Smith and Powell, 2004). In a study in which the determinants of relocating HQ to overseas is examined, Birkinshaw et al (2006) state that there is no definitive way to measure corporate HQ location. They consider three relevant indicators of HQ location: the legal domicile, the location of top management team and the location of the various HQ functions. Following their study, first, I identify the location of corporate HQ in a cluster area by firms' registered address[5]. Second, based on the location of HQ functions approach I also look at the location of R&D functions because biopharmaceutical sector is highly research intensive, and research is conducted in formal R&D-Laboratories. In general, firms have R&D-Labs in their corporate headquarters locations (more than two thirds of firms in my sample have R&D-Labs in headquarters locations). Further, most of the biopharmaceutical companies that have corporate headquarters location outside of clusters, particularly big firms, have R&D-Laboratories located within cluster areas. For example, Abbott Laboratories is identified as out-cluster firm based on its headquarters location but Abbott also has R&D-Labs in various clusters. By the same token, Chacar and Lieberman (2003) found that geographic organization of firms' R&D-Laboratories

[5] One drawback of choosing corporate HQ address is that it may not show the physical location where the HQ functions are performed (Birkinshaw et. al. 2006). For example, some companies may form a shell holding company in an offshore location to benefit from tax advantages. Fortunately, with my sample this is not an issue because I focused on US biopharmaceutical companies and an examination of my dataset indicates that none of my sample firms have locations outside of US.

have significant effect on research productivity of pharmaceutical firms. This indicates that by having R&D-Laboratories in cluster areas firms might benefit from clusters to some extent if not in full.

In summary, I measure cluster membership in two different ways. First, I identify in-cluster firms based on their corporate headquarters location in any of 12 clusters identified above. I use a dummy variable which takes the value of 1 if a firm is headquartered within a cluster and 0 otherwise. Second, I also identify cluster membership based on R&D facilities' location data. I identify firms having at least one R&D-Laboratory in a cluster area as in-cluster firms. Again, I use a dummy variable in order to identify in-cluster and out-cluster firms based on their R&D-Laboratory location. I assign the value of 1 if a firm has at least one R&D-Lab within a cluster, 0 otherwise.

3.3.2 Network structure variables

Although my study period includes 1998 through 2004, I established complete alliance network structure for each year for the period between 1995 and 2004. This confirms my best effort that alliances established prior to 1998 are represented in my alliance network structure. I calculate network measures based on cumulative alliance network matrices for R&D alliances for the period of 1998 and 2004. I used UCINET-6 network analysis software in order to calculate the network measures (Borgatti, S.P., Everett, M.G. and Freeman, L.C. 2002). My network structure variables are calculated based on the complete network that includes the entire biopharmaceutical firms as well as other organizations with which they have alliances.

3.3.2.1 Centrality

In hypotheses 1a and 1b I argue that firms' in-cluster location is positively associated with its number of alliances. This actually indicates how active a firm is in its alliance network. Thus, to measure firms' centrality in their alliance network I use Freeman's degree centrality measure. A firm's degree centrality is the sum of its alliances with its partners. The degree centrality measure is a well accepted measure and it is widely used in studies where the focus is on firms' alliance activity (Madhavan, 1996; Ahuja, 2000). Although there are different ways to measure centrality in a network I specifically focus on the opportunities or alternatives that cluster membership brings for firms in terms of alliances. Therefore, degree centrality is an appropriate measure for my study. Other approaches in measuring centrality include closeness centrality and betweennes centrality. Closeness centrality emphasizes the distance of ego to all others in the network while betweennes centrality focuses on centrality based on being on the path of two actors (Hanneman and Riddle, 2005).

3.3.2.2 Structural Holes

Structural holes indicate what proportion of ego's ties are non-redundant (Burt, 1992). Following the prior literature, I measure the structural holes a firm spans in its alliance network by using the ratio of non-redundant contacts to total contacts (Burt, 1992; Ahuja, 2000, McEvily and Yao, 2005). This measure is calculated as an index:

$$\left[\sum_{j=1}^{n}\left[1-\sum_{q=1}^{n} p_{iq}m_{jq}\right]\right] / C_i$$

Where focal firm *i* has partners of *j* and *q*. P_{iq} is the ratio of firm i's alliances with firm q to its total number of alliances; m_{jq} is the marginal strength of the alliance between alliance

partner j and alliance partner q; and C_i is the total number of alliances for firm i. A higher index value for a firm indicates that this firm spans more structural holes, in other words its alliance partners do not have alliances with each other. If a focal firm's alliance partners do not have alliances with each other then the index value for that firm is 1. I use efficiency measure in UCINET-6 in order to calculate the structural holes. In UCINET I use the whole network method when calculating the efficiency measure. The whole network model includes the entire network when calculating the efficiency measure. In other words, structural holes among focal firm's indirect ties are also included in the measure.

3.3.3 Moderator variable

3.3.3.1 Absorptive Capacity

I measure firm's absorptive capacity by its R&D intensity. Since some of the firms in my sample have zero sales for some years I take R&D intensity as a ratio of R&D expenditures over total assets. R&D intensity as a measure of absorptive capacity is appropriate measure for my context, because using absolute number of R&D expenditure might bias my results as my sample consists of large and small biopharmaceutical firms. In the empirical literature absorptive capacity has been measured in several ways. Some studies use patent citations (Rothaermal and Thursby, 2005), patent stock (Dushnitsky and Lenox, 2005), R&D intensity (Arora and Gambardella, 1994), R&D expenditures (Cohen and Levinthal, 1990; Negassi, 2004), compensation policies, and dominant logic (Lane and Lubatkin, 1998). Evidence on appropriateness of measures for absorptive capacity has been inconsistent largely due to the context of studies and the definition of absorptive capacity construct (Lane, Koka, and Pathak. 2006). Although limitations of R&D as a measure of absorptive capacity have been raised it is

still a common practice to measure firms' absorptive capacity with R&D expenditure or R&D intensity (Cohen and Levinthal, 1990; Arora and Gambardella, 1994; Dushnitsky and Lenox, 2005).

3.3.4 Interaction Variables

I create two multiplicative interaction variables to measure the moderating effect of absorptive capacity for the centrality and innovation, and structural holes and innovation relationship. To represent the interaction between centrality and absorptive capacity I first centered the centrality and absorptive capacity variables and then multiplied the centered values. Centering the interaction variables before their multiplication is necessary in order to reduce the correlation between the interaction and main variables. The same procedure also applied for structural holes and absorptive capacity interaction.

3.3.5 Dependent Variable

3.3.5.1 Innovation

I adopt the definition of innovation as incorporating new technology into the means of production or creation of new product that range from breakthrough products to incremental improvements in products (Feldman, 2000). I measure innovation performance of firms using a firm's annual count of patents granted. There are a number of measures of a firm's innovation performance adopted in the empirical literature (see Hagedoorn and Cloodt, 2003, for a recent review). Some studies use surveys of new product announcements (Acs and Audretsch, 1988) while others use R&D expenditures as a measure of a firm's innovation competencies

(Henderson and Cockburn, 1994). Patents (Griliches, 1990), and patent citations (Trajtenberg, 1990; Harhoff et al., 1999) are also among the accepted measures of innovative performance. However, the use of patent data for measuring innovation performance has its drawbacks (Griliches, 1990). Despite their drawbacks, patents are widely accepted as a measure for innovation performance. In the biopharmaceutical sector, R&D takes a long time and the outcome of such research is not reflected immediately in firms' sales figures. Therefore, the use of patent data as a measure of innovation of biopharmaceutical firms is an appropriate measure of innovation performance in the context of this research.

3.3.6 Control Variables

3.3.6.1 Firm size

I measure firm size by number of employees since previous studies have indicated that firm size can influence innovation performance in the biopharmaceutical industry (Shan et all., 1994). Biopharmaceutical firms with large number of employees are perceived to have more scientists devoted to R&D and therefore a greater amount of patent output. I use log of number of employees.

3.3.6.2 Firm age

Since firm age affects the rate at which firms patent (Sorensen & Stuart, 2000), I control for the number of years passed since founding of firm i to the year of the observation of the dependent variable.

3.3.6.3 Indirect ties

A focal firm's partners can bring information from their alliances with other partners to the focal firm. Firms' alliance networks may act as an information gathering or as an information processing device (Ahuja, 2000; Freeman, 1991; Leonard-Barton, 1984). Therefore, both the amount and diversity of information that is acquired by a focal firm is affected by its indirect ties within its alliance network. For example, let's take a pharmaceutical company that has an alliance with a biotech company. Now let's assume that the biotech company has an alliance with a university that is involved in basic research in the biotech field. The pharmaceutical company through its alliance with the biotech company might be aware of the basic research conducted in the university even though the pharmaceutical company does not have a direct alliance with the university. Similarly, Ahuja (2000) showed that the indirect ties of a firm in the chemical industry have a positive effect on firms' number of patents. I use reach centrality function that is built in UCINET 6 in order to control for the effect of indirect ties on innovation. This measure provides the proportion of firms that a focal firm can reach in j or fewer steps in its alliance network (Borgatti, S.P., Everett, M.G. and Freeman, L.C. 2002, Ucinet 6).

3.3.6.4 Time (year effects)

Biopharmaceutical industry is research intensive industry. Scientific breakthroughs during certain years might affect firms' innovation in the following years. For example, deriving of the first human embryonic stem cell line at the University of Wisconsin-Madison in 1998 was followed by various research activities in the stem cell research. Thus, in order to capture temporal trends that are related to current technological and environmental conditions and that might affect firms' innovation I control for time effects. This is controlled by including a dummy variable for all but one year (Wooldridge, 2003, pg. 427). I take 1998 as a base year and

use a dummy variable for each of the following year. I also estimate my models without the time effects. The results do not change. Table 2 provides a summary of my variables and relevant interaction terms.

3.4 SAMPLE CHARACTERISTICS

A summary of the geographic locations of my sample based on metropolitan statistical areas can be found in Table 3. Further, an examination of average statistics in Table 4 yields the following observations about my sample in particular and clustering phenomenon in general in the biopharmaceutical sector. However, I should note that one should not draw conclusions based on the sample characteristics in Table 4. This table also illustrates how looking at and driving conclusions about the relationships among variables based on raw data on sample characteristics might be misleading in the empirical research. Table 4 is based on the static analysis of data with the normality assumption. However, data for several of the variables in this study are not normal and relationships among variables change once I specify regression models based on the correct distribution of data. Results of our regression analysis includes the effect of several independent and control variables on the dependent variable in the same model while accounting for endogeneity of variables, unobserved effects over time and associated time effects.

Therefore, keeping in mind the important points stated above, based on the headquarters location, I observe that 49% of firms have headquarters outside of cluster areas. These out-cluster firms also have higher number of patents than firms that have their headquarters location inside clusters (on average 94 patents for out-cluster firms versus 33 firms for in-cluster firms, pvalue=00, significant). On the other hand, when I look at the R&D-Lab location data, which is

based on firms' having at least one R&D-Lab inside the cluster average statistics are closer. If I identify in-cluster firms as those firms having at least one R&D-Lab inside cluster, then there is not a big difference between in-cluster and out-cluster firms (in terms of average sales: 1,680MM for in-cluster versus 1,433MM for out-cluster firms, pvalue=0.56). Further, on average out-cluster firms have 67 patents while in-cluster firms have 63 patents (pvalue= 0.77). Further analysis related to sample characteristics is provided in the Appendix, Table 1A and Figures 1A-3A.

My dataset consists of panel data for the period between 1998 and 2004 for firms in my sample. Since the number of observations for each firm is not the same my dataset is therefore unbalanced. Panel data design is appropriate for this study as I have a diverse sample including both established pharmaceutical and biotech companies. Unobservable firm characteristics such as competitive strategy, organizational culture, and ethical stance of biopharmaceutical firms towards controversial treatments may affect firms' innovation as well. Therefore, I have to account for these unobservable factors in my model in order to have consistent coefficient estimates for independent variables. Panel dataset is advantageous over cross-sectional datasets because it allows dealing with aforementioned unobserved effects across individual firms and allows unobserved effects to be correlated with the explanatory variables (Greene, 2003, pp. 284; Wooldridge, pp.13, pp. 471).

4.0 ANALYSIS

I tested my hypotheses using negative binomial regression, generalized least squares regression, and an exponential regression with Generalized Methods of Moment (GMM) estimation. The exponential regression with GMM estimation includes an exogenous variable (Cluster membership), endogenous explanatory variables (Centrality and Structural holes), instrumental variables (Headquarters location, HQ; at least one R&D-Lab within a cluster, and lagged patent-by one year- variable) and a count dependent variable (number of patents). I test hypothesized relationships in my model in two stages.

In the first stage, I test the theoretical relationship between cluster membership, centrality and structural holes variables (Hypotheses 1 and 2) by a random effects model. Since my independent variable HQ location (or R&D-Lab location) is time invariant, fixed effects model is not appropriate. In other words, no firm relocated to another geographical area during my study period. As my dependent variable, Centrality in the first hypothesis (cluster membership-centrality relationship) is constrained to be count, nonnegative integer values I test the hypothesized relationship by a nonlinear regression model to avoid heteroskedastic, non-normal residuals (Hausman, Hall, & Griliches, 1984). Specifically, I use a negative binomial regression. Although the Poisson regression is a first model choice considered for count data, the assumption is too restrictive (Wooldridge, 2003). In particular, it is assumed that variance is equal to mean (that is equi-dispersion of data). I, however, have over dispersed Centrality data in which

variance exceeds mean (variance= 181.30 > mean= 7.83). In cases of over dispersed data, negative binomial regression is more appropriate (Cameron and Trivedi, 2005). I estimate the model by using the random effects xtenbreg function in STATA-9.

I test hypothesis 2 (cluster membership-structural holes relationship) by using random effects generalized least squares (GLS) regression. Ordinary least squares (OLS) is not appropriate for my study as I have unbalanced panel data. OLS regression is based on the assumptions of homoscedasticity (error terms have constant variance) and no autocorrelation of error terms. However, panel datasets exhibit heteroscedasticity (error terms have different variances) and autocorrelation (Greene, 2003, pp. 192). Taking this information into account I use GLS model which corrects for the heteroscedasticity and autocorrelation of error terms observed with unbalanced panel data (Greene, 2003, pp. 192). Using GLS produces BLUE - best linear unbiased estimators (Wooldridge, 2003, pp. 404). I test the hypothesis using the xtpcse function with np1 option in STATA-9. This function produces panel corrected standard error estimates for panel data models where the parameters are estimated by Prais-Winsten estimation. Prais- Winsten estimation specifies that panel specific autocorrelations are weighted by number of observations in each panel (STATA-9).

In the second stage, to test the moderating effect of absorptive capacity for the centrality-innovation and structural holes innovation hypotheses (hypotheses 3 and 4) I employ an exponential regression model with GMM estimator due to the endogenous nature of my independent variables. Particularly, I use a fixed effects model with General Method of Moments (GMM) estimation[6]. I use the fixed effects model in an exponential form because my

[6] GMM only involves structural equation estimation with the help of instruments, instruments are orthogonal to structural errors and by benefiting from this property no reduced form equation is estimated in the GMM estimation. In contrast, in 2SLS with MLE a reduced form equation is estimated first.

dependent variable (patent) is a count variable. The model takes the following general form (Cincera, 1997):

$$P_{it} = \exp (X_{it}\beta + \varepsilon_i) + u_{it}$$

Where P_{it} represents dependent variable, number o patents granted; X_{it} indicates vector of independent and control variables, and ε_i represents the unobserved effects not captured by the variables in the model.

Count data such as patent data have several significant features that require specific econometric methods (Crepon and Duguet, 1997). While negative binomial and Poisson models are commonly used in the patenting literature (Lenox and King, 2003; Iwasa and Odagiri, 2004; Lim, 2004) they do not account for endogeneity of regressors. Therefore, they are not appropriate for my model since I have endogenous variables. In the first stage of my model, my analysis shows that both headquarters location cluster and at least one R&D-Lab inside cluster has significant positive effect on both the centrality and structural holes (HQ and R&D-Lab location, $p<0.05$). These significant results show the positive effect of cluster membership on firms' network structure thereby, establishing the endogenous nature of the centrality and structural holes variables in the model. I also tested for endogeneity by using the Durbin-Wu-Hausman test in STATA. Results of this test also confirm the endogeneity of centrality and structural holes variables. Please see Appendix for results of Durbin-Wu-Hausman test.

Having established the endogeneity of independent variables (centrality and structural hoes), I have to account for the endogeneity of centrality and structural holes variables in the second stage of my model. I use headquarters location (HQ), at least one R&D-Lab location inside a cluster (R&D-Lab), and lagged patent variable (lagged patent data by one year) as instruments in the exponential regression model. Taking all this information into account I use

fixed effects model with General Methods of Moments (GMM) estimation to test hypotheses 3 and 4. Recent empirical research in economics and finance has largely used GMM estimation (Greene, 2003). In models with endogenous explanatory variables, fixed effects exponential regression model with GMM estimation has several advantages over Poisson and negative binomial models with Maximum Likelihood Estimation (MLE). First, GMM estimation does not assume equality of variance and mean of count data (in Poisson Model) or over-dispersion (variance is larger than mean) of data in negative binomial model. In other words, in contrast to MLE, GMM estimation assumption is distribution free. Second, GMM estimation accounts for heteroscedasticity and autocorrelation of error terms. Finally, it relaxes the strict exogeneity assumption of explanatory variables[7] (Cincera, 1997; Crepon and Duguet, 1997). I use a Gauss program that accounts for both endogeneity and count dependent variable to test hypotheses 3 and 4. As I stated previously, although negative binomial model is not appropriate for my analysis because my explanatory variables (centrality and structural holes) are endogenous, I run my analysis using negative binomial model for comparison purposes. I provide results of negative binomial model in Models 3-4 in Table 8, and Models 3-4 in Table 9.

In the second stage of my analysis, the inclusion of time effects requires further elaboration. The error term in the regression models including panel data may include time varying error due to the unobserved factors that change over time and affect the dependent variable (Wooldridge, 2003). Generally, in instrumental variable estimation time dummy variables are included to account for omitted variables bias due to time effects. This may occur because instruments used in the regression models may be correlated with time effects. However, in my models I use HQ and R&D-Lab as instruments. As I stated previously these

[7] In my model I have endogenous regressors: centrality and structural holes.

instruments (or exogenous variables) are time invariant. Thus, there is no need to separately account for time effects by using time dummies in the second stage of my analysis which includes GMM estimation.

5.0 RESULTS

5.1 FINDINGS

Table 5 presents descriptive statistics and correlations for the 847 observations in the sample. The descriptive statistics indicate that the firms are characterized by significant diversity on key variables such as patent (number of patent ranges from 0 to 1,624), centrality (number of alliances ranges from 0 to 100), absorptive capacity (range from 0 to 697.9), and company age (1 to 118 years old). Thus, inclusion of 147 biopharmaceutical firms in the sample ensures that there is a considerable variance on almost all dimensions of the data. On average, firms have 8 alliances and 65 patents. The average age of firms in the sample is 19 years.

The correlation matrix shows low to moderate correlations among variables. However, these should be interpreted with caution as I do not have a linear relationship among some variables. Correlations are based on the assumption of linear relationship. For example, between headquarters (HQ) location and centrality I have an exponential relationship due to the negative binomial distribution of data for the centrality variable. Thus, it is not appropriate to interpret that there is a negative correlation between HQ location and centrality variables (corr = -0.048).

Results of the first and second stage regression analysis are provided in Tables 6-7, and 8-9 respectively. Table 6 presents the results of negative binomial regression analysis for

hypothesis 1. Model 1 includes effect of HQ location (cluster membership defined as having HQ inside cluster) on centrality. Model 2 includes effect of R&D-Lab location (cluster membership defined as having at least one R&D-Lab inside cluster) on centrality. In hypothesis 1, I propose competing predictions for the effect of firms' in-cluster location on their central position in their alliance network structure. The data indicate, in support of hypothesis 1a that firms' in-cluster location when measured by HQ location is positively associated with being more central in their R&D alliance network structure compared to firms located elsewhere ($p<0.05$). That is, in-cluster location complements firms' central position in their alliance networks structure. Therefore, the competing hypothesis 1b is rejected. Results of hypothesis 1a are also significant when I estimate the model with R&D-Lab location variable as a proxy for cluster membership ($p<0.05$). The significant findings for the impact of HQ location and R&D-Lab location on centrality indicate that firms that have headquarters location or R&D-Lab inside a cluster area will have positive network effects in terms of increased centrality compared to out-cluster firms. However, whether this network advantage translates into innovation will be explored in Hypothesis 3. Both Models 1 and 2 include control variables of absorptive capacity, firm size, company age, indirect ties, and time effects. Except the absorptive capacity variable all control variables are significant in both HQ location and R&D-Lab location models.

In Table 7, I report the results of the first stage regression analysis using random effects GLS model for hypothesis 2. Model 1 presents the effect of HQ variable (cluster membership measured by HQ location) on firms' structural holes. Model 2 includes the effect of R&D-Lab location variable (cluster membership measured by at least one R&D-Lab in cluster) on structural holes. Absorptive capacity, firm size, company age, and time effects are control variables in the models. Similar to hypothesis 1, hypothesis 2 also proposed competing

explanations for the in-cluster location and structural holes relationship. The results support hypothesis 2a, that in-cluster firms span more structural holes in their R&D alliance networks than firms located elsewhere ($p<0.001$). Similar to hypothesis 1a, in-cluster location complements firms' structural holes in their alliance network structures. The competing hypothesis 2b is rejected. Results are also significant when I ran the analysis with R&D-Lab location variable as a proxy for in-cluster location ($p<0.001$). The significant findings for Hypothesis 2 (cluster membership and structural holes relationship) indicate that having a headquarters (or at least one R&D-Lab) within a cluster leads to higher structural holes compared to firms that do not have headquarters (or at least one R&D-Lab) within cluster. Similar to arguments in hypothesis 1, in-cluster firms have structural holes advantage, which brings in information diversity. I will explore whether firms can convert this benefit into innovation in Hypothesis 4.

Results for the control variables in Hypothesis 2 are interesting. In contrast to Hypothesis 1, absorptive capacity is significant in both HQ location and R&D-Lab location models. This states that firms' absorptive capacity influences their structural holes while absorptive capacity does not influence centrality. I should note that I included absorptive capacity of firms as a control variable in models for hypotheses 1 and 2 in order to account for the effect of firm's absorptive capacity on firms' centrality and structural holes they span. This is necessary because firms that have high absorptive capacity are in a better position to exploit their knowledge and thus become both alliance initiators and targets. This positively influences firms' centrality. Further, firms' absorptive capacity may also affect structural holes firms span because absorptive capacity is path dependent and firms build on existing knowledge. Therefore, it is more likely that firms do not collaborate with other technologically distant firms

(Ahuja, 2000) due to their limitations in acquiring, assimilating, and exploiting external knowledge. The inclusion of absorptive capacity as a control variable in the first stage analysis does not change the results of the second stage analysis in any way because the estimation of second stage model (the moderating effect of absorptive capacity for the centrality, structural holes and innovation relationship) is estimated independent of the first stage estimation. One point related to the control variable of indirect ties also requires additional explanation. In testing the second hypothesis I do not control for the effect of indirect ties because the structural holes measure already includes the effect of indirect ties in the entire network. UCINET 6 provides two ways to calculate structural holes measure by using the efficiency measure: one that is based on the ego network calculation, another that is based on the whole network calculation. I chose to calculate the structural holes (efficiency measure) based on the whole network to account for the effect of indirect ties.

Table 8 provides the results for the second stage exponential regression analysis that includes fixed effects model with GMM estimation for hypothesis 3. I predict that firms' absorptive capacity positively moderates the centrality and innovation relationship. Coefficient of the interaction variable (0.001), centrality X absorptive capacity in Table 8 (Model 1) provides support for hypothesis 3, that the interaction between firms' absorptive capacity and centrality is positive and significant. This indicates that based on firms' absorptive capacity central firms innovate more than other firms when endogeneity of centrality is controlled with HQ location. However, when I do not control for endogeneity the moderating effect is not significant (Model 3). This finding is important because it shows that the relationship between centrality and firm innovation is more complex than it is originally studied. Although it is not one of my hypothesis, the positive and significant coefficient of centrality variable (0.3) supports the prior

literature that the higher the centrality of firm in its alliance network the higher the innovation ($p<0.05$) (Ahuja, 2000). This further, provides a strong support for earlier literature, where centrality and innovation has been positively linked (Ahuja, 2000; Owen-Smith and Powel, 2004). I should note that there might still be differences in the magnitude of coefficients in models where endogeneity controlled and magnitude of coefficients in models where endogeneity is not controlled. I also estimate the models by controlling for endogeneity with R&D-Lab location variable. The results are similar. Control variables are not significant except absorptive capacity. The negative and significant coefficient of the absorptive capacity variable indicates that firm's absorptive capacity negatively affects firms' innovation when accounted for endogeneity. That is the positive finding between absorptive capacity and innovation in the prior literature might be due to other omitted variables in the empirical model (Cohen and Levinthal, 1989). Thus, when we include the effect of geographic location we find that absorptive capacity is negatively related to innovation.

In support of hypothesis 4, which predicts that that firms' absorptive capacity positively moderates the relationship between firms' structural holes and innovation, fixed effects model with GMM estimation results in Table 9 (Model 1) indicates a significant relationship. Thus, hypothesis 4 is supported when I account for endogeneity by HQ location variable. However, results are not significant when I account for endogeneity with R&D-Lab location variable. Although it is not among my hypothesized relationships, in the models where I do not account for endogeneity (Models 3 and 4) the coefficient of the structural holes variable indicates a positive relationship between firms' structural holes and the innovation output similar to the prior research (Hargaddon and Sutton, 1997). Yet, the structural holes and innovation relationship is not significant in Table 9 (Models 1 and 2) where I account for endogeneity of

structural holes variable. The positive coefficient of my interaction variable- structural holes X absorptive capacity indicates a significant and positive moderation of absorptive capacity. Interestingly, when I do not account for endogeneity I find that structural holes variable is positive and significant in both HQ location and R&D-Lab location models in Table 9 (Models 3 and 4). This finding shows that mixed findings related to structural holes and innovation relationship in prior literature might be due to the absence of control for endogeneity of structural holes. In testing the hypothesis 4 in order to avoid multicollinearity among variables I dropped the indirect ties control variable from my model. As it is also seen from the correlation table (Table 5) the correlation between indirect ties and structural holes variable is significant (0.979). Dropping this variable does not change results as I also discussed earlier the measure for structural holes variable already accounts for indirect ties in the entire network.

As it is also stated above, the interactions of centrality and absorptive capacity and structural holes and absorptive capacity are not significant when I account for endogeneity with the R&D-Lab location variable. This finding is interesting and requires further elaboration. According to Zahra and George (2002) absorptive capacity can be characterized as potential and realized absorptive capacity. Potential absorptive capacity includes acquisition and assimilation of external knowledge. Realized absorptive capacity includes transformation and exploitation of the acquired and assimilated knowledge into commercially viable form. Combining this view with the findings of this study indicates that various units within an organization may house either potential absorptive capacity or realized absorptive capacity. However, sometimes both potential and realized absorptive capacity might be housed within the same unit. In the context of the biopharmaceutical industry, firms' R&D-Laboratories might house potential absorptive capacity because potential absorptive capacity is associated with research and development or

exploration of new chemical components or new target proteins. For example, scientists in R&D-Laboratories might be interested in developing new chemical compositions and might be concerned with the R&D aspect of drug development rather than commercial aspect of it.

Thus, firm's absorptive capacity does not moderate the relationship for firm's centrality and structural holes and innovation relationship. Because, firms' information benefits acquired by their central position or structural holes influenced by their R&D-Lab location might be different from information benefits they receive if their headquarters are in a cluster area. That is, the information benefits they receive due to R&D-Lab location might be relevant only to research and development and even if firms have absorptive capacity it is les likely that they will convert this information into a commercial viable form. However, in the case of headquarters location it is more likely that firms' absorptive capacity will positively moderate the centrality, structural holes, and innovation relationship because headquarters have both potential and realized absorptive capacity in place in order to commercialize information acquired due to centrality and structural holes firms have in their alliance network structure.

5.2 INTERPRETATION OF FINDINGS

Several aspects of the above results are worth inquiring further. First, in order to test hypothesis 1 I used a negative binomial model which is a non-linear, exponential model. Many count data models, such as negative binomial model use the general exponential form of:

$E[y|x] = \exp(x\beta + \varepsilon)$, and the estimated coefficients should be interpreted as semi-elasticity (Cameron and Trivedi, 2005, pp. 124). This indicates that one unit change in the independent variable, x results in $100 \times \beta$ % change in the dependent variable, y (Stock and Watson, 2003,

pp. 211). Accordingly, in the HQ model in Table 6 (Model 1) the positive coefficient (0.309) for hypothesis 1 denotes that in-cluster firms increase their number of alliances by approximately 31 percentage points more than out-cluster firms' increase. For example, if out-cluster firm (firm's HQ is out cluster) increases its number of alliances by 10%, then an in-cluster firm (firm's HQ is in cluster) increases its number of alliances by 41%.

Second, interpretation of coefficient in hypothesis 2 in Table 7 (Model 1) is straight forward as I have a linear relationship between independent and dependent variable. Therefore, the difference in the structural holes variables between in-cluster and out-cluster firms is 0.146. For example, if a firm that is located outside of a cluster and has a structural holes (calculated as an efficiency index) of 0.15, the structural holes (efficiency index) of an in-cluster firm is 0.30. In other words in-cluster firm spans more structural holes than out-cluster firm does. The higher structural holes (efficiency index) value means that firms span many structural holes; value of 1 in structural holes (efficiency index) denotes that partners of a focal firm do not have connections with each other, indicating that focal firm does not have any redundant contact. The interpretation of coefficients in R&D-Lab location model is also similar to the above interpretations.

Finally, models for hypothesis 3 and 4 also employ an exponential relationship. Interpreting coefficients requires a similar logic to above exponential interpretation for hypothesis 1. For example, hypothesis 3 predicts that absorptive capacity positively moderates the relationship between centrality and patents. The coefficient on the interaction term, centrality X absorptive capacity is the effect of a unit increase in centrality and absorptive capacity, above and beyond the sum of the individual effects of a unit increase in centrality alone

and a unit increase in absorptive capacity alone (Stock and Watson, 2003, pp.211-229). Since I have an exponential model I present the equation in a general log-linear form as:

Δ Log (patent) = [β_1 + β_3 (absorptive capacity)] Δ (centrality) + [β_2 + β_3 (centrality)] Δ (absorptive capacity) + β_3 Δ (centrality) Δ (absorptive capacity)];

where, $\beta_{1=}$ coefficient of centrality, β_2 = coefficient of absorptive capacity, β_3 = coefficient of interaction term.

Let us take the HQ model (Model 1, Table 8) and suppose, a firm has 3 alliances and its absorptive capacity is 0.15 and let's increase centrality by 1 unit and absorptive capacity by 0.1 unit, then the effect of interaction between its centrality and absorptive capacity on number of patents will be calculated as follows:

Δ log (patent) = [0.3 + (0.001) (0.15)] (1) + [(-0.012) + (0.001) (3)] (0.1) + (0.001) (1) (0.1)

Δ log (patent) = [0.30]

Thus, using the above semi-elasticity interpretation, there will be a 30% increase in the number of patents as a result of the interaction effect. If there were no interaction between the centrality and absorptive capacity variables based on 1 unit change in centrality and 0.1 unit change in absorptive capacity then the change in patent will be:

Δ log (patent) = [$\beta_1$centrality + $\beta_2$absorptive capacity]

Δ log (patent) = 0.3(1) + (-0.012) (0.1) = 0.29; 29% change in patents. Thus, the positive interaction between centrality and absorptive capacity brings an additional 1 percentage points change in number of patents.

6.0 DISCUSSION AND CONCLUSION

6.1 DISCUSSION AND IMPLICATIONS

In this study I examine the endogenous impact of cluster membership defined as the geographical location of a firm within a cluster area on firms' alliance network structure and how this alliance network structure influences innovation contingent on firms' absorptive capacity. I find that firms' headquarters location (or at least one R&D-Lab) inside a cluster affects firms' position in their overall alliance network. In-cluster firms are more central and span more structural holes than other firms (for illustrations see Figures 3 and 4). Thus, the results provide support for the basic premise that network position can be enhanced by locating firms' headquarters (or at least one R&D-Lab) in a cluster area. Further, my findings suggest that network structure is necessary but not a sufficient condition for innovation. Specifically, firms need to have developed capabilities to acquire, assimilate, transform, and commercialize external information that is acquired through their network structure. These results have important theoretical, empirical and practical implications.

First, researchers have found that location in geographical clusters to be important for strategic choices of firms (Porter, 1998; Saxenian, 1994; Furman, 2003). The importance of clusters has mainly evolved around two main arguments. On one hand, firms located within cluster areas have benefits of physical location and the resources associated with it. On the other

hand, location within a cluster provides free spillover benefits but these spillovers are limited to firms within cluster boundaries. One important implication of these arguments is that it is not clear whether in-cluster location substitutes for or complements firm strategic choices such as alliances. These arguments are tested in the context of the biopharmaceutical industry because this industry is a knowledge based industry and there are geographical boundaries associated with knowledge spillovers, therefore, biopharmaceutical firms are clustered in certain geographic areas. These cluster areas include major research universities and other institutions such as government institutions, other biopharmaceutical firms. Given the clustering effects in the biopharmaceutical industry one would expect that biopharmaceutical firms that are located within cluster areas do not form alliances with other firms. In spite of cluster benefits, both research and practice show that biopharmaceutical industry is one of the most alliance intensive industries due to the high cost of bringing a new biopharmaceutical product into the market. Particularly, alliances between a large pharmaceutical firm and a small biotech firm are initiated through personal relationships which are facilitated by proximity.

Further, contrary to the popular belief that geography does not matter due to the advanced communication technology, I find that it does matter. My findings show that firms' location within a cluster area does not substitute for firms' strategic choices specifically their alliance strategies. This finding is reasonable given that innovation is more likely to be an outcome of formal alliance rather than outcome of knowledge spillovers in the cluster areas. This can be attributed to intellectual property rights. Because firms protect their technology or processes by a legal process and thereby firms cannot simply use the same free knowledge spillover to innovate. Further, my results provide a positive answer to a question of whether firms' R&D alliances are a complement to geographic location (Aharonson, Baum, and Feldman, 2004).

Furthermore, my study examines the consequences of location across 12 clusters in the US. Previous literature has focused on one cluster area in studying the effects of cluster membership (Saxenian, 1994, Owen-Smith and Powell, 2004). Thus, my study presents a more general test of the role of cluster membership by examining location in multiple clusters over multiple time periods. By incorporating appropriate statistical technique to account for each network structure variable I obtain robust results. For example, the centrality data shows a negative binomial distribution, which requires to use negative binomial model in order to test my first hypothesis including the centrality- innovation relationship.

Second, I theoretically argue and empirically demonstrate that the strategic choice of alliance network structure is an endogenous phenomenon with respect to cluster membership. Although prior literature indicates that alliance network structure have significant innovation outcomes (Ahuja, 2000; Owen-Smith and Powell, 2004), these studies are based on the premise that network structure is exogenous (Reagans et al. 2005). That is, some organizational outcomes are regressed on firms' network structure variables and results are interpreted as the effect of network structure on these performance variables. My results suggest that the relationships may be even more complex than I initially believed them to be and may be affected by other firm attributes. My findings indicate that theorizing and then empirically testing network structure as an endogenous phenomenon with respect to cluster membership and its innovation implications has important consequences for the empirical conclusions based on prior theoretical propositions. Specifically, I find that taking this endogeneity into account might change the relationship in which performance is examined to be an outcome of alliance network structure (Shaver, 1998; Hamilton and Nickerson, 2003).

Since it has been extensively studied in prior research I do not hypothesize for the effect of main variables- centrality and structural holes- on innovation in my study. However, in the first part of my theoretical model (cluster membership and network structure relationship) I develop my theory arguing the endogenous nature of alliance network structure with respect to cluster membership. I also confirm the endogeneity of these main variables in my empirical models. In order to demonstrate the differences between traditional analysis and my analysis, I estimate two models: one that accounts for endogeneity and another that does not account for endogeneity. Based on the comparison of two models I find that even when I account for endogeneity I still find a significant effect for the centrality and innovation relationship. This also confirms prior findings in which firm centrality is found to have a significant effect on innovation. Thus, I conjecture that the effect of centrality on firm innovation is very strong that even when I account for endogeneity of centrality with respect to cluster membership I still find a positive and significant effect. Therefore, I can confidently say that prior literature's results hold in terms of direction but might differ in terms of magnitude of this effect when I control for the endogeneity of firms' centrality in their alliance network structure.

In contrast to prior literature (Ahuja, 2000; Hargaddon and Sutton, 1997), the effect of firms' structural holes on innovation is not significant when I control for endogeneity of structural holes variable. This finding is important given the mixed findings for the structural holes and innovation relationship in the prior literature. I contemplate that mixed findings in the prior literature might be largely due to treatment of structural holes as an exogenous phenomenon. In particular, the structural holes and innovation relationship might be largely influenced by firm specific attributes such as firms' geographic location as demonstrated in this study. This shows us that the significant effect of structural holes on innovation might result

from firm specific factors rather than structural holes. For example, in the context of biopharmaceutical clusters, firms might benefit from existing diverse information within the cluster boundaries (free knowledge spillover) even if this firm does not have any formal alliances with other organizations. In prior studies it is impossible to separate between firm attributes and alliance effects on firms' innovation. As in this study once we separate the effect of firm attributes and structural holes spanned in the alliance network structure we find that structural holes do not have a significant effect on firms' innovation. Another possible explanation to this finding is that firms' network positions attributes such as structural holes limit opportunities available to firms because these firms are focused on getting diverse information from their network position rather than focusing on other opportunities that exist around them such as being a cluster member. Stuart (1998) also supports this explanation because he concludes that firms' position in their network structure create and limit firms' abilities to implement alliance strategies successfully.

Third, my findings also show how network structure and absorptive capacity interact. Supporting prior findings I find that absorptive capacity positively moderates the relationship for centrality and innovation and also the relationship for structural holes and innovation. These findings are interesting because prior literature has focused on the moderating effect of absorptive capacity in explaining innovation without addressing whether the effect might depend on other firm attributes (McEvily and Yao, 2005; Tsai, 2001). In this study, I examine one such firm attribute: the cluster membership. I find that after accounting for this attribute I find positive and significant results for the moderating effect of absorptive capacity for network structure and innovation relationship.

Cluster membership may enhance firms' network structure thereby increasing the volume and diversity of information a firm can access but at the same time firms need absorptive capacity to acquire, assimilate and exploit external information in order to innovate. Indeed, according to an industry survey, biopharmaceutical firms choose their alliance partners based on their expertise area. For example, biopharmaceutical executives consider the talent and knowledge base of their alliance partners in their own therapeutic area as very important in choosing their alliance partner (Deloitte Research Life Science Study, 2005). My informal interview with biopharmaceutical industry expert also confirms the above point. As he stated, it is not the financial resources but it is the human capital and absorptive capacity limitations of firms that keep biopharmaceutical firms from being more innovative. In particular, biopharmaceutical firms' absorptive capacity positively interacts with firms' information benefits they acquire due to their alliance network position in two ways. First, firms' experience in a certain therapeutic area will motivate the biopharmaceutical firm to further extract value from this experience by using the high amount of information volume acquired due to its central position in its alliance network structure. Second, absorptive capacity of a biopharmaceutical firm that spans many structural holes, thereby has access to diverse information, will enable but also limit this biopharmaceutical firm to choose from diverse information that might be related to various therapeutic areas and built on the similar therapeutic area.

Finally, emphasizing endogeneity of key network structure dimensions reminds us that firms' strategic choice of alliance network structure is dependent upon firm characteristics. Firms may manipulate their network positions based on their external environment (Koka, Madhavan, Prescott, 2006). Given that firms' location might bring advantages (or disadvantages) in terms of alliance opportunities it is natural to conclude that firms' location

affect their alliance strategies thereby their alliance network structure. Out-cluster (or non-member) firms might access cluster resources through different ways such as direct investment acquisition, or alliance (Tallman et all, 2005). Indeed, my anecdotal evidence suggests that a biopharmaceutical company located in Florida specifically forms alliances with other institutions in Boston area in order to have access to ongoing cutting edge research in Boston cluster.

6.2 LIMITATIONS AND FUTURE RESEARCH

As with any study, my research has limitations. Although I included the entire biopharmaceutical clusters in the US I did not control for cluster specific factors in my model. Future research could examine differences across clusters and how these differences affect firms' network structure. For example, a firm located in Boston cluster might differ in terms of strategic actions it takes compared to a firm located in Seattle cluster due to resources associated with clusters and cluster size. Similarly, future research could explore why approximately 50% of firms are still located outside of cluster areas given research showing the benefits of clusters. More specifically, what are the determinants of cluster membership? For example, Eli Lilly is located outside of any cluster why did a cluster not start where Eli Lilly is located?

Perhaps another limitation is my restriction of alliance network to include R&D alliances only. In this study I examined the effect of cluster membership on firms R&D alliances. Prior literature has mainly associated firms' innovation as an outcome of their R&D alliances (Ahuja, 2000). Following the prior literature I also limit my alliance to only R&D alliances given that my dependent variable is innovation. Future research might also explore if cluster membership is associated with other types of alliances for example, commercial alliances.

In this study I used firms' R&D intensity to measure absorptive capacity. There has been some debate surrounding the issue of using R&D intensity as an indicator of absorptive capacity (for a review, see Lane et. al., 2006). The conclusion of this debate has been that absorptive capacity is contextual and it should be measured not only by R&D but also by other proxies that capture different dimensions of this construct. In the biopharmaceutical industry context firms' R&D intensity is an indication of firms' ability to engage in basic research and applied research, which essentially reflects firms' absorptive capacity. Although R&D intensity seems to be an appropriate measure of absorptive capacity in this particular setting future studies ought to examine whether other proxies can be used in testing the moderating effect of absorptive capacity for the network structure and innovation relationship in a similar fashion. For example, number of PhD scientists in a biopharmaceutical industry maybe used as a proxy for absorptive capacity in this context.

Testing for endogeneity in this study has focused on the endogeneity due to omitted variable bias and unobserved firm effects. Nonetheless, innovation might also affect firms' network structure indicating endogeneity due to recursive relationship between a dependent variable and an independent variable. For example, Shipilov (2006) tests for recursive relationship between performance and network structure in the investment banking industry and finds that network structure is not endogenous with respect to a recursive relationship between market share (as a proxy for performance) and network structure. However, I am confident that given my theoretical boundary and methodological approach, the endogeneity problem due to recursive relationship between dependent variable and independent variable is mitigated in my model. In a similar vein, one may argue that cluster membership is not entirely exogenous or put differently, endogeneity bias may be associated with cluster

membership as well. That is, firms choose their location and there are strategic factors influencing this location choice. Because of this study's theoretical boundary, however, I start with firms' given geographic location and study the influence of this location for strategic actions. Additional studies could also investigate the endogenous nature of cluster membership and how this affects firms' innovation.

Another intriguing area for future research might be to consider the relationship between firms' cluster membership and their absorptive capacity. This question assumes importance because I find that firms' absorptive capacity does not significantly moderate the network structure and innovation relationship when I do not account for endogeneity with cluster membership. Thus, does it mean that there is an effect of cluster membership on firms' absorptive capacity? Relevant to above question, another question one can further pursue is does cluster membership have similar effects on firms' potential and realized absorptive capacity (Zahra and George, 2002)?

In spite of these qualifications, this study contributes to the body of research examining the impact of firm's geographic location on strategic actions particularly alliance network structure, geographic clusters, and the firm's innovation performance (Sorenson and Baum, 2003; Owen-Smith and Powell, 2004; Tallman et al. 2004). It points to the possibility that firms' position in their alliance network structure is determined by these firms' location within a cluster area. Executives' failure to recognize the importance of geographic location for alliance building strategies could result in strategic actions that might be detrimental for their firms' alliance building actions and in turn innovation performance. However, I cautiously invite managers that before they take any strategic actions relevant to relocation the feasibility of such action should

be analyzed. If communication costs or other relevant costs of managing alliances exceed the costs of relocation, it might be feasible to relocate.

Figure 1. Research Model

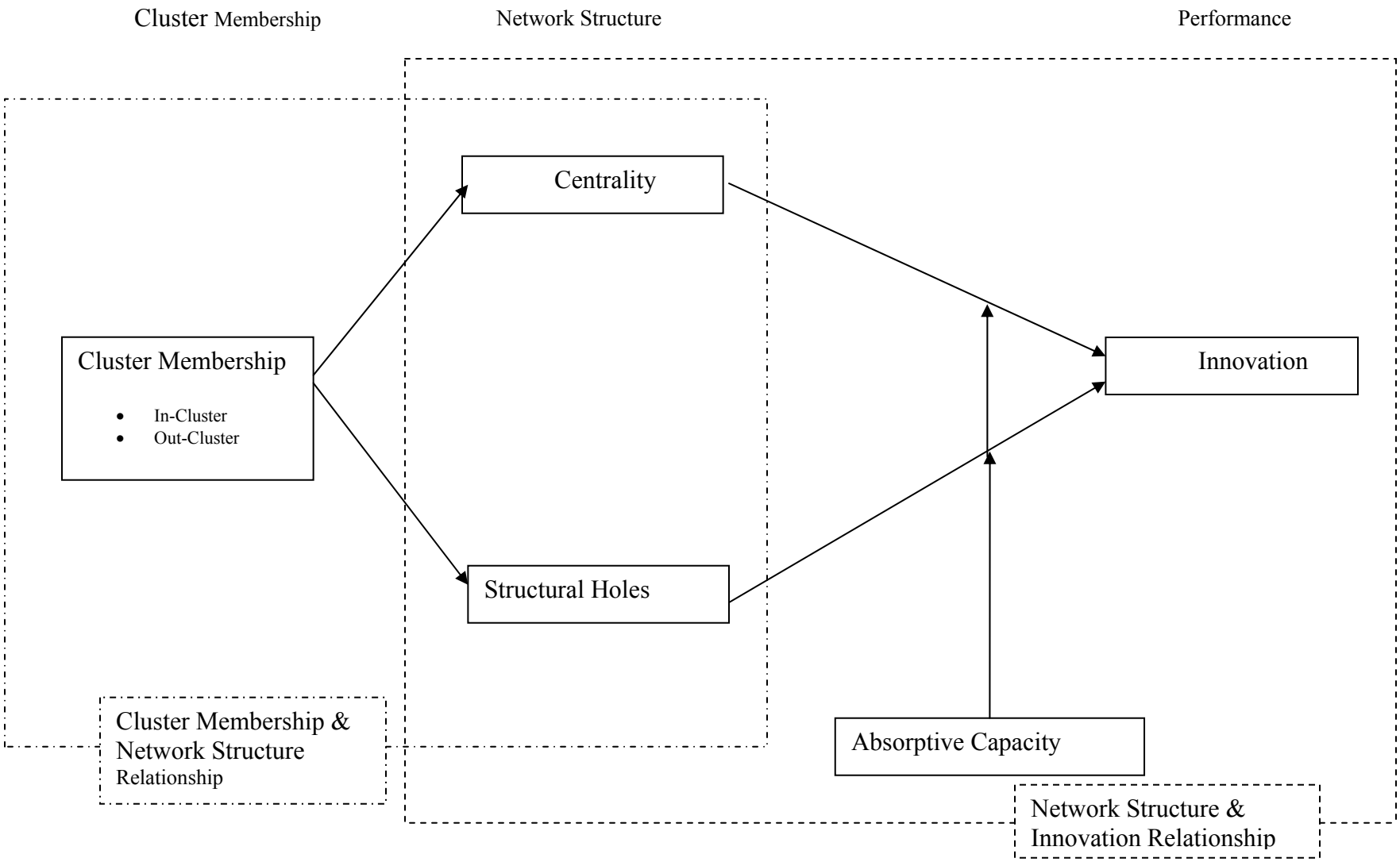
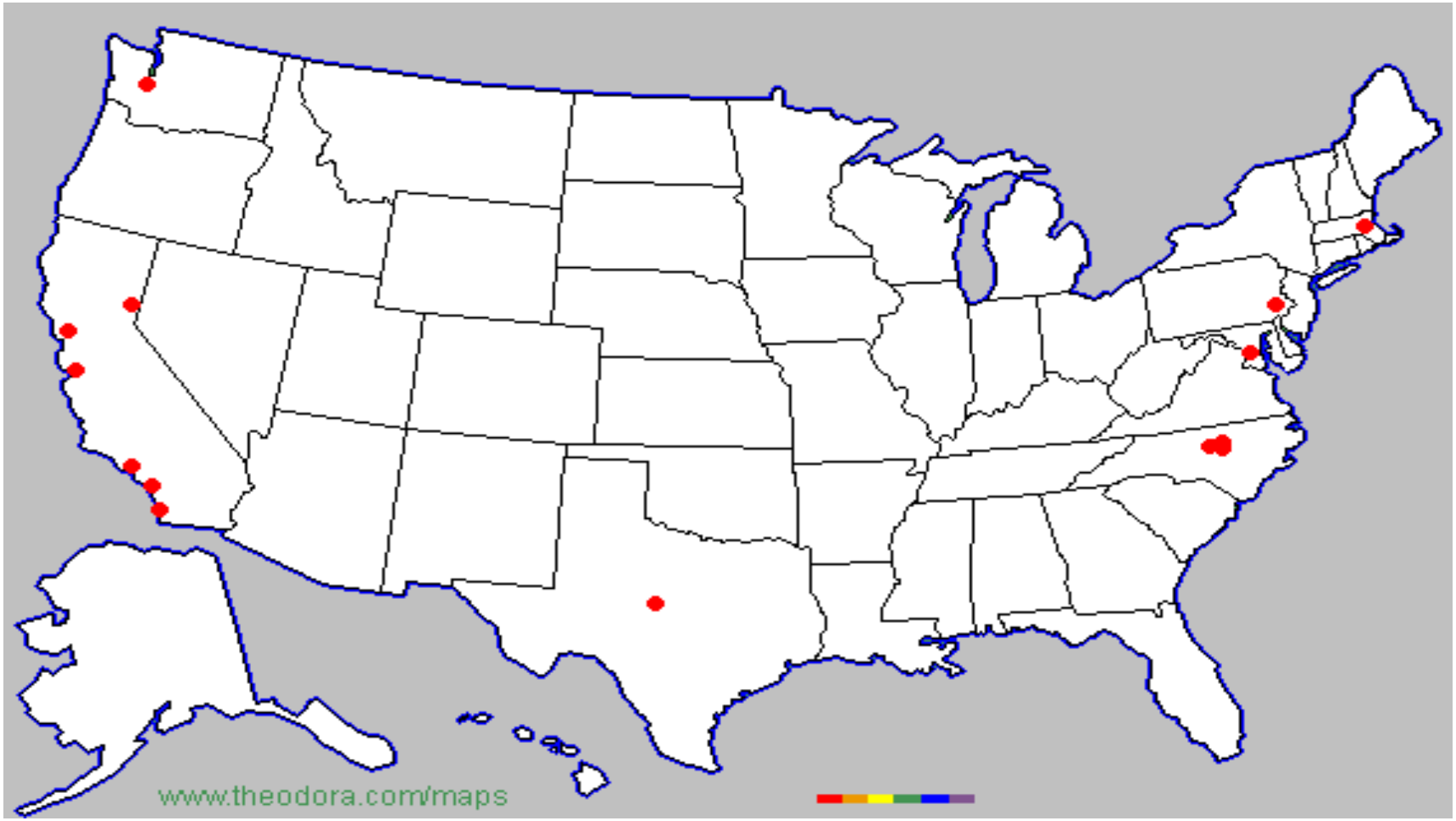


Figure 2. Biopharmaceutical Cluster Areas in the US



Clusters are identified based on the Milken Study, 2004: Seattle, Oakland, San Francisco, San Jose, Los Angeles, San Diego, Orange County, Austin, Raleigh-Durham-Chapel Hill, Washington DC, Philadelphia, Boston

Figure 3. Ego network of an in-cluster firm: Vertex Pharmaceutical

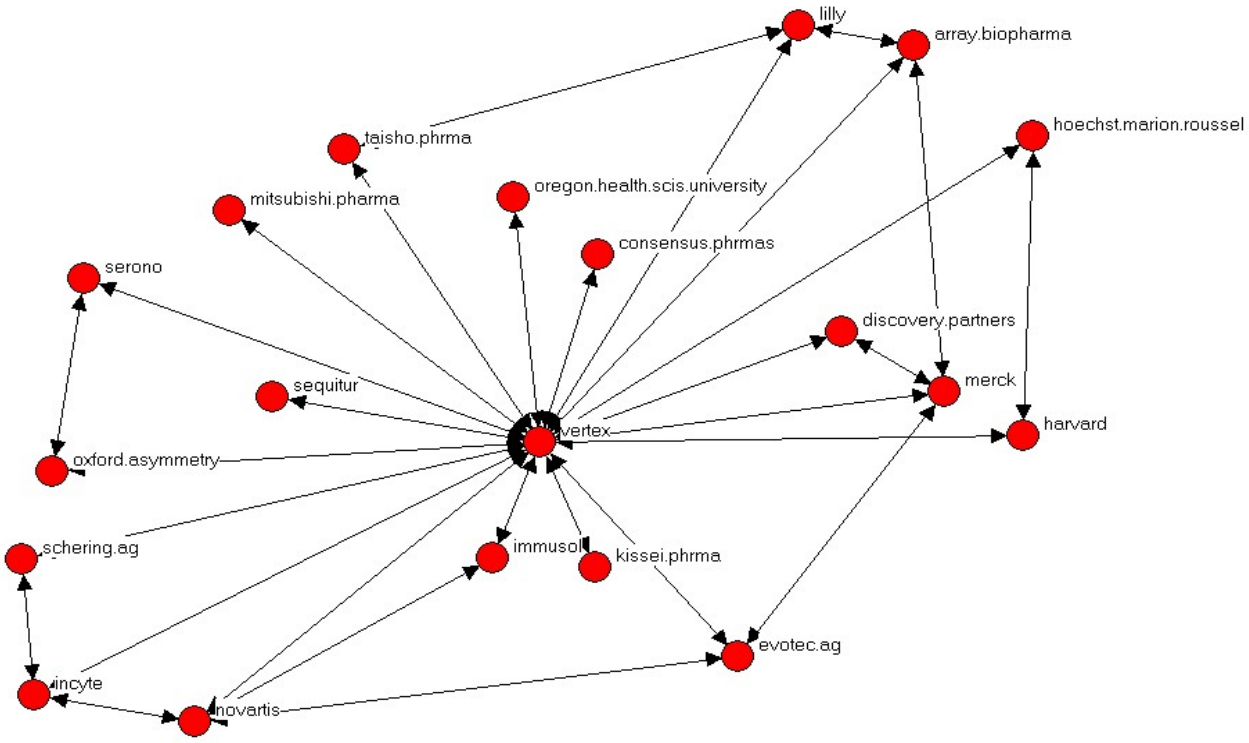


Figure 4. Ego network of an out-cluster firm: Penwest Pharmaceutical

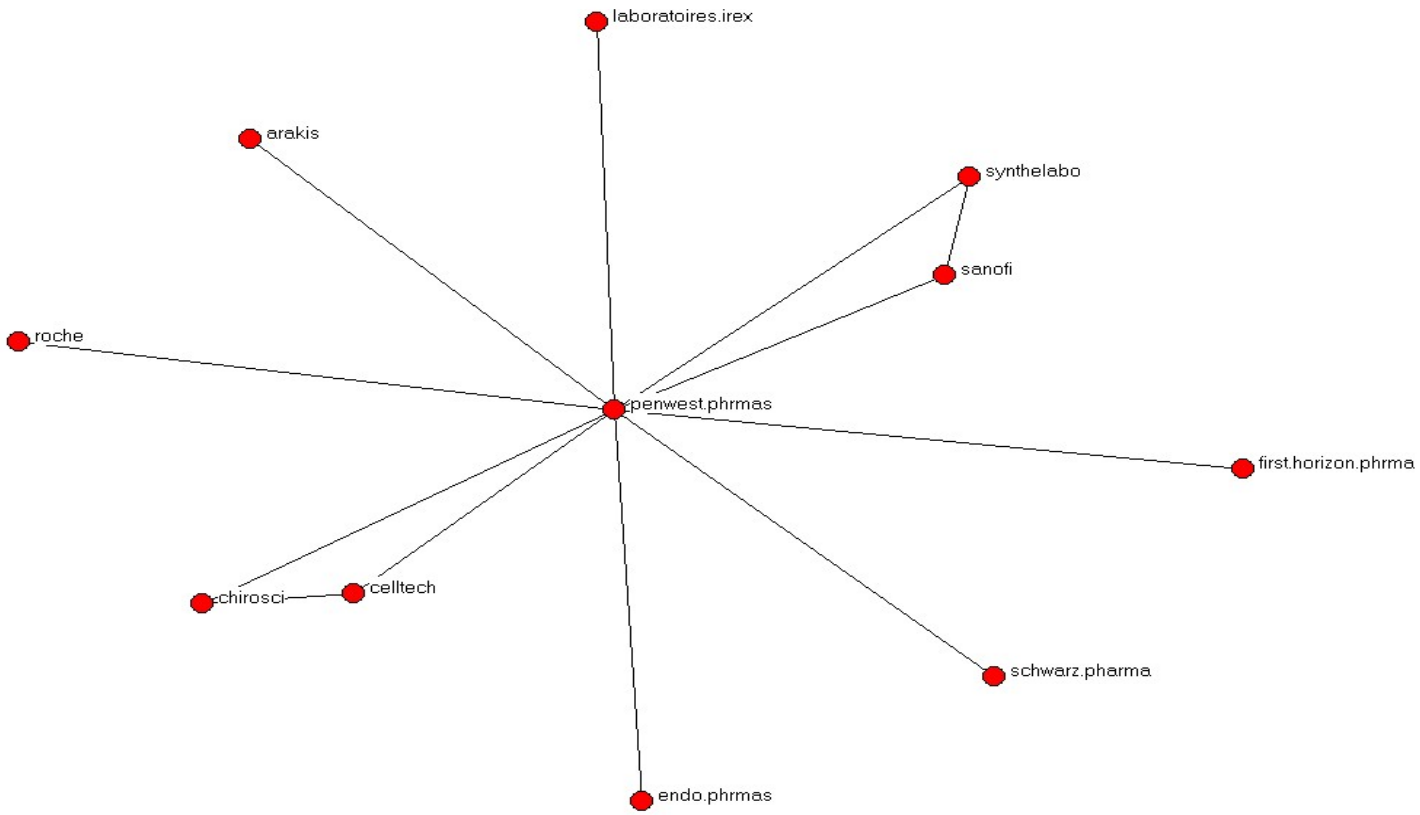


Table 1. A Summary of Hypothesized Relationships in the Study

Hypotheses	Relationship	Theoretical Framework
H1a H1b	In-cluster firms are **more central** in their alliance network than firms located elsewhere. In-cluster firms are **less central** in their alliance network than firms located elsewhere.	Economic Geography: Space and Place Arguments Transaction Costs Resource Complementarities Embeddedness
H2a H2b	In-cluster firms span **more structural holes** in their alliance network than firms located elsewhere. In-cluster firms span **fewer structural holes** in their alliance networks than firms located elsewhere.	Economic Geography: Space and Place Arguments Transaction Costs Resource Complementarities Embeddedness
H3	Given the endogeneity of firms' centrality in their alliance network structure with respect to their cluster membership, firms' absorptive capacity positively moderates the relationship between firms' centrality in their alliance networks and innovation	Social Capital Absorptive Capacity Bounded Rationality
H4	Given the endogeneity of firms' structural holes in their alliance network structure with respect to their cluster membership, firms' absorptive capacity positively moderates the relationship between firms' structural holes in their alliance networks and innovation**.**	Social Capital Absorptive Capacity Bounded Rationality

Table 2. Variable Labels and Definitions

Variable	Definition
Dependent Variable	
Patent	Yearly count of patents granted
Independent Variables	
HQ location	Dummy variable, 1 = firm's headquarter location is in cluster area, 0= otherwise. i.e. if firm is a cluster member
R&D-Lab location	Dummy variable, 1 = firm has at least 1 R&D-Lab location in cluster area, 0= otherwise. i.e. if firm is a cluster member
Endogenous Variables	
Centrality	Degree centrality, number of alliances in alliance network
Centrality X Absorptive capacity	Interaction between centrality and Absorptive capacity
Structural Holes	Measure of structural holes, Ratio of nonredundant contacts to total contacts, calculated by UCINET 6, efficiency index.
Structural holes X Absorptive capacity	Interaction between structural holes and Absorptive capacity
Control Variables	
Absorptive capacity	R&D expenditure over assets, measure for absorptive capacity
Firm Size	Log (number of employees), control for firm size
Firm age	Age in years since founding
Indirect ties	Measure of indirect ties in the entire network. Calculated based on reach centrality measure in UCINET 6
Time effects	Measure of time related effects in the model. Dummy variable

Table 3. Geographic Summary of Sample

Location (MSA)	n= number of firms
Boston	15
San Diego	9
San Jose	4
Raleigh-Durham-Chapel Hill	5
Philadelphia	8
Seattle-Bellevue-Everett	4
San Francisco	18
Washington, DC	3
Oakland, CA	0*
Los Angeles-Long-Beach	1
Orange County	5
Austin-San Marcos	0*
Out Cluster Firms	75
Total: 12 Clusters	147 Firms

* Among 147 firms in our sample no firm is located in Oakland or Austin-San Marcos

Table 4. Sample characteristics based on In-Cluster and Out-Cluster Firms[a]

	Average HQ-IN	Stdev HQ-IN	Average HQ-OUT	Stdev HQ-Out	HQ:IN-HQ:OUT t-test	Average R&D-LAB-IN	Stdev R&D-LAB-IN	Average R&D-LAB-OUT	Stdev R&D-LAB-OUT	R&D-LAB:IN-R&D-LAB:OUT t-test
Patents	33	78.5	94	281.0	000***	63	182.6	67	244.6	0.77
Centrality	7.15	8.93	8.47	16.56	0.15	9.26	13.22	6.04	13.58	0.0005***
Structural holes	0.92	0.23	0.76	0.41	000***	0.92	0.24	0.74	0.42	000***
Asset	346.87	1055.3	3,991.42	12,189.4	000***	2,572.4	1,046.8	1,827.69	6,700.0	0.23
Sale	141.86	446.3	2,888.18	8,273.0	000***	1,680,44	6,416.3	1,433.65	5,751.1	0.56
R&D Exp	53.2	98.7	369	1,118.9	000***	261.42	961.11	161.98	606.7	0.08*
Absorptive Capacity	23.93	94.3	4.41	35.9	000***	24.35	93.53	0.32	0.52	000***
Firm age	14	10.0	24	24.6	000***	18	21	21	19	0.03**
Employee	656	1860.6	8,388	22,137.8	000***	5,529	19,169	3,605	12,168	0.16
Indirect ties	0.937	0.235	0.769	0.417	000***	0.930	0.246	0.748	0.431	000***
Observations	406		441			474		373		
No of firms	75 (51%)		72 (49%)			85 (57%)		62 (43%)		

[a] This table also illustrates how looking at and driving conclusions about the relationships among variables based on raw sample characteristics might be misleading in the empirical research. This table is based on the static analysis of data with the normality assumption. However, data for several of the variables in this study are not normal and relationships among variables change once I specify regression models based on the correct distribution of data. Results of our regression analysis includes the effect of several independent and control variables on the dependent variable while accounting for endogeneity of variables, unobserved effects over time and associated time effects.

Table 5. Summary Statistics and Correlations for the period 1998- 2004

	Variable	Obs	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Patent	847	64.73	212.0	0	1624	1										
2	HQ location	847	0.48	0..499	0	1	-0.144*	1									
3	R&D-Lab location	847	0.56	0.496	0	1	-0.009	0.775*	1								
4	Centrality	847	7.84	13.47	0	100	0.828*	-0.048	0.118*	1							
5	Centrality X Absorptive capacity	847	32.48	608.1	-4464.68	10456.74	-0.261*	0.096*	0.012	-0.133*	1						
6	Structural holes	847	0.84	0.35	0	1	0.109*	0.239*	0.260*	0.222*	-0.050	1					
7	Structural holes X Absorptive capacity	847	1.73	10.37	-20.51	106.42	-0.088*	-0.001	0.030	-0.076*	0.065	-0.374*	1				
8	Absorptive capacity	847	13.77	70.95	0	697.94	-0.043	0.137*	0.168*	0.034	0.125*	0.070*	0.865*	1			
9	Firm size	847	2.26	1.02	0	5.09	0.566*	-0.200*	0.019	0.598*	-0.168*	0.099*	-0.066	-0.019	1		
10	Firm age	847	19	19.8	1	118	0.575*	-0.266*	-0.07	0.504*	-0.171*	0.020	-0.079*	-0.082*	0.610*	1	
11	Indirect ties	847	0.85	0.35	0	0.99	0.103*	0.238*	0.257*	0.226*	-0.046	0.979*	-0.362*	0.076*	0.094*	0.020*	1

*p<0.05

Table 6. Hypothesis 1: Cluster membership and centrality relationship

Dependent Variable (DV): Centrality
Random Effect Negative Binomial Model

Variables	Model 1:HQ	Model 2: R&D-LAB
Independent Variables		
HQ location	0.309* (0.151)	
R&D-Lab location		0.346* (0.151)
Control Variables		
Absorptive capacity	0.0000894 (0.00033)	0.00007 (0 .0003)
Firm size	0.375*** (0.0732)	0.354*** (0.074)
Firm Age	0.016*** (0.005)	0.015*** (0.005)
Indirect ties	4.197*** (0.489)	4.195*** (0.488)
Time effects	*Yes*	*Yes*
Log Likelihood	-1610.72	-1610.21
Wald Chi2	495.77***	496.05***

Coefficient
(Standard Error)
†p<0.10
*p<0.05
**p<0.01
***p<0.001

Table 7. Hypothesis 2: Cluster membership and structural holes relationship

Dependent Variable (DV): Structural holes
Random Effect Generalized Least Squares (GLS) Model

Variables	Model 1: HQ	Model 2:R&D-LAB
Independent Variables		
HQ location	0.146*** (0.037)	
R&D-Lab location		0.149*** (0.045)
Control Variables		
Absorptive capacity	0.00012† (0.000065)	0.00013** (0.00005)
Firm size	0.0375 (0.0229)	0.031 (0.0223)
Firm Age	0.0018 (0.0012)	0.0006 (0.001)
Indirect ties	*Dropped*	*Dropped*
Time effects	*Yes*	*Yes*
R-Squared	0.67	0.672
Wald Chi2	45.52***	50.10***

†We do not control for the effect of indirect ties in this model because the structural holes measure we use already includes the effect of indirect ties.
Coefficient
(Standard Errors)
†p<0.10
*p<0.05
**p<0.01
***p<0.001

Table 8. Hypothesis 3: Centrality and patent relationship

Dependent Variable (DV): Patent
Fixed Effects Model with Endogenous Regressors with Generalized Method of Moments (GMM) estimation for count DV

	Fixed Effects Model with endogenous regressors with GMM estimation for count DV: Models account for endogeneity		Random Effects Negative Binomial Model: Models do not account for endogeneity	
Variables	Model 1: HQ	Model 2: R&D-LAB	Model 3: HQ	Model 4: R&D-LAB
Endogenous Variables				
Centrality	0.3* (0.138)	0.04* (0.017)	0.007* (0.003)	0.008** (0.003)
Centrality X Absorptive capacity	0.001† (0.0005)	0.0006 (0.006)	-0.00003 (0.00005)	-0.00002 (0.00005)
Independent Variables				
Absorptive capacity	-0.012* (0.004)	-0.009*** (0.002)	0.0003 (0.0005)	0.0004 (0.0005)
Firm size	0.607 (2.89)	1.44* (0.573)	0.138† (0.083)	0.104 (0.084)
Firm age	-0.103 (0.083)	-0.04† (0.024)	-0.004 (0.0043)	-0.007 (0.004)
Indirect ties	0.036 (18)	0.03 (3)	0.310* (0.147)	0.371* (0.149)
GMM Objective Function[a]	0.07	0.03	*NA*	*NA*
HQ			0.574*** (0.153)	
R&D-Lab location				0.087 (0.147)
Log Likelihood			-2858.66	-2865.4217

[a]GMM objective function is calculated by the optimization program in Gauss Software. The closer the function to zero the better the model fit is.
Coefficient
(Standard Errors)
†p<0.10
*p<0.05
**p<0.01
***p<0.001

Table 9. Hypothesis 4: Structural holes and patent relationship

Dependent Variable (DV): Patent
Fixed Effects Model with Endogenous Regressors with Generalized Method of Moments (GMM) Estimation for Count DV

	Fixed Effects Model with endogenous regressors with GMM estimation for count DV: Models account for endogeneity		Random Effects Negative Binomial Model: Model does not account for endogeneity	
Variables	Model 1: HQ	Model 2: R&D-LAB	Model 3: HQ	Model 4: R&D-LAB
Endogenous Variables				
Structural holes	0.163 (3.326)	0.422 (602)	0.352† (0.211)	0.400† (0.216)
Structural holes X Absorptive capacity	0.048** (0.017)	0.009 (45)	-0.0005 (0.011)	-0.002 (0.011)
Control Variables				
Absorptive capacity	-0.02*** (0.002)	-0.002 (6.66)	0.0002 (0.001)	0.0007 (0.001)
Firm size	0.49 (0.616)	-0.517† (0.290)	0.198** (0.080)	0.177* (0.081)
Firm age	0.046† (0.031)	-0.084*** (0.010)	-0.003 (0.004)	-0.006 (0.004)
Indirect ties[a]	*Dropped*	*Dropped*	*Dropped*	*Dropped*
GMM Objective Function[b]	0.06	0.07	*NA*	*NA*
HQ location			0.569*** (0.155)	
R&D-Lab location				0.026 (0.151)
Log Likelihood			-2861.19	-2867.83

[a]We do not control for the effect of indirect ties in this model because the structural holes measure we use already includes the effect of indirect ties. In addition, the structural holes and indirect ties variables are highly correlated.
[b]GMM objective function is calculated by the optimization program in Gauss Software. The closer the function to zero the better the model fit is.
Coefficient
(Standard Errors)
†p<0.10
*p<0.05
**p<0.01
***p<0.001

APPENDIX

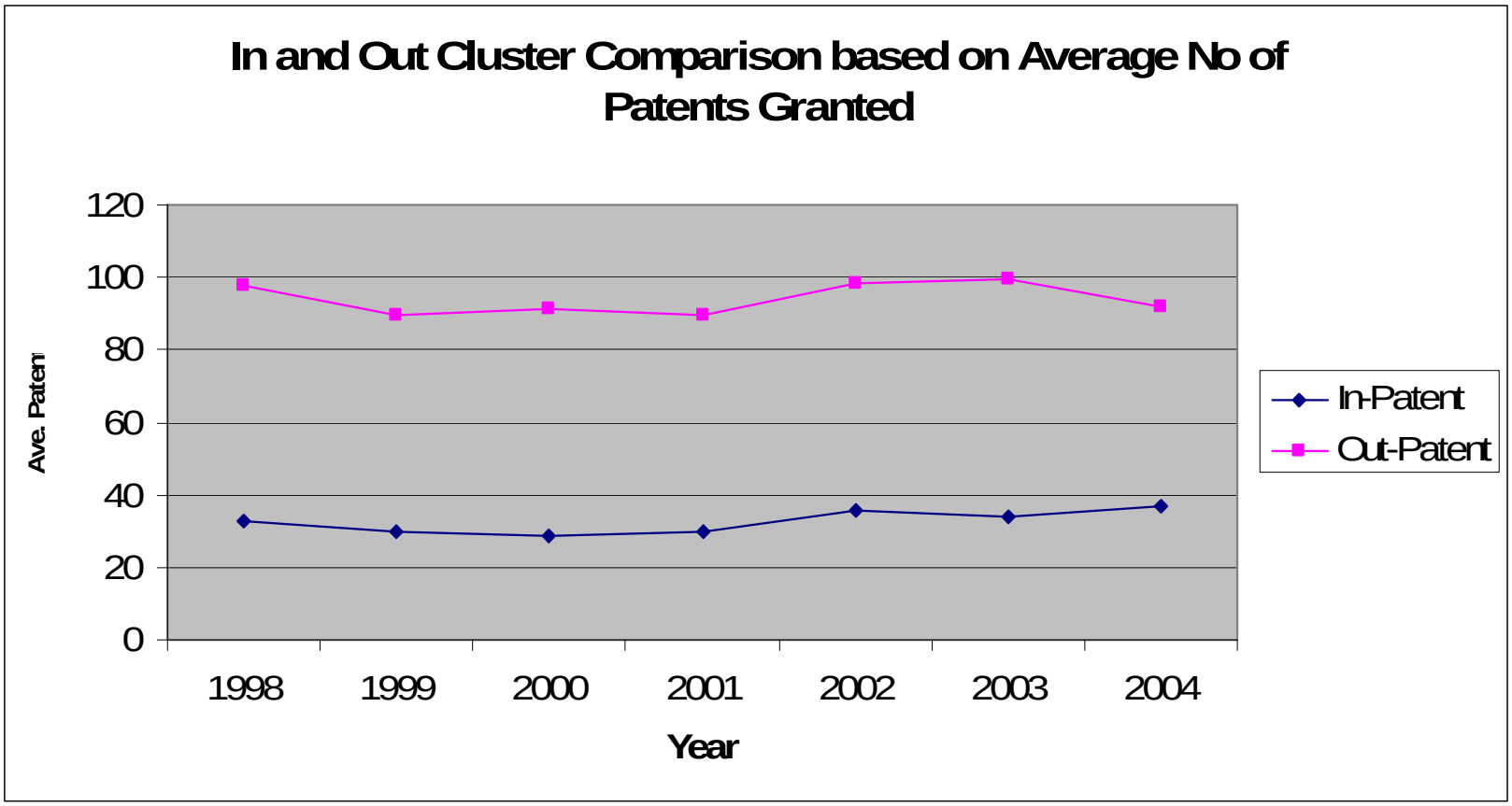
SUPPLEMENTAL ANALYSIS FOR DISSERTATION

Table 10. Sample Distribution based on In and Out Cluster Identification

72	3	**R&D-LAB****							
13	59	**IN**				**OUT**			
HQ	**IN**	Acadia	Collagenex	Icagen	Northwest	Boston life sci			**75**
		Acsuphere	Connetics	ICOS	Pain therap	Endo pharma			
		Adolor	Corcept	IMCOR Immunicon	Pharmacyslics	Introgen			
		Advancis	Corgentech	ImmuniGen	Pozen				
		Aeolus	Cortex	Indevus	Praecis				
		Alkermes	Critical therapeutic	InSite	Questcor				
		Allergen*	Cubist	Inspire	regeneRX				
		Amylin	Cytokinetics	InterMune	Renovis				
		Arena	Dendreon	Intrabiotics	Salix				
		ArQule	Depomed	ISIS pharma	Select				
		Auxilium	Durect	ISTA pharma	Spectrum				
		Avanir	Dusa pharna	Ligand	superGen				
		Biomarin	Dynavax	MacroChem	united therapeutics				
		Cardiotech	Edwrds life sci	MannKind	Valeant*				
		Cell genesys	Ergo sci	Maxim	Vertex				
		Cell therapeutics	Genentech*	Metabasis	ViroPharma				
		Cephalon*	GenVec	NAstech	Vyrex				
		Chiron*	Geron	Nektar Therapeutics					
	OUT	Abbott*				Aastrom	Cortech	Memory pharma	**72**
		Alexion				Access	Derma sciences	Merck inc*	
		Eyetch				Advanced V.R.	DOR biopharma	Miravant	
		Johnosn & Johnson*				Akorn Inc	DOV Pharma	Mylan*	
		Kos pharma				Allos Therap	Emisphere Tech	Neurogen	
		MGI pharma				Alpharma*	eXegenics	New river pharma	
		Myriad				Alteon	Fist horizon	Nexmed	
		Pfizer*				Amarillo	Forest labs*	Noven	
		Schering Plough*				Americam Pharma	Inhibitex	Oxis	
		Sentigen				Array biopharma	Insmed	Par pharma	
		Sirna				Avi biopharma	Interpharm	Penwest	
		Tanox				Axonyx	IOMED	Perrigo	
		Wyeth*				Bentley	Ivax*	PML	
						Biodelivery	Keryx	Progenics	
						Biosante	King*	Regeneron	
						Bradley	Large Scale biology	SIGA	
						Bristol-MS	Eli Lilly*	Theragenics	
						Carrington	Manhattan pharma	Vribac	
						Chattem	Medicis pahrma*	Watson*	
						Columbia labs		Zila	
		85				**62**			**147**

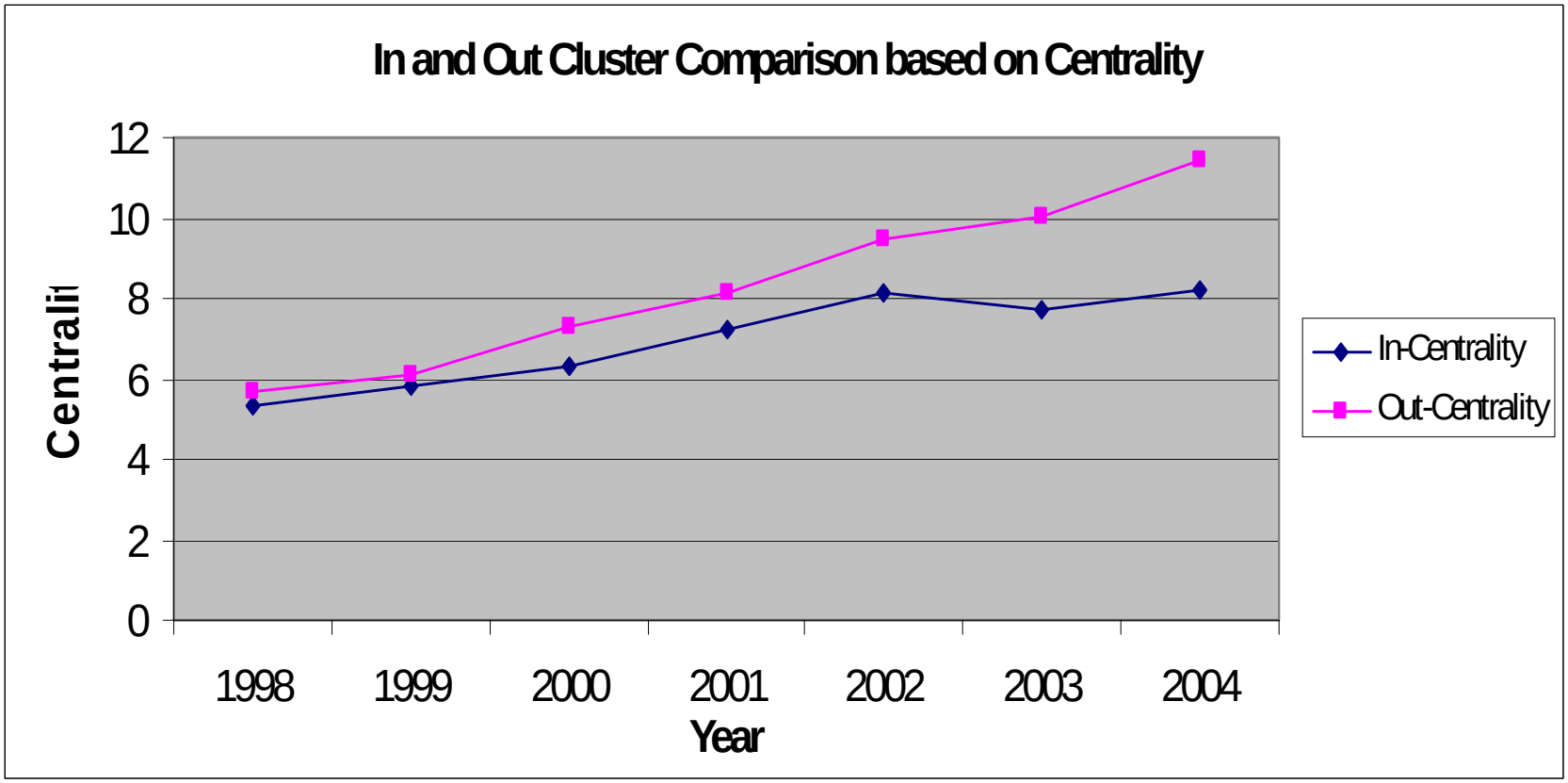
* Established Firms: Assets over 1Billion; **83% of firms have R&D facility at HQ location

Figure 5. Descriptive Data Analysis- Average Patents per year



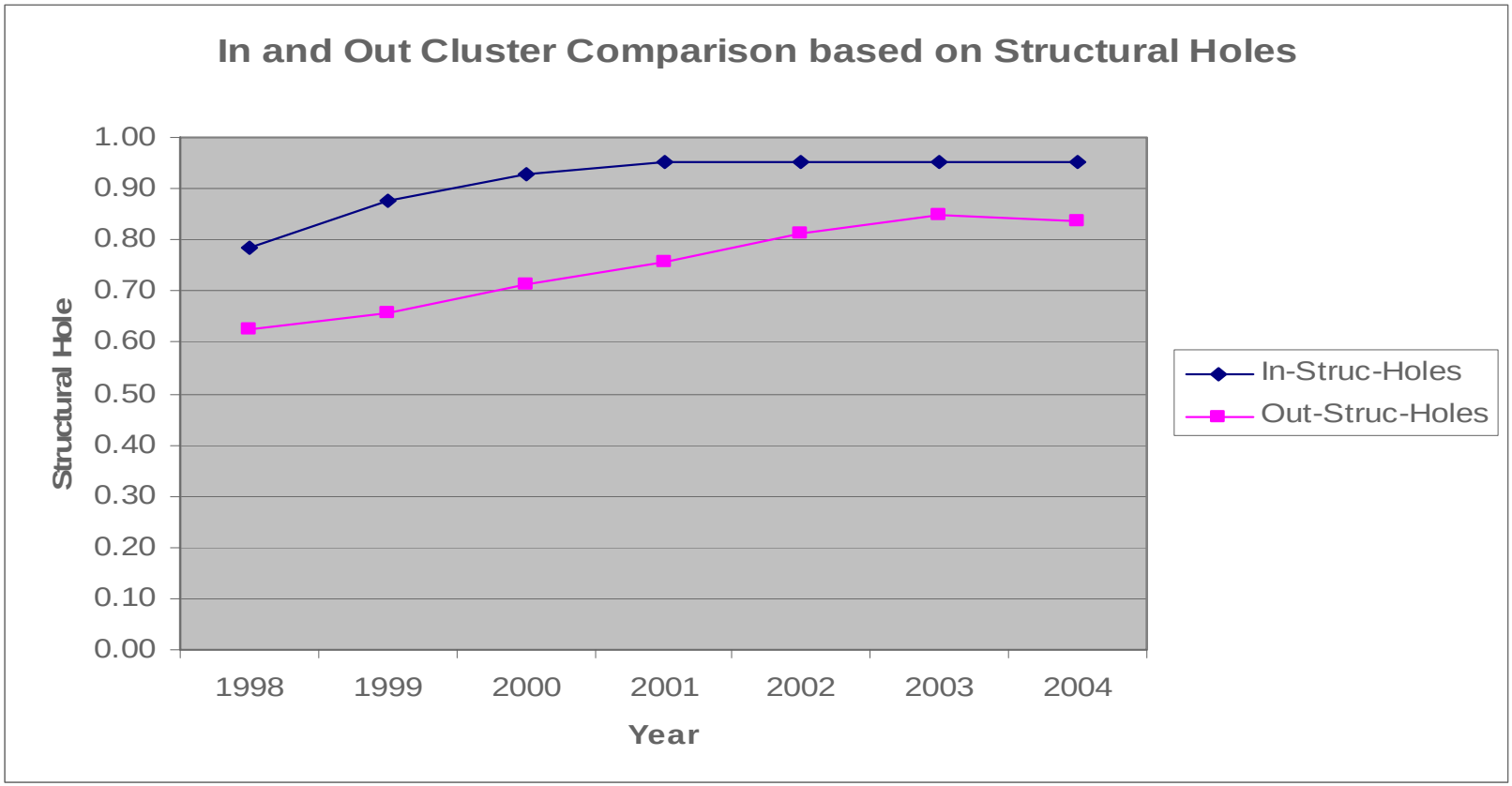
In-Patent: Average no of patents granted for in- cluster firms
Out-Patent: Average no of patents granted for out- cluster firms
Patent is measured by the count of number of patents granted for each firm

Figure 6. Descriptive Data Analysis- Average Centrality per year



In-Centrality: Average centrality of in- cluster firms
Out-Centrality: Average centrality of out- cluster firms
Centrality is measured by the count of number of alliances for each firm

Figure 7. Descriptive Data Analysis- Average Structural Holes per year[b]



In-Struc-Holes: Average structural holes for in-cluster firms
Out-Struc-Holes: Average structural holes for in-cluster firms
Structural holes is measured by the efficiency index which is calculated by UCINET 6

[b]Important Note: Figures 5, 6, and 7 are merely the descriptive representations of average data for patents, centrality, and structural holes respectively. Averages are calculated based on 147 firms' data. For example, average structural holes in 1998 represent the average structural holes of 147 firms in the sample, in 1998. These figures do not represent the hypothesized relationships that are identified in my study. Also, please see footnote of Table 4.

Biopharmaceutical clusters in the US based on the Milken Institute study (2004)

In this study I use the cluster identification of the Milken Institute, America's Biotech and Life Science Clusters, 2004 study.

Milken study defines clusters as *"geographic concentrations of sometimes competing, sometimes collaborating firms, and their related supplier network. A cluster represents an entire value chain of a broadly defined industry sector from suppliers to end products, including its related suppliers and specialized infrastructure."* (Milken Institute America's Biotech and Life Sciences Clusters, pg. 1).

Milken Institute identifes 12 biopharmaceutical clusters based on the specialization and concentration of biopharmaceutical industry in the United States. The identification of clusters is based on Metropolitan Statistical Areas (MSAs). MSA is defined as "*An area containing a recognized population nucleus and adjacent communities that have a high degree of integration with that nucleus*" (Office of Management and Budget, 2000). MSAs are used widely to define the industry boundaries. For example in a recent study Miller and Eden used MSAs (2006) in order to define local density of commercial banks in a geographic area.

The Milken study also compares the relative strength of these top 12 clusters including each MSA's research and development (R&D) dollar per capita, NSF research funding to Biotech, NIH funding to metro cities, NIH funding to institutes, NIH funding to research universities, Biotech R&D assets, Biotech VC investment growth, number of

biotech firms receiving VC. Biotech patents issued biotech patent citations, business starts, biotech graduate students, Biotech PhDs awarded, bachelor degrees granted in biotech field, number of PhD granting institutions, biotech scientist, biomedical engineers, intensity of medical scientists, biomedical location quotient, biomedical employment size, gross metro product (GMP), and employment (for a detailed report please see Milken Institute America's Biotech and Life Sciences Clusters, 2004). Based on these criteria, the following table (Table 11) provides the ranking of Biopharmaceutical clusters in the US.

Table 11. Biopharmaceutical Cluster in the US

MSA	Rank	Composite Score
San Diego	1	100
Boston	2	95.1
Raleigh-Durham-Chapel Hill	3	92.5
San Jose	4	87.8
Seattle-Bellevue-Everett	5	83.8
Washington, DC	6	79.4
Philadelphia	7	76.5
San Francisco	8	75.8
Oakland	9	74.3
Los Angeles- Long Beach	10	66.5
Orange County	11	54.1
Austin-San Marcos	12	47.8

Source: America's Biotech and Life Sciences Cluster, Milken Institute, 2004

Cluster membership and firm characteristics

In general, I find that older firms are more likely to be located outside of clusters. This finding is consistent with the intuition that larger firms have necessary resources in place that they might not need cluster benefits. For example, Eli Lilly is located outside of a cluster area but due to its size and financial resources Lilly can attract alliance partners even if it is not located in a cluster area. Findings also show that R&D intensity is positively related with the probability of biopharmaceutical firms' location in a cluster area. This is natural given that biopharmaceutical clusters are research intensive areas and firms that are research intensive are more likely to be located in these clusters.

Specifically, I analyzed the effect of following firm attribute variables:

- age
- size
- financial condition, e.g. sales, asset.
- R&D intensity

In the analysis, first, I ran a full logit model which estimates the probability of cluster membership based on firm characteristics. Since the correlation between sales and assets are high (0.93), I also estimated the model by excluding first the 'sales' variable and then excluding the 'asset' variable, results did not change in any models. In all models firm age and absorptive capacity are significant. Second, I also conducted post-estimation in STATA and provide the outcome of this post-estimation analysis in graphical format.

Table 12. Correlation Table for Firm Attributes

	Asset	Sale	Firm size	Firm age	Absorptive Capacity
Asset	1	.9327*	.5809*	.6458*	-0.048
Sale		1	.6113*	.7146*	-0.047
Firm size			1	.6106*	-0.019
Firm age				1	-0.082
Absorptive Capacity					1

*p< .05

Table 13. The relationship between Firm Characteristics and Cluster Membership

Random-effects logistic regression

Variables	**HQ Model**	**R&D-LAB Model**
Assets	0.0008 (0.0005)	0.00016 (0.00011)
Sales	-0.0022 (0.0014)	-0.000036 (0.00012)
Firm age	-0.076* (0.270)	-0.061*** (0.023)
Firm size	-0.090 (0.374)	0.262 (0.400)
Absorptive capacity	0.008* (0.004)	0.495* (0.263)
Time Effects	Yes	Yes
Log Likelihood	-190.60	-192.41
Wald Chi2	21.46**	10.99**
No of Observations	847	847
No of Firms	147	147

Interpretation of Logit coefficients in the table

According to Wooldridge (Introductory Econometrics, 2003, pg. 561) we can get a rough equivalent of a linear probability model coefficient if we multiply the logit coefficient with 0.25 (or divide by 4). In this way we make the logit coefficients comparable to linear probability model coefficients for easy interpretation. In the linear probability model the coefficient of the independent variable indicates the percentage point change in the probability that dependent variable is equal to 1 caused by a one-unit increase in the independent variable (Studenmund, Using Econometrics, pg. 448, 2006).

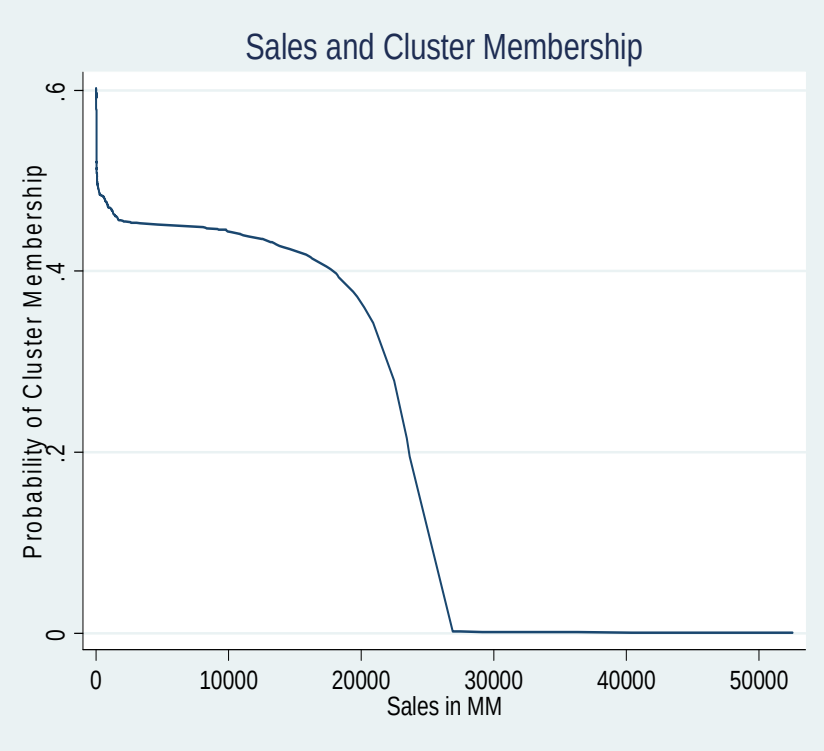
For example: logit coefficient of absorptive capacity = 0.008

LPM coefficient of absorptive capacity = (0.008*0.25) = 0.002

Interpretation: if we increase absorptive capacity by one unit the probability that the firm is a cluster member will increase by 0.2 %.

Figure 8. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-Lab location)
1a. Firm Sales and cluster membership: In the full model this relationship is *not significant*.	**1a**. Firm Sales and cluster membership: In the full model this relationship is *not significant*.



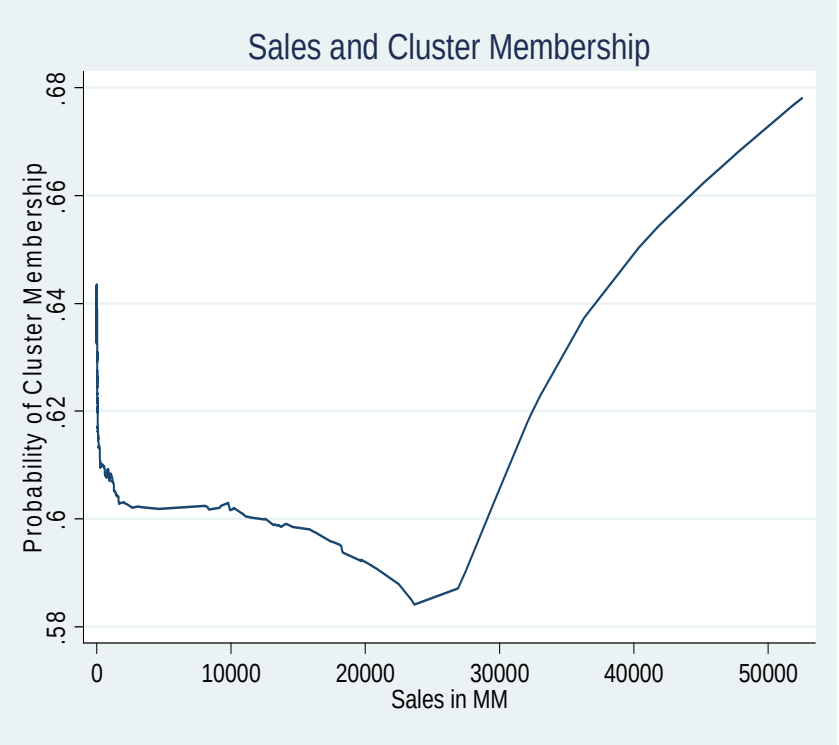
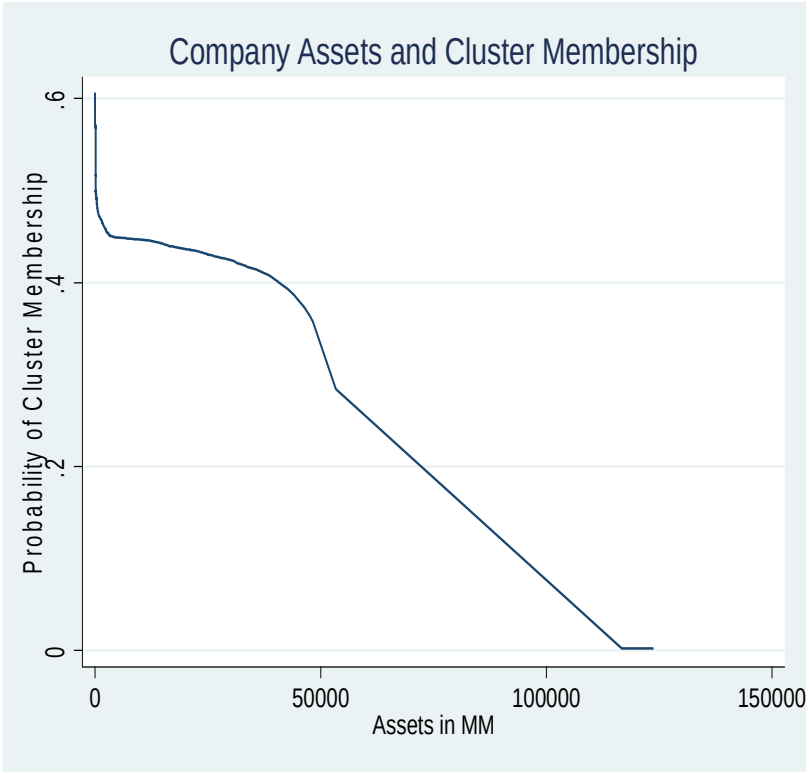


Figure 9. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-LAB location)
1b. Firm Assets and cluster membership: In the full model this relationship is *not significant*.	**1b.** Firm Assets and cluster membership: In the full model this relationship is *not significant*.



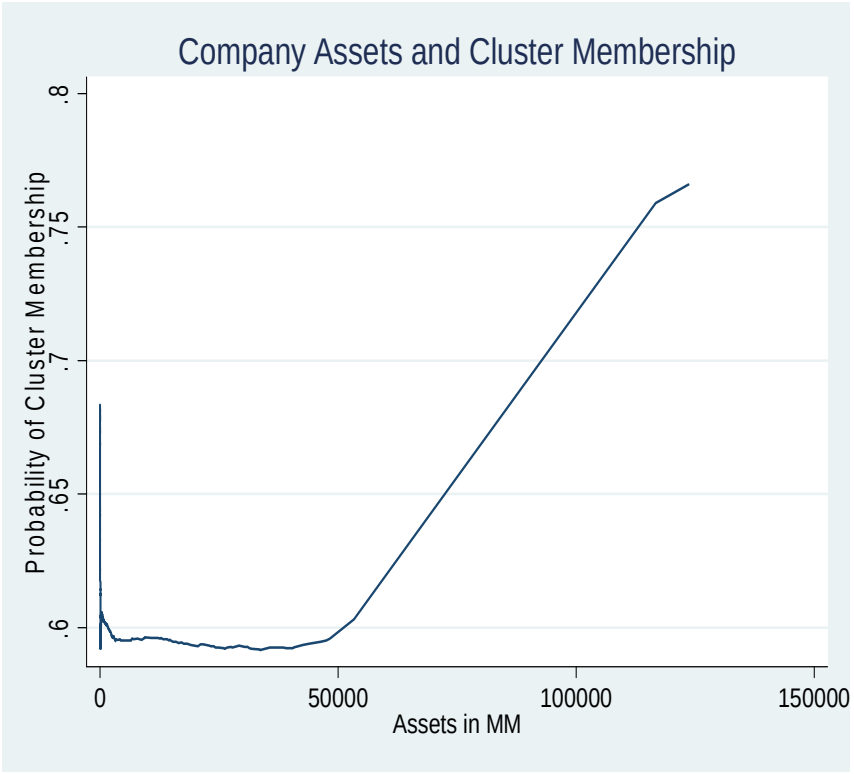


Figure 10. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-Lab location)
1c. Firm age (measured in years passed since founding) and cluster membership: In the full model this relationship is *significant*.	1c. Firm age (measured in years passed since founding) and cluster membership: In the full model this relationship is *significant*.

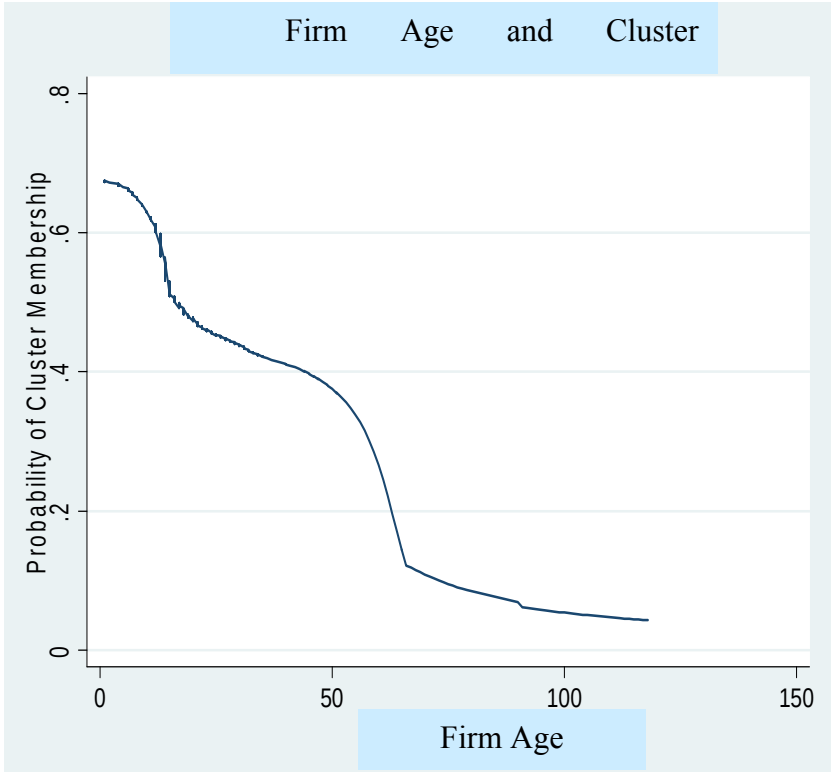
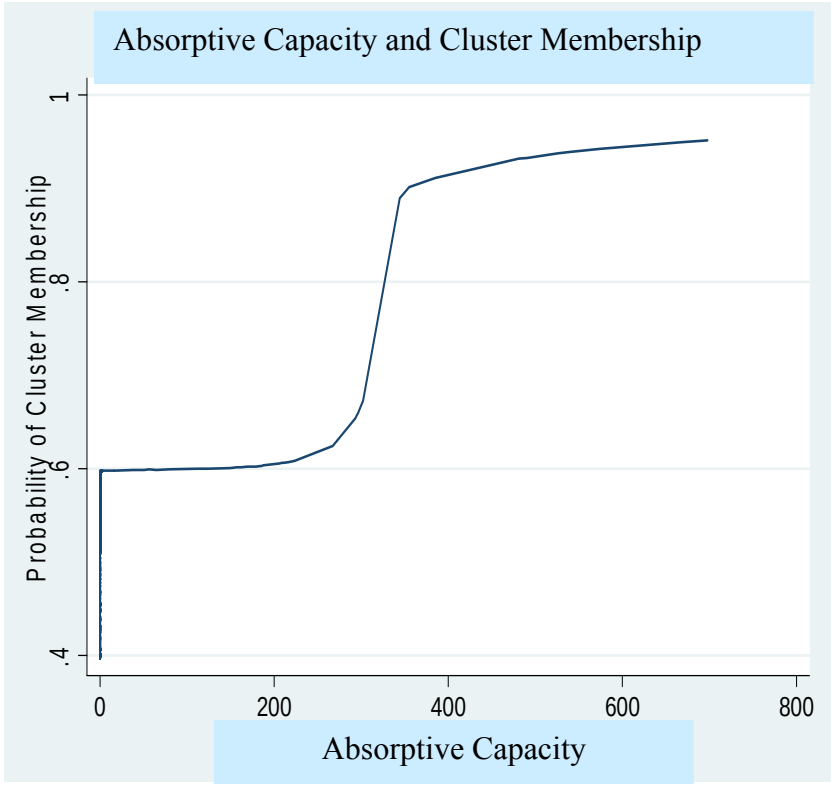


Figure 11. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-LAB location)
1d. Absorptive capacity (measured in R&D exp/Asset) and cluster membership: In the full model this relationship is *significant*.	1d. Absorptive capacity (measured in R&D exp/Asset) and cluster membership: In the full model this relationship is *significant*.



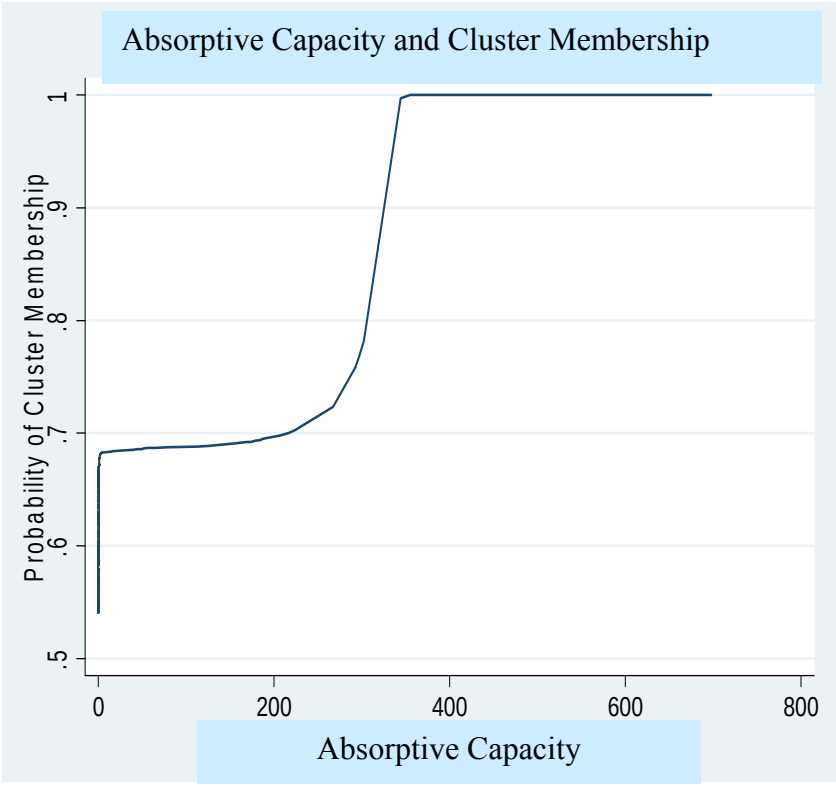
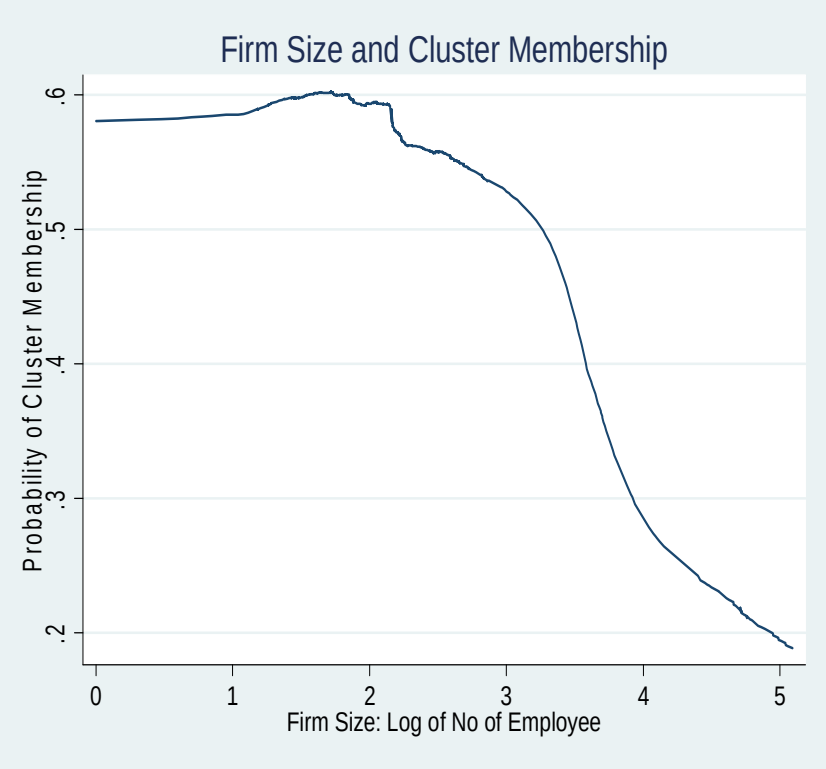


Figure 12. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-LAB location)
1e. Firm Size (measured in Log of Employee No) and cluster membership: In the full model this relationship is *not significant*.	1e. Firm Size (measured in Log of Employee No) and cluster membership: In the full model this relationship is *not significant*.



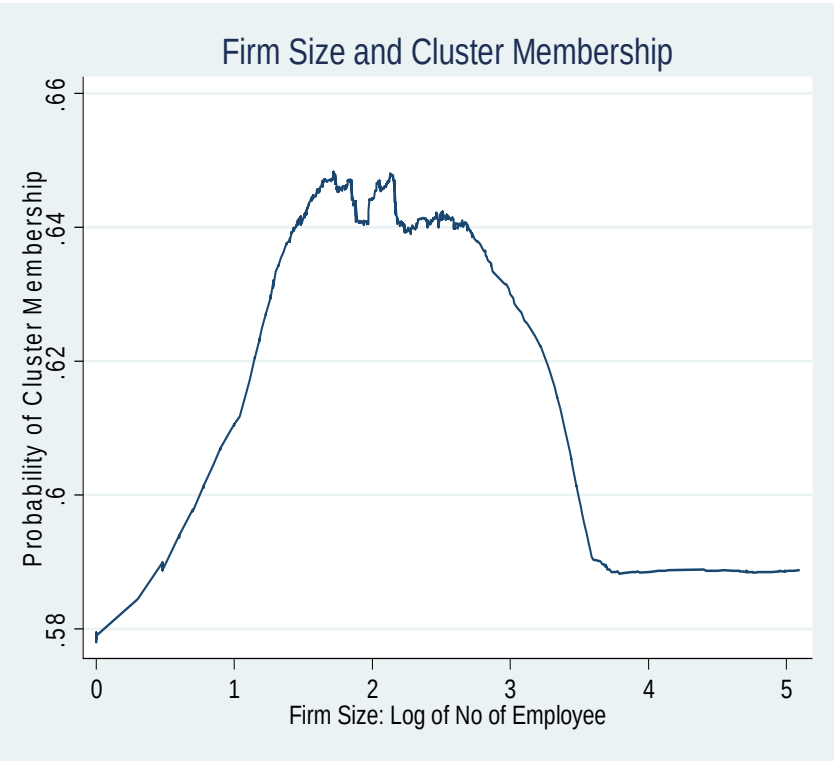
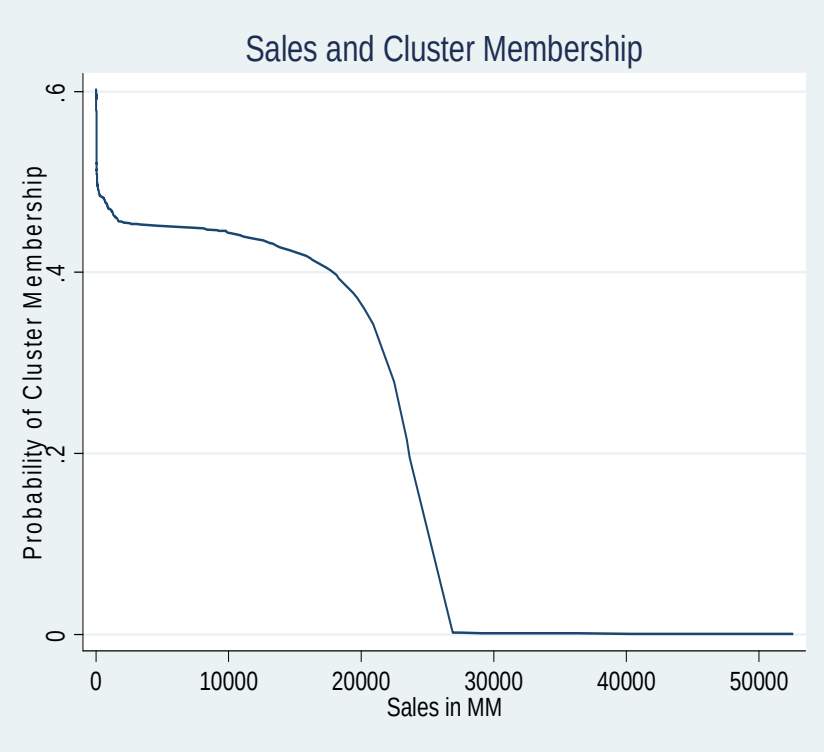


Figure 13. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-Lab location)
1a. Firm Sales and cluster membership: In the full model this relationship is *not significant*.	**1a**. Firm Sales and cluster membership: In the full model this relationship is *not significant*.



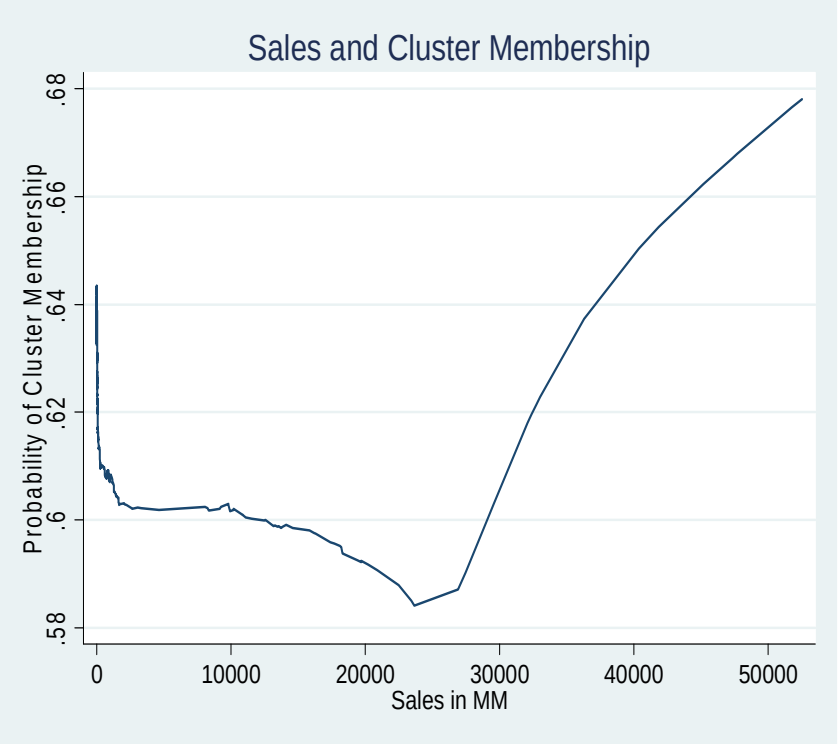
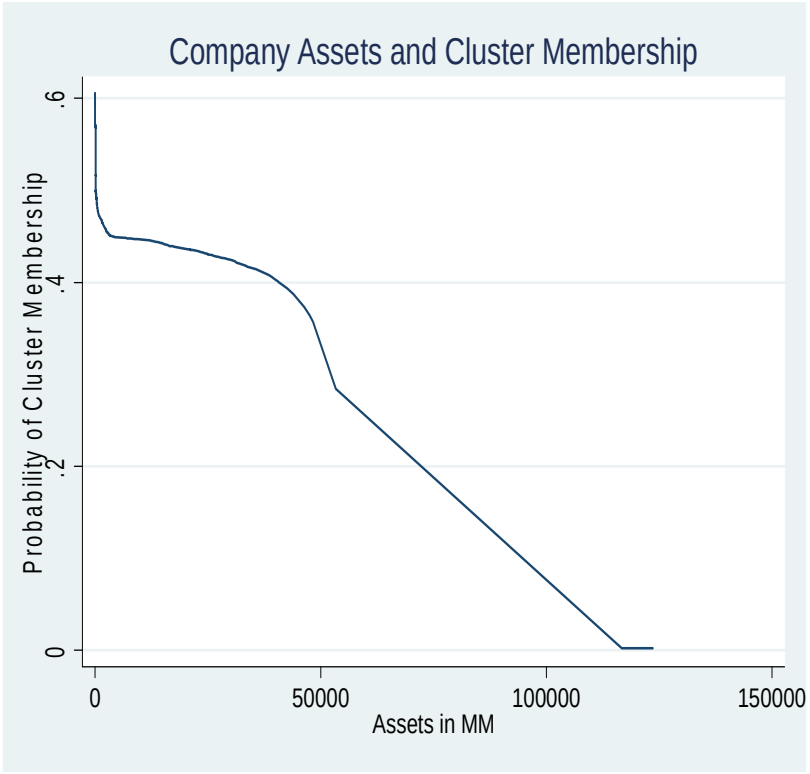


Figure 14. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-LAB location)
1b. Firm Assets and cluster membership: In the full model this relationship is *not significant*.	**1b.** Firm Assets and cluster membership: In the full model this relationship is *not significant*.



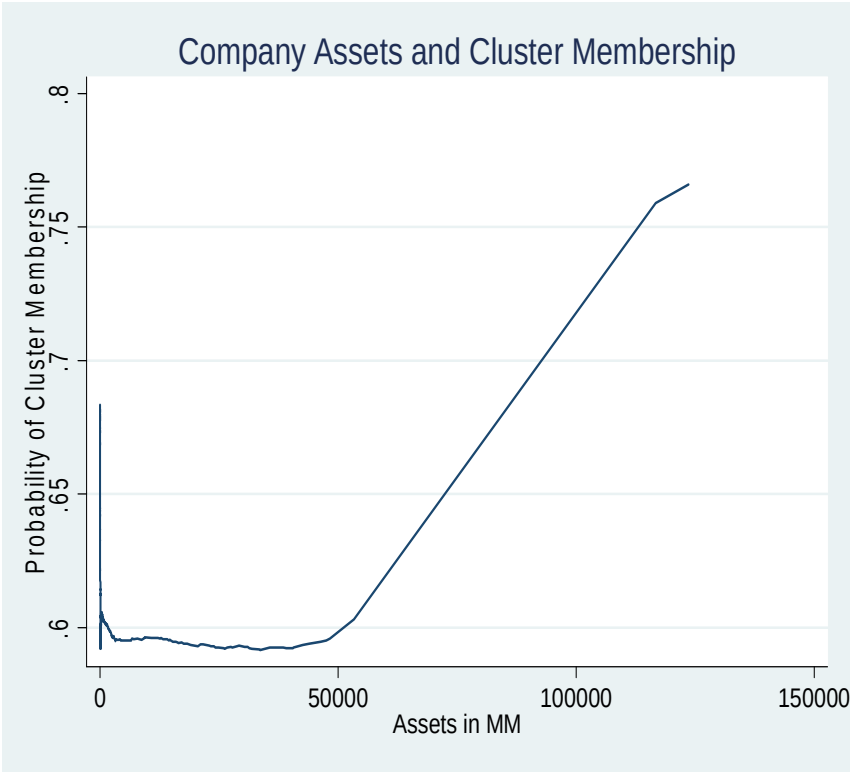
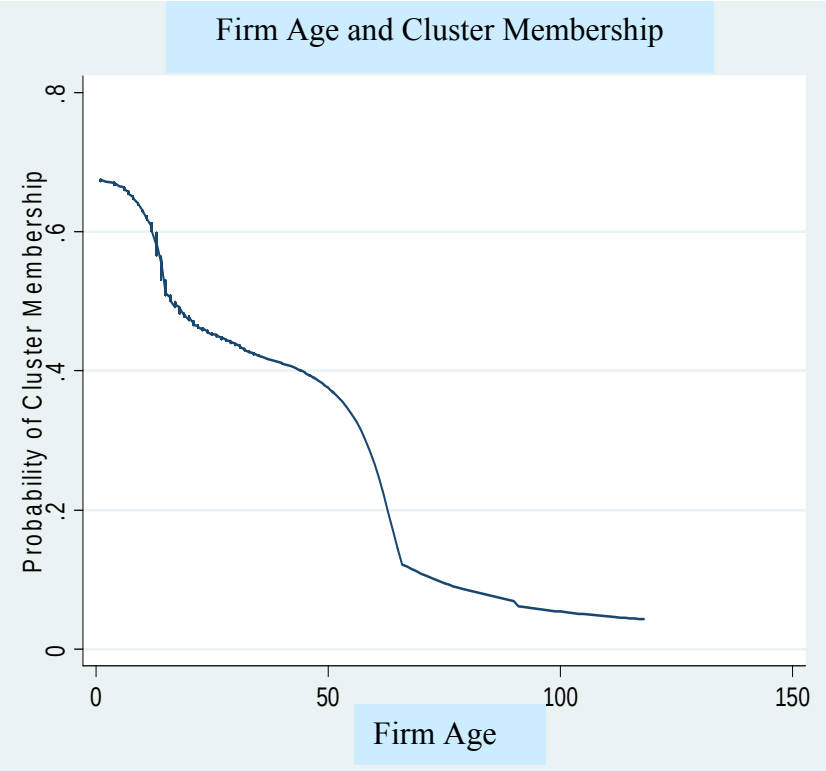


Figure 15. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-Lab location)
1c. Firm age (measured in years passed since founding) and cluster membership: In the full model this relationship is *significant*.	1c. Firm age (measured in years passed since founding) and cluster membership: In the full model this relationship is *significant*.



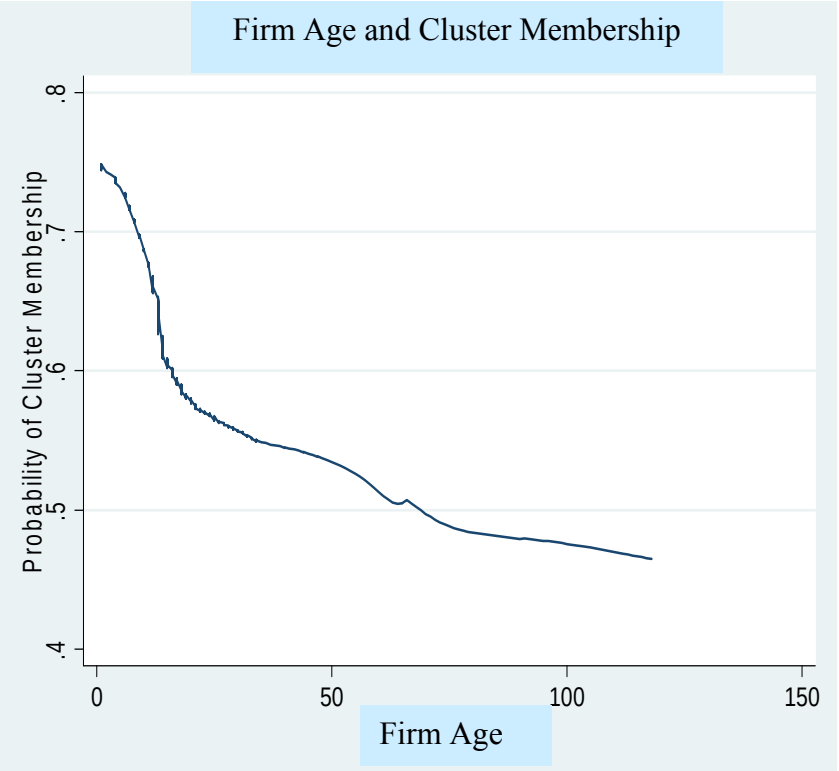
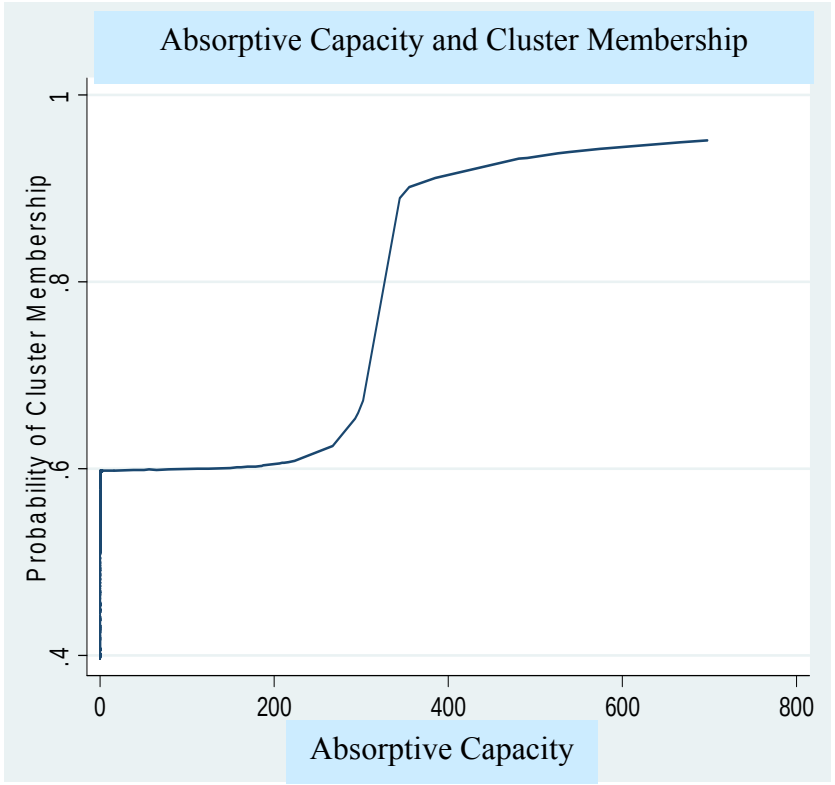


Figure 16. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-LAB location)
1d. Absorptive capacity (measured in R&D exp/Asset) and cluster membership: In the full model this relationship is *significant*.	1d. Absorptive capacity (measured in R&D exp/Asset) and cluster membership: In the full model this relationship is *significant*.



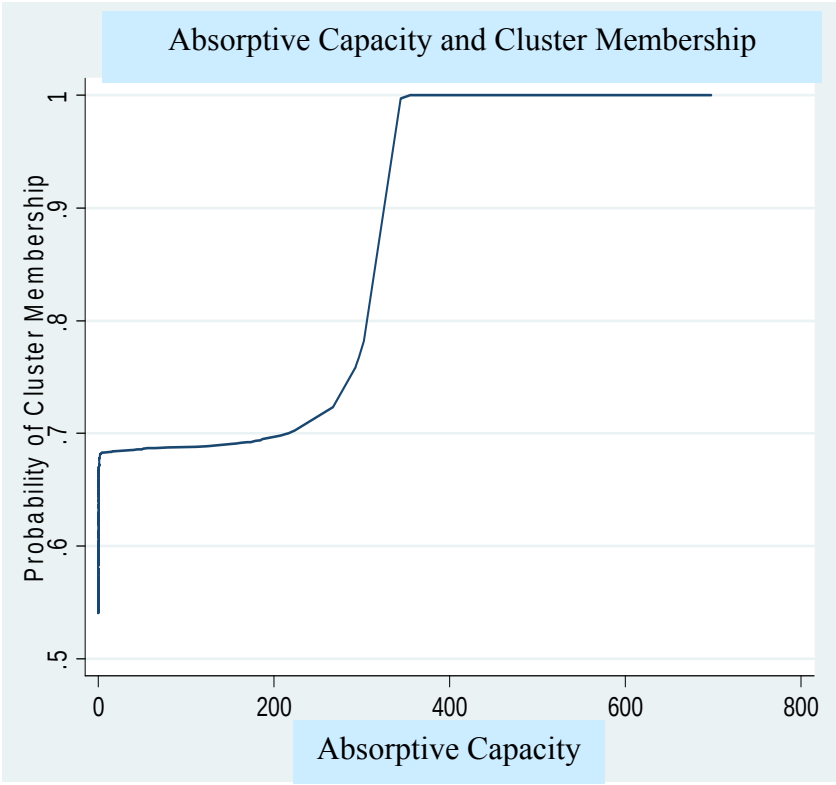
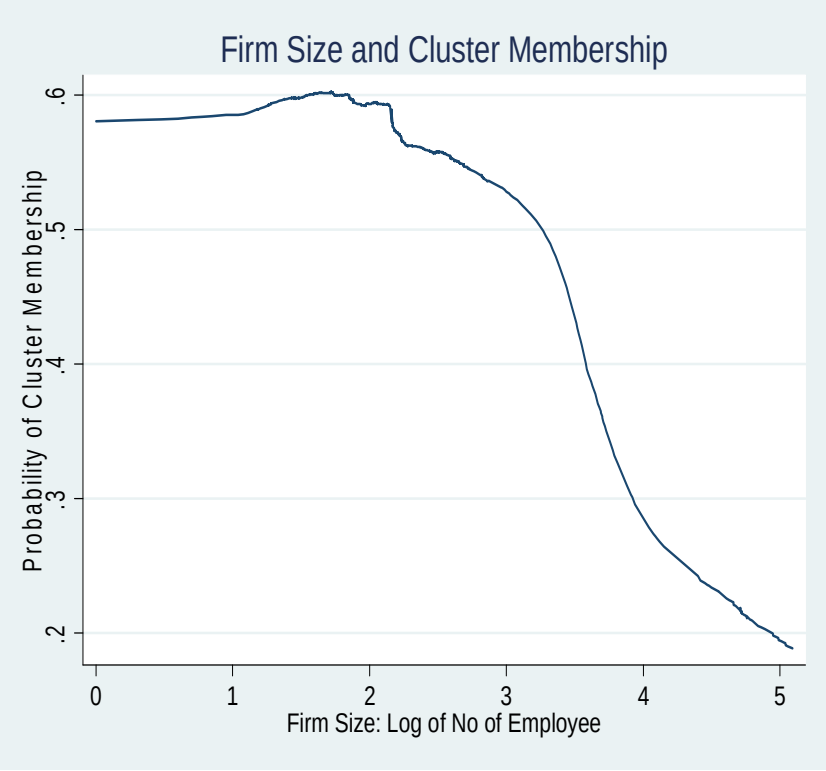
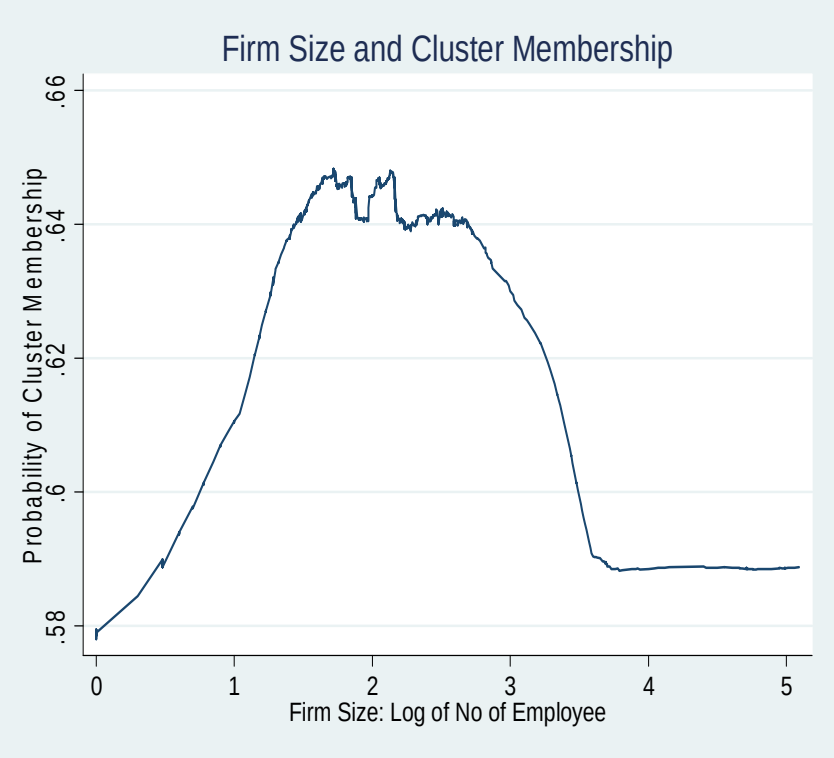


Figure 17. Graphical Analysis of Firm Characteristics and Cluster Membership

Effect of each independent variable on Cluster Membership (measured by HQ location)	Effect of each independent variable on Cluster Membership (measured by R&D-LAB location)
1e. Firm Size (measured in Log of Employee No) and cluster membership: In the full model this relationship is *not significant*.	1e. Firm Size (measured in Log of Employee No) and cluster membership: In the full model this relationship is *not significant*.





Test for the endogeneity of network structure variables

According to the STATA website, Davidson and MacKinnon (1993) suggest an augmented regression test (Durbin-Wu-Hausman test) to test for endogeneity of variables. This regression includes the residuals of each endogenous right-hand side variable (in our model centrality and structural holes), as a function of all exogenous variables (in our model headquarter location-or HQ), in a regression of the original model.

- **Test for the endogeneity of centrality variable**

Thus I have the following simultaneous models:

centrality = a0 + a1*HQ + epsilon1
patent = b0 + b1*centrality + epsilon2

centrality = c0 + c1*HQ + epsilon3
calculate residuals centrality_res, then perform an augmented regression:

patent = d0 + d1*centrality + d2*centrality_res + epsilon4

If d2 is significantly different from zero, then OLS is not consistent.

STATA Code for the Test of Endogeneity of centrality

. xtreg centrality HQ

. predict centrality_res, ue **** ue is the combined residual usubi + esubit****

. xtreg patent centrality centrality_res

. test centrality_res

I also ran these cross sectional models for each year. The results did not change.

STATA Program Results

```
. xtreg centrality hq

Random-effects GLS regression                   Number of obs      =       847
Group variable (i): coid                        Number of groups   =       147

R-sq:  within  = 0.0000                         Obs per group: min =         2
       between = 0.0034                                        avg =       5.8
       overall = 0.0024                                        max =         7

Random effects u_i ~ Gaussian                   Wald chi2(1)       =      0.50
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.4817

------------------------------------------------------------------------------
  centrality |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          hq |   -1.384815   1.968069    -0.70   0.482    -5.24216     2.47253
       _cons |    7.831387   1.403504     5.58   0.000     5.08057     10.5822
-------------+----------------------------------------------------------------
     sigma_u |   11.750155
     sigma_e |   4.4092397
         rho |   .87656848   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. predict centrality_re, ue
```

```
. xtreg patent centrality  centrality_re

Random-effects GLS regression                   Number of obs      =       847
Group variable (i): coid                        Number of groups   =       147

R-sq:  within  = 0.0273                         Obs per group: min =         2
       between = 0.7365                                        avg =       5.8
       overall = 0.6789                                        max =         7

Random effects u_i ~ Gaussian                   Wald chi2(2)       =    214.94
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
     patent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
  centrality |    39.85584   12.30063     3.24   0.001     15.74705    63.96462
centrality~e |  -34.01749   12.30735    -2.76   0.006    -58.13945   -9.895523
       _cons |    -228.298   88.11478    -2.59   0.010    -400.9998   -55.59618
------------+-----------------------------------------------------------------
     sigma_u |   88.046837
     sigma_e |    51.234073
         rho |    .74704772   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. test  centrality_re

 ( 1)  centrality_re = 0

       chi2(  1) =    7.64
     Prob > chi2 =    0.0057
```

The small p-value indicates that OLS is not consistent, and centrality is an endogenous variable.

- **Test for Endogeneity of Structural holes variable**

```
. xtreg  Structural holes hq

Random-effects GLS regression                   Number of obs      =       847
Group variable (i): coid                        Number of groups   =       147

R-sq:  within  = 0.0000                         Obs per group: min =         2
       between = 0.0863                                        avg =       5.8
       overall = 0.0573                                        max =         7

Random effects u_i ~ Gaussian                   Wald chi2(1)       =     13.56
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0002

------------------------------------------------------------------------------
 Structural holes |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
              hq |   .1733476   .0470774     3.68   0.000     .0810777    .2656176
           _cons |   .7508496   .0334412    22.45   0.000     .685306     .8163931
------------------+-----------------------------------------------------------------
         sigma_u |  .27017211
         sigma_e |  .20309475
             rho |  .63894158   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. predict structural holes_re, ue
```

```
. xtreg  patent  Structural holes  Structural holes_re

Random-effects GLS regression                   Number of obs      =       847
Group variable (i): coid                        Number of groups   =       147

R-sq:  within  = 0.0003                         Obs per group: min =         2
       between = 0.0248                                        avg =       5.8
       overall = 0.0248                                        max =         7

Random effects u_i ~ Gaussian                   Wald chi2(2)       =      3.83
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.1477

------------------------------------------------------------------------------
     patent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+----------------------------------------------------------------
  Structural holes |  -315.8318   177.2812    -1.78   0.075    -663.2966    31.63289
Structural holes~e |   323.5334   177.5402     1.82   0.068    -24.43901    671.5058
      _cons |   320.4572   149.5528     2.14   0.032     27.33914    613.5753
------------+----------------------------------------------------------------
    sigma_u |  184.35748
    sigma_e |  51.939674
        rho |   .92646314   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. test  Structural holes_re

 ( 1)  Structural holes_re = 0

           chi2(  1)      =    3.32
         Prob > chi2  =    0.0684
```

The small *p*-value indicates that OLS is not consistent, and structural holes is an endogenous variable.

Reference:
http://www.stata.com/support/faqs/stat/endogeneity.html
Davidson, R. and J. G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.

A comparison of this study with a previous study

Table 14. Comparison of this study with a prior study by Ahuja (2000)

Study	Centrality	Structural holes	Model
Ahuja (2000)	0.040***	-0.284***	Poisson No account for endogeneity
This Study	0.3**	0.163	Exponential model with GMM estimation Accounts for endogeneity
Interpretation	1 unit change in centrality is associated with 100xβcentrality% increase in patents		

The above table shows the difference between two studies. In my study both centrality and structural holes variables are treated as endogenous variables. In Ahuja (2000) study centrality and structural holes variables are treated as exogenous variables. As it is also seen from the table treating network structure variables as endogenous variables changes the direction and magnitude of coefficients of these variables in the network structure and innovation model. We should note, however, that this is a rough comparison and other factors such as industry differences that might affect this relationship have not been taken into account. For example, my study includes biopharmaceutical industry while Ahuja's study includes chemical industry.

Table 15. Determinants of R&D Intensity in the Biopharmaceutical Industry

Determinants	Literature Review	Study
Drug Prices	Drug prices have significant positive effect on firms' R&D spending in the pharmaceutical industry due to demand and cash flow effects.	Giacotto,C; Santerre, E.R.; and Vernon, J. V. ,2005
Expected returns and cash flows	Expected returns and cash flow are important determinants of firm research intensities for a pooled sample of 11 major U.S. drug firms over the period 1974 to 1994.	Grabowski, H.G., and Vernon, J.M. , 2000
Size	While the relationship between firm size and R&D spending has been studied the literature a consensus has not been developed.	Kim, J., Lee, S., Marschke, 2004, Relation of Firm Size to R&D Productivity, working paper.
	According to some researchers R&D spending (measured as patent numbers) decreases with firm size while others argue that there is no such effect.	Acs and Audretsch, 1991; Bound et al, 1984; and Hausman et al, 1984)
	There is no relationship between R&D expenditure (measured by the number of patents produced per inventor) and firm size in the pharmaceutical industry.	Lee et. all (2004)

Determinants of R&D intensity in the biopharmaceutical industry

- **Company Age and R&D Intensity Relationship**

Analysis and Results

Generalized Least Squares Model with unbalanced Panel Data, Time effects included

Prais-Winsten regression, correlated panels corrected standard errors (PCSEs)

Group variable: coid	Number of obs = 847
Time variable: panelyr	Number of groups = 147
Panels: correlated (unbalanced)	Obs per group: min = 2
Autocorrelation: panel-specific AR(1)	avg = 5.761905
Sigma computed by pairwise selection	max = 7
Estimated covariances = 10878	R-squared = 0.0725
Estimated autocorrelations = 147	Wald chi2(7) = 34.00
Estimated coefficients = 8	Prob > chi2 = 0.0000

rdasset	Coef.	Panel-corrected Std. Err.	z	P>|z|	[95% Conf.	Interval]
coage	-1.204017	.2501161	-4.81	0.000	-1.694236	-.7137988
yr99	5.672863	6.686047	0.85	0.396	-7.431547	18.77727
yr00	-5.028853	8.62363	-0.58	0.560	-21.93086	11.87315
yr01	-.6346234	9.529091	-0.07	0.947	-19.3113	18.04205
yr02	4.538502	9.915903	0.46	0.647	-14.89631	23.97332
yr03	4.177401	9.629551	0.43	0.664	-14.69617	23.05097
yr04	3.566291	9.18051	0.39	0.698	-14.42718	21.55976
_cons	74.08824	15.58379	4.75	0.000	43.54457	104.6319

- **Company Size (in sales) and R&D Intensity Relationship**

Prais-Winsten regression, correlated panels corrected standard errors (PCSEs)

Group variable: coid	Number of obs = 847
Time variable: panelyr	Number of groups = 147
Panels: correlated (unbalanced)	Obs per group: min = 2
Autocorrelation: panel-specific AR(1)	avg = 5.761905
Sigma computed by pairwise selection	max = 7
Estimated covariances = 10878	R-squared = 0.0626
Estimated autocorrelations = 147	Wald chi2(7) = 29.09
Estimated coefficients = 8	Prob > chi2 = 0.0001

rdasset	Panel-corrected Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sale	-.0017178	.0004608	-3.73	0.000	-.002621	-.0008147
yr99	4.418202	6.783807	0.65	0.515	-8.877816	17.71422
yr00	-6.819232	8.909434	-0.77	0.444	-24.2814	10.64294
yr01	-3.430413	10.02272	-0.34	0.732	-23.07458	16.21376
yr02	.7167241	10.59516	0.07	0.946	-20.0494	21.48285
yr03	-.5909473	10.55316	-0.06	0.955	-21.27476	20.09286
yr04	-2.052498	10.3414	-0.20	0.843	-22.32126	18.21627
_cons	55.77701	12.97459	4.30	0.000	30.34727	81.20674

Figure 18. Determinants of R&D Intensity in the Biopharmaceutical Industry Based on the Study Sample

Generalized Least Squares Model with unbalanced Panel Data, Time effects included

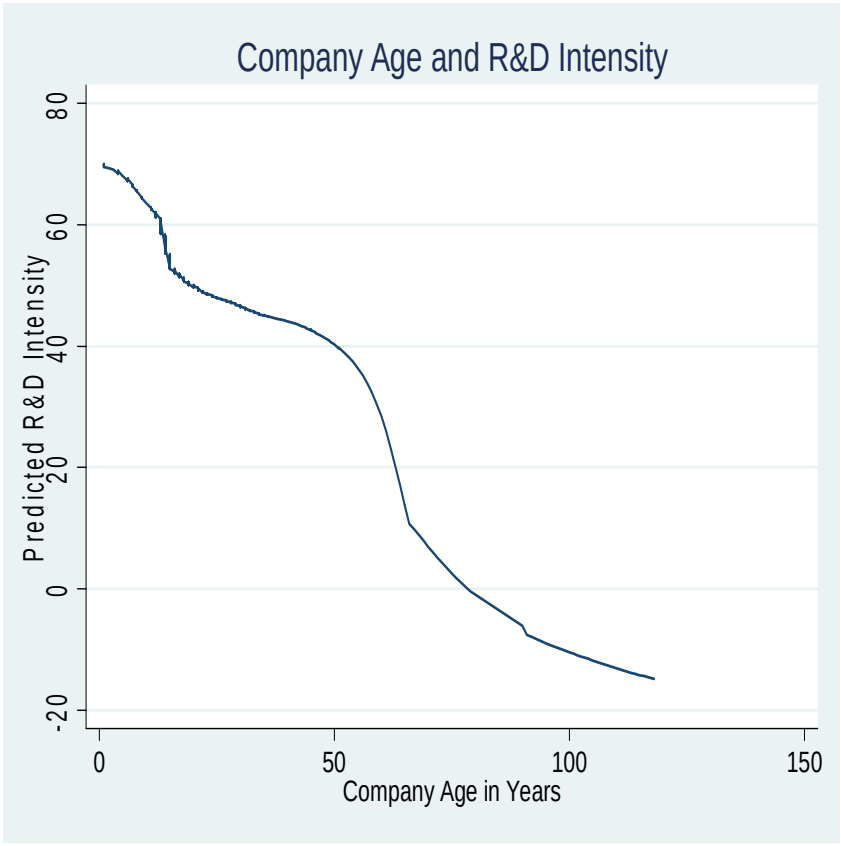
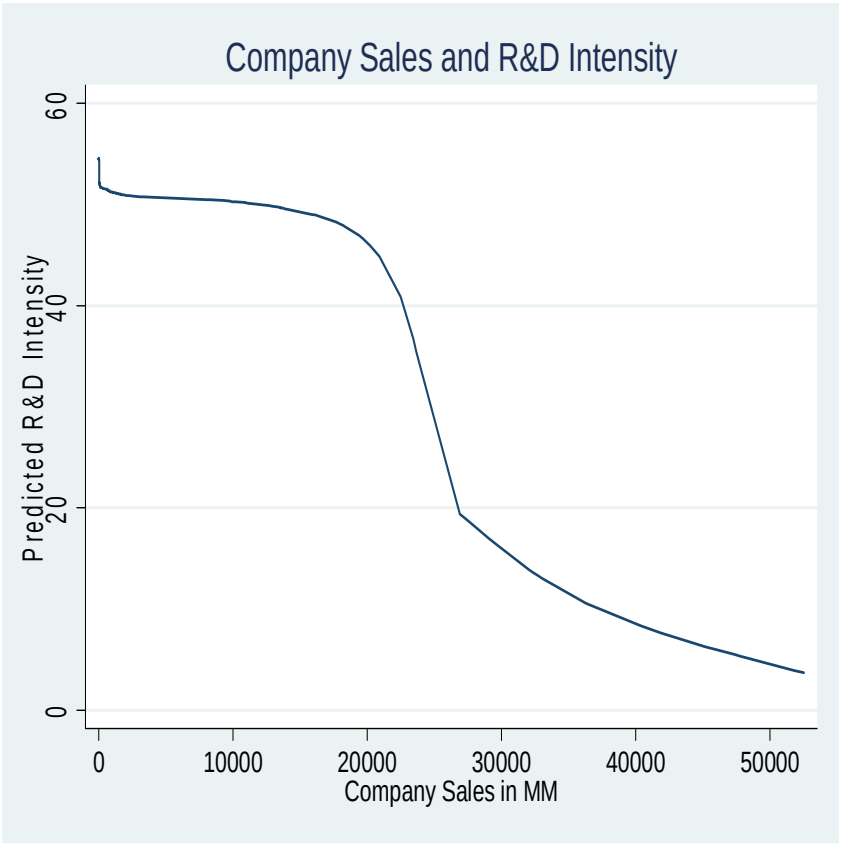
Coefficient of Company Age is negative and significant Coeff: (-1.204*** Std Err: 0.250)	Coefficient of Company Sales is negative and significant (Coeff: -0.001*** Std Er: 0.0004)
	

Figure 19. Supplemental Data Analysis

In Cluster and Out Cluster Comparison
Based on Centrality, Structural Holes and Innovation

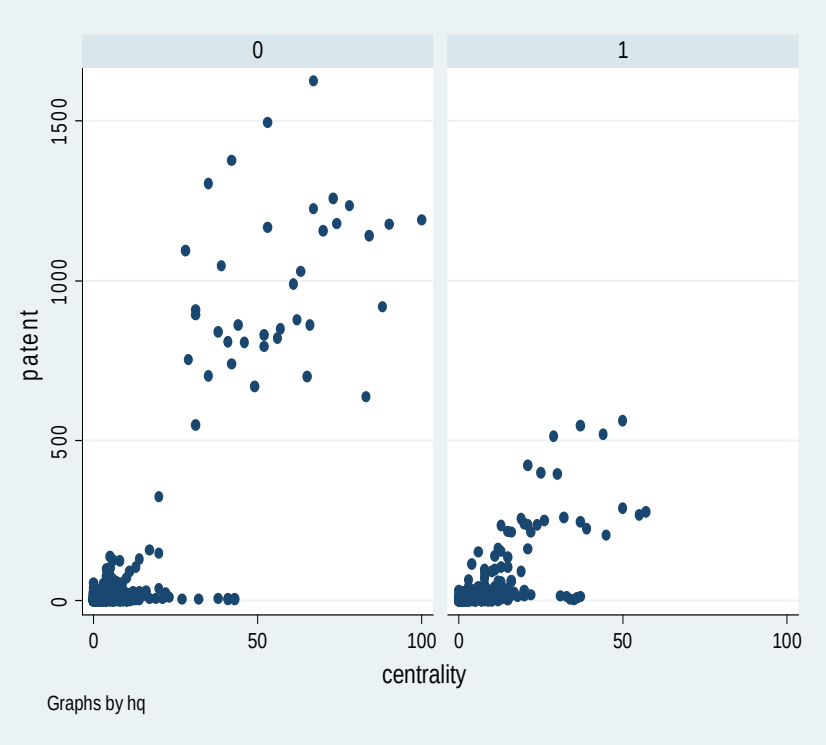
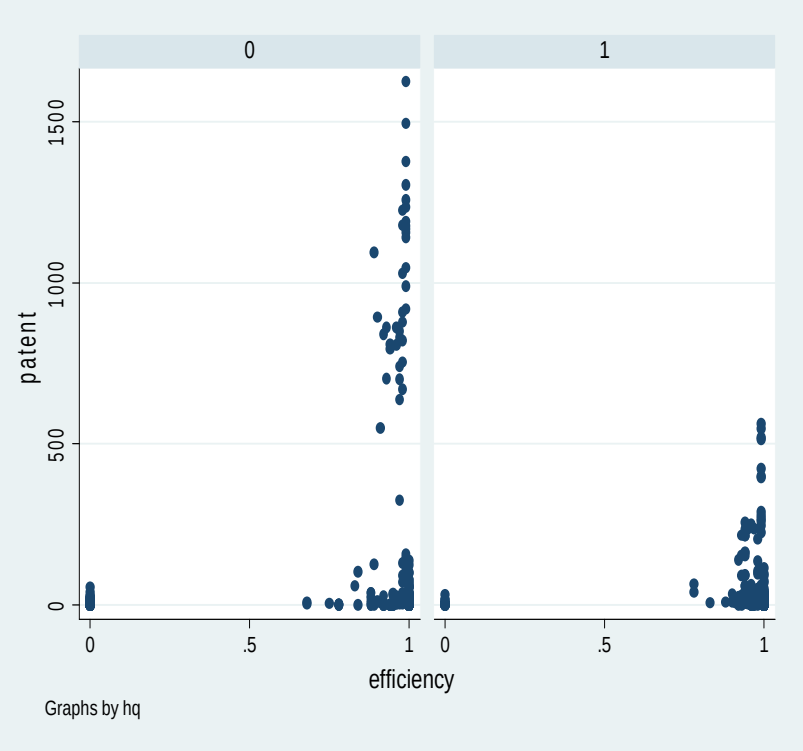
Centrality and Patent relationship for Out-cluster (0) and In-cluster (1) firms, using data from 1998 to 2004	Structural Holes (Structural holes Index) and Patent relationship for Out-cluster (0) and In-cluster (1) firms, using data from 1998 to 2004
	

Figure 20. Supplemental Data Analysis: Centrality and Patents[8]

Annual Data Analysis

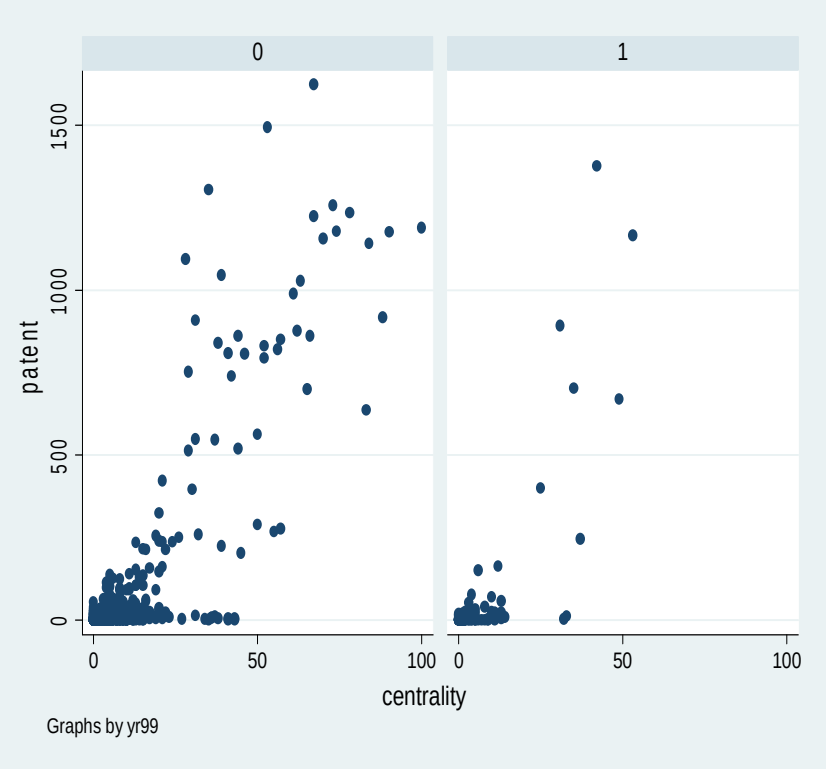
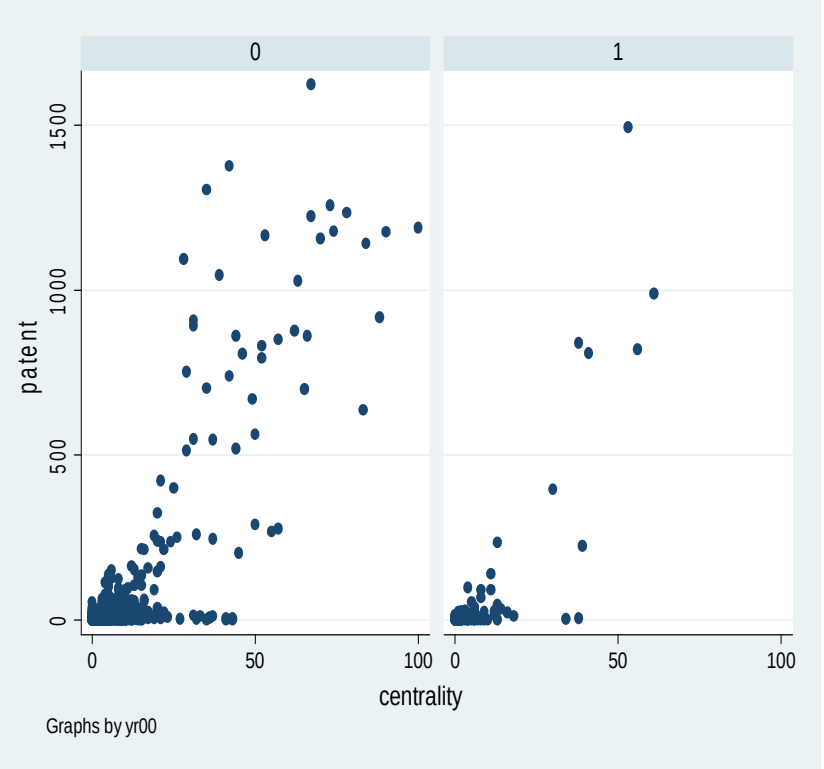
1= Data for the year 1999 0= Data for all other years, except 1999	1= Data for the year 2000 0= Data for all other years, except 2000
	

Figure 21. Supplemental Data Analysis: Centrality and Patents

Annual Data Analysis

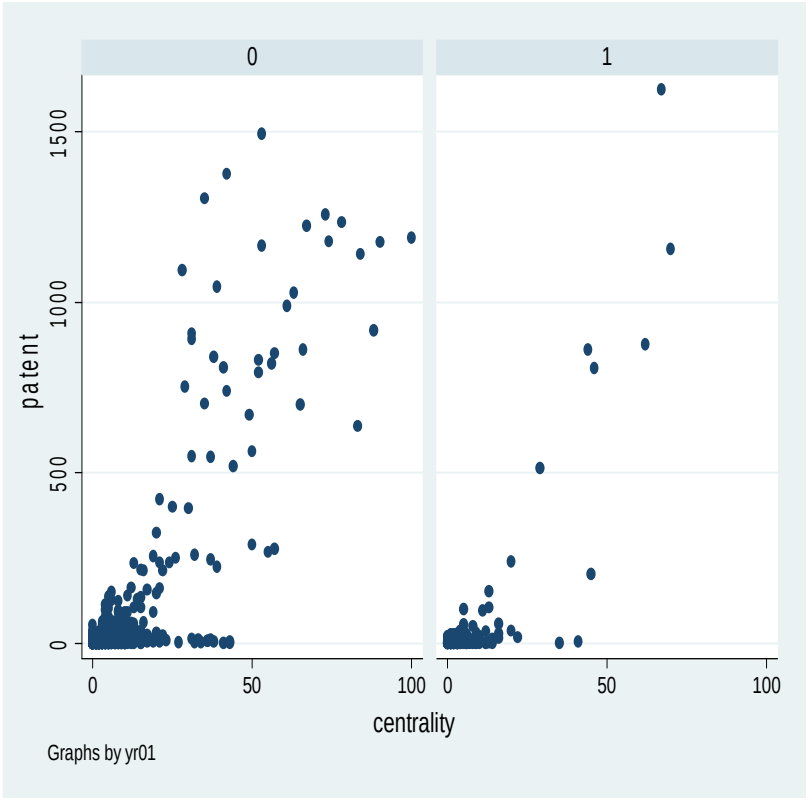
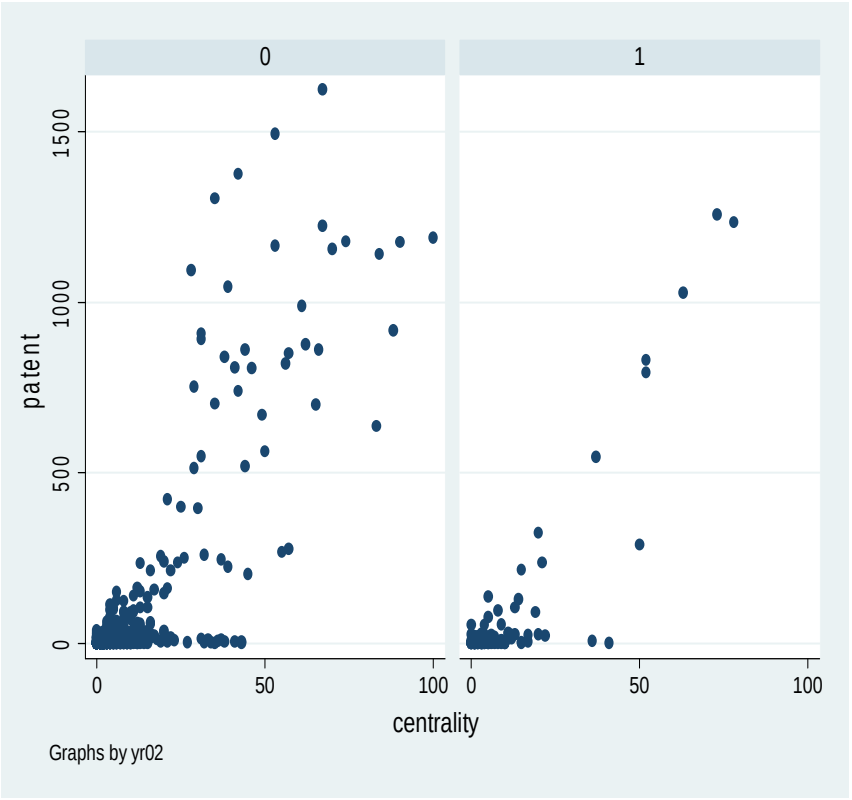
1= Data for the year 2001 0= Data for all other years, except 2001	1= Data for the year 2002 0= Data for all other years, except 2002
	

Figure 22. Supplemental Data Analysis: Centrality and Patents

Annual Data Analysis

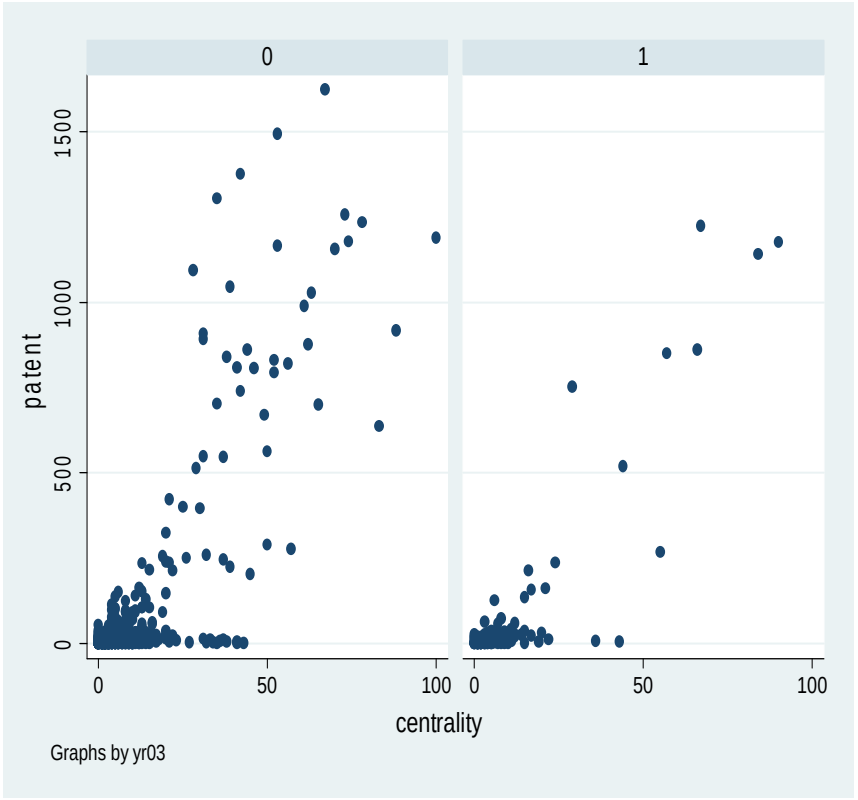
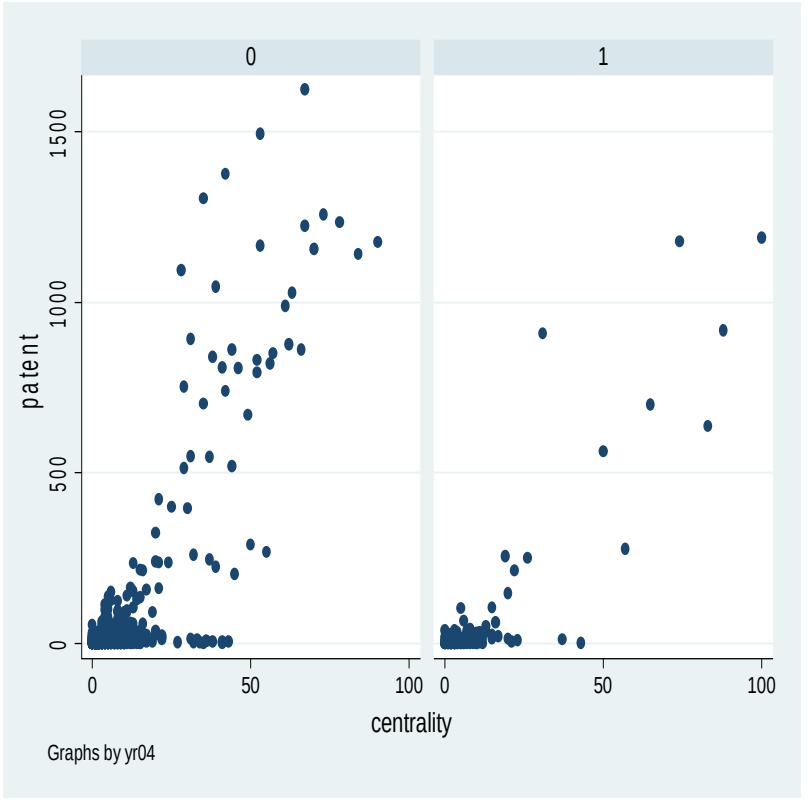
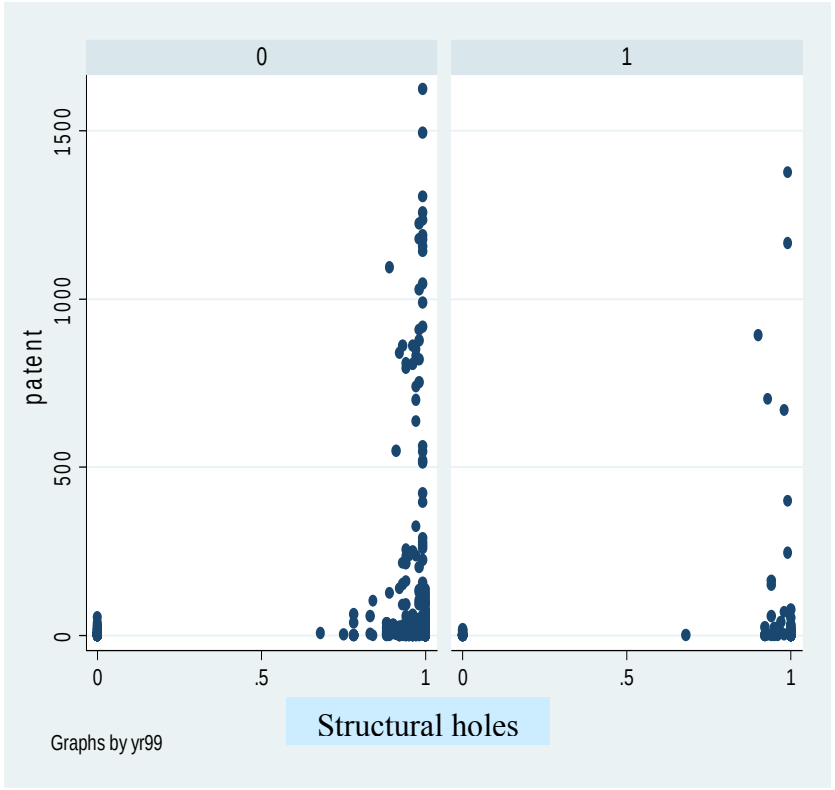
1= Data for the year 2003 0= Data for all other years, except 2003	1= Data for the year 2004 0= Data for all other years, except 2004
	

Figure 23. Supplemental Data Analysis: Structural Holes and Patents

Annual Data Analysis

1= Data for the year 1999 0= Data for all other years, except 1999	1= Data for the year 2000 0= Data for all other years, except 2000



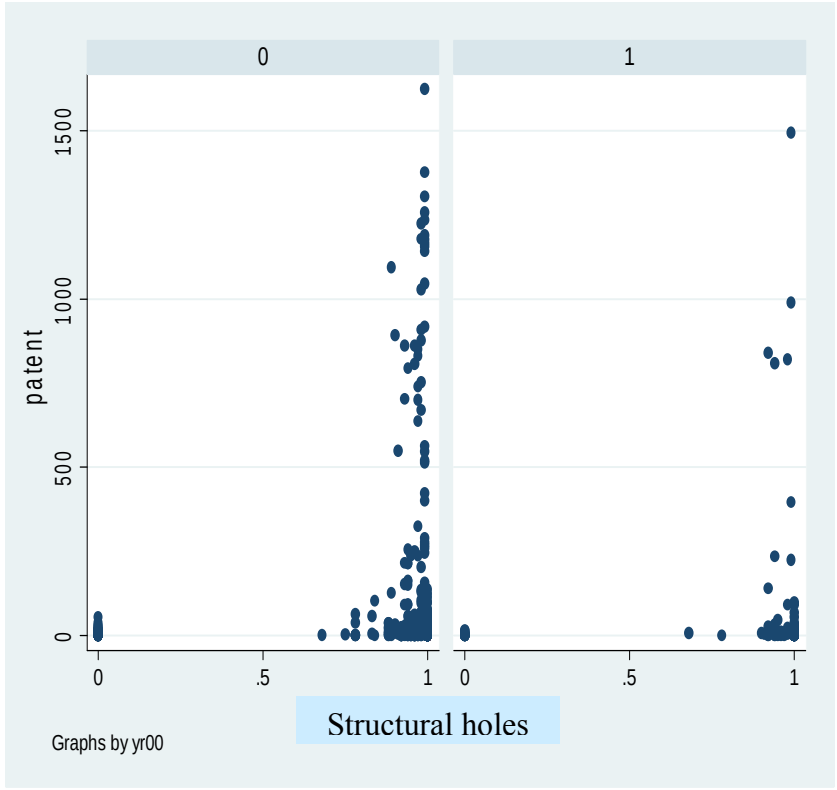


Figure 24. Supplemental Data Analysis: Structural Holes and Patents

Annual Data Analysis

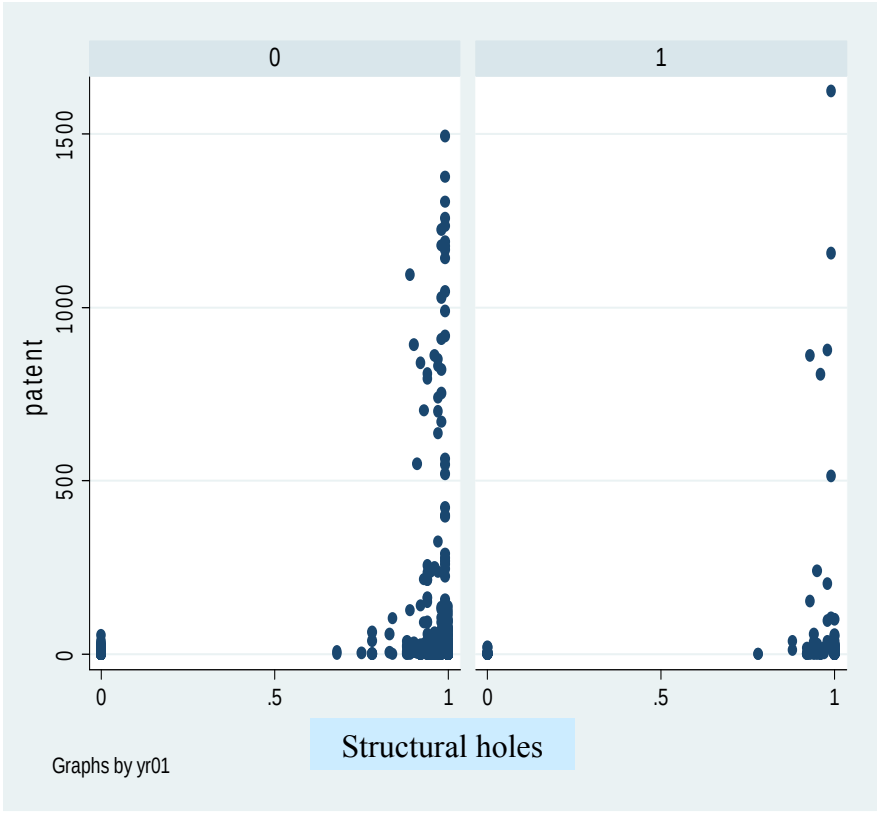
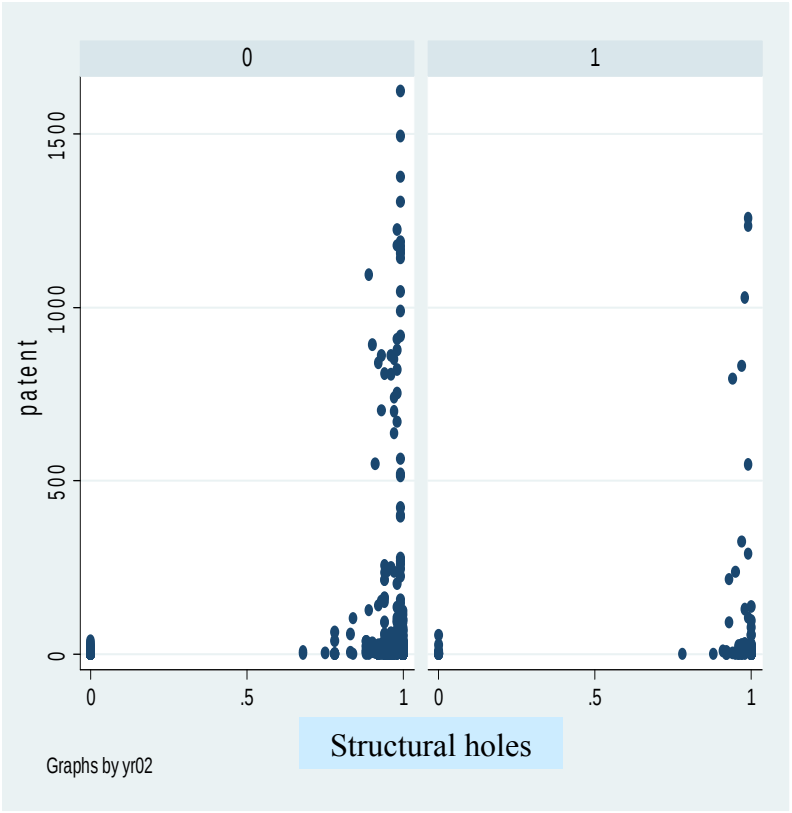
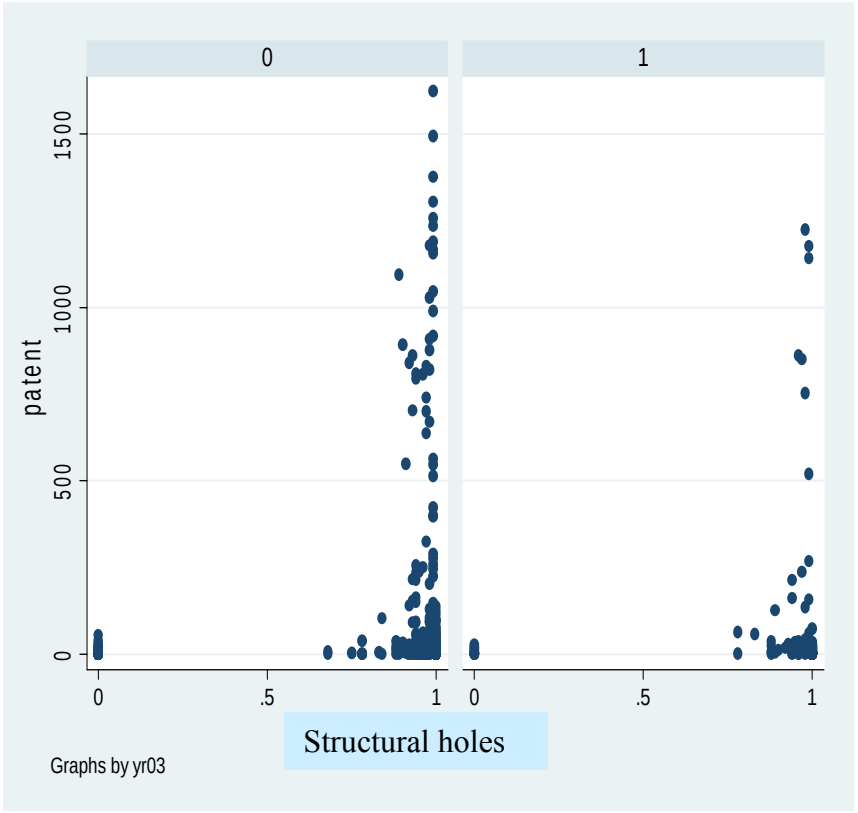
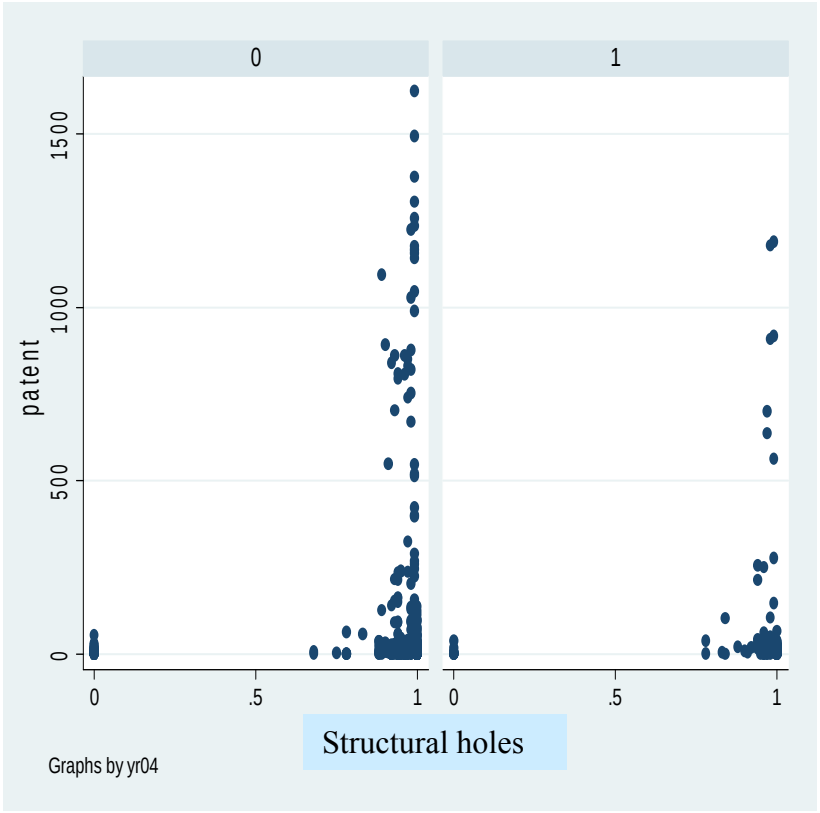
1= Data for the year 2001 0= Data for all other years, except 2001	1= Data for the year 2002 0= Data for all other years, except 2002
	

Figure 25. Supplemental Data Analysis: Structural Holes and Patents

Annual Data Analysis

1= Data for the year 2003 0= Data for all other years, except 2003	1= Data for the year 2004 0= Data for all other years, except 2003
	

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