2006

The multiple dimensions of the interfirm network: the critical sources of product innovation

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THE MULTIPLE DIMENSIONS OF THE INTERFIRM NETWORK: THE CRITICAL SOURCES OF PRODUCT INNOVATION

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
In partial fulfillment of the
Requirements for the degree of
Doctor of Philosophy

in

The William W. and Catherine M. Rucks Department of Management
E. J. Ourso College of Business

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August, 2006

ACKNOWLEDGEMENTS

I would like to thank all my family members who have supported me from the beginning until now. Without them I would not be here. I owe thanks to all teachers at Thammasat University and Seattle University who kindly provided their time and efforts to stimulate my academic interest in the field of economics and finance. Additionally, I appreciate all supports in terms of motivation from several superiors at National Electronics and Computer Technology Center (NECTEC) in Thailand. Their skills and perspectives encouraged me to pursue a doctoral degree in Strategic Management. I am grateful for all professors at Louisiana State University (LSU) who offered critical knowledge in the field of management and excellent researching tools necessary to accomplish this project. Also, I appreciate Joe Abraham of the LSU Writing Center who has provided help through out several projects including this dissertation.

All my dissertation committee—Jim Moore, Andreas Schwab, Tim Chandler, and Bob Justis—deserve my special gratitude. Specifically, I thank Jim who provided financial support to acquire the critical database of this project.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS ii

LIST OF TABLES v

LIST OF FIGURES vi

ABSTRACT vii

CHAPTER 1 INTRODUCTION 1

CHAPTER 2 EMPIRICAL CONTEXT 10
2.1 The Scope of the Biopharmaceutical Industry 10
2.2 Important Characteristics of the Biopharmaceutical Industry 12
2.2.1 Drug Development Process 15
2.2.2 Roles of Biotechnology in the Drug Development Process 18
2.3 Roles of Patent Protection in the Biopharmaceutical Industry 19
2.3.1 Basic Patent Law Concepts 20
2.3.2 Specific Issues of Patents in the Biopharmaceutical Industry 22
2.4 Collaborative Environments in the Biotech and Pharmaceutical Industry 24
2.5 Data Sources in the Biopharmaceutical Industry 29

CHAPTER 3 INNOVATION STUDIES 33
3.1 Several Theoretical Perspectives in Innovation Studies 33
3.2 Innovation as an Uncontrollable Outcome 39
3.3 Innovation as a Controllable Outcome 41
3.3.1 Product and Process Innovations 46
3.3.2 Invention 49
3.3.3 Commercialization 50
3.4 Interorganizational Networks and Innovation Activities 52
3.4.1 Interfirm Networks as Invention Generators 54
3.4.2 Interfirm Networks as Diffusion Drivers 59
3.4.3 Integrated Framework of Interfirm Linkages and Innovation Activities 65
3.5 Summarizing Innovation Studies 69

CHAPTER 4 THEORETICAL FRAMEWORK 78
4.1 Theoretical Backgrounds 80
4.2 Interorganizational Network Variables 84
4.2.1 Direct and Indirect Ties 86
4.2.2 Structural Holes 90
4.2.3 Strength of Ties 94
4.2.4 Prominence of Direct Partners 98
4.2.5 Exploration vs. Exploitation Oriented Partners 100
4.2.6 Horizontal and Vertical Networks 101
4.2.7 Performance of the Invention and Commercialization Activities 106

CHAPTER 5 DATA AND MEASUREMENT 108
5.1 Data and Sample 108
5.2 Measures 111
5.2.1 Invention Performance of the Focal Firms 112
5.2.2 Commercialization Performance of the Focal Firms 113
5.2.3 Direct and Indirect Ties 116
5.2.4 Structural Holes 118
5.2.5 Strength of Direct Ties 120
5.2.6 The Prominence of the Focal Firm's Partners 121
5.2.7 Exploration and Exploitation Networks 122
5.2.8 Upstream and Downstream Horizontal and Vertical Networks 123
5.3 Control Variables 124

CHAPTER 6 ANALYTICAL TECHNIQUES AND RESULTS 131
6.1 Model Specification and Estimations 131
6.1.1 Fixed-Effects versus Random-Effects Models 131
6.1.2 The Panel Negative Binomial Regression 132
6.1.3 The Zero Inflated Negative Binomial Regression for Panel Data 133
6.2 Results and Basic Information 136

CHAPTER 7 DISCUSSION AND CONCLUSION 167
7.1 Revisited Significant Predictors 169
7.1.1 Direct and Indirect Ties 169
7.1.2 Structural Holes (Density and Brokerage) 171
7.1.3 Strength of Ties 173
7.1.4 The Prominence of Partners 174
7.1.5 Exploration and Exploitation Partners 175
7.1.6 Upstream and Downstream Horizontal Networks 176
7.1.7 Upstream and Downstream Vertical Networks 178
7.2 Internal and External Validity 179
7.3 Managerial Implications 182
7.4 Research Implications 185
7.5 Limitations 186
7.6 Conclusion 190

REFERENCES 191

APPENDIX A: MEASUREMENTS AND DATA SOURCES 202

APPENDIX B: CORRELATION OF ALL VARIABLES AND RESULTS 203

APPENDIX C: BIOSCAN FIELDS AND THEIR DESCRIPTIONS 232

APPENDIX D: FREQUENTLY ASKED QUESTIONS OF DRUG@FDA DATABASE 234

VITA 238

LIST OF TABLES

2.1: Pharmaceutical Industry 2001 (NAICS 3254) 12

2.2: Sources of the Biopharmaceutical Industry and Its Studies in Management 31

3.1: Innovation Concepts 43

3.2: Summaries of Empirical Innovation Studies between 1991 and 2004 73

4.1: Predicted Directions of Network Variables and Innovation Performances 107

5.1: All Variables and Their Measurements 130

6.1a: Evidence of Over-dispersion in Dependent Variables 133

6.1b: Evidence of Zero-inflation 134

6.2: List of All Focal Firms and their Observation Periods 137

6.3: Important Analytical Data of the Focal Firms 140

6.4: Basic Descriptive Statistics on the Linkages Network 141

6.5: Descriptive Statistic and Correlation Matrix 143

6.6a: The Panel Negative Binomial Regression Estimates of Patenting 147

6.6b: The Panel Zero-inflated Negative Binomial Regression Estimates of Marketed Drug Applications 149

6.6c: The Panel Regression Estimates of Total Annual Sales 151

6.7: Predicted Directions and Findings for Hypothesis 7 166

7.1: Empirical Contributions from This Study 168

LIST OF FIGURES

2.1: The Modern Drug Development Process....16

2.2: Collaborative Environments in the Biopharmaceutical Industry....27

4.1: Interorganizational Networks for Product Innovation....84

5.1: Hypothetical Number and Positions of Direct and Indirect Ties....118

5.2: Two Scenarios of Structural Hole....120

5.3: Horizontal and Vertical Collaborations....124

6.1: Relationships of Patents and Annual Revenues....145

6.2: Relationships of Marketed Drug Applications and Annual Revenues....145

6.3: Relationships of Marketed Drug Applications and Patents....145

6.4: Two Scenarios of Density and Brokerage Measures....157

ABSTRACT

This dissertation examines the impacts of interfirm variables on both invention and commercialization activities, following Greve's (2003) suggestion that innovation research will be enriched if more studies integrate invention and commercialization activities to understand the entire innovation development process. Utilizing two established theoretical perspectives—organizational learning and institutional theory—six sets of hypotheses are developed containing the following interfirm variables: 1) direct and indirect ties, 2) strength of direct ties, 3) structural holes, 4) prominence of direct partners, 5) exploration and exploitation partners, and 6) horizontal and vertical networks. The dissertation also predicts that these interfirm variables would contribute to either invention or commercialization activities.

Examining 262 publicly traded biopharmaceutical firms from 1986 to 2003, the study demonstrates that the interfirm variables significantly influence the invention and commercialization outcomes. While some interfirm variables positively influence the number of patents of a focal firm, they could have a negative impact upon the number of marketed drug applications and revenue. A managerial implication from the findings is that a focal firm may want to clarify its objectives before engaging in any interfirm collaboration by examining the multiple dimensions of its interfirm network and to identify its posture toward alliances. Due to the complexity and length of invention and commercialization activities, future research is warranted to investigate further the impacts of these interfirm predictors on important, but relatively ignored, product innovation outcomes (i.e., the number of new projects and licensing, marketing, and sales fees).

CHAPTER 1: INTRODUCTION

Scholars have attempted to understand innovation-related factors since Schumpeter (1934) wrote a seminal paper about innovation activities. At present, scholars have identified several factors that are located both inside and outside any managerial control of influence. Among several innovation-related factors, three uncontrollable factors include organizational inertia, technological breakthrough, and institutional and market dynamics. Regarding controllable factors, several scholars suggested that management could influence the outcomes of innovation through their strategies, organizational structure, and behaviors of management. Despite notions that management may influence the outcomes of innovation, nobody comprehends how innovation occurs and to what extent management may achieve successful innovation activities. Regardless of innovation-related factors, scrutinized carefully and continuously for several decades, Damanpour (1996) suggested that the development of innovation knowledge had not been adequate.

An analysis of prior research in innovation areas reveals that the terms and concepts of innovation studies are still messy and unorganized. For instance, scholars applied the term "innovation" in diverse contexts and definitions. Despite Schumpeter's early suggestion that innovation consists of three sequential types of activities—invention, innovation, and imitation—later researchers apparently ignored these terms and used the term "innovation" at their own discretion. For example, Rogers (1995) used the terms "innovation" and "technology" interchangeably. He also used the term of "diffusion of innovation" to replace Schumpeter's term of "innovation" and/or "imitation." Additionally, most management studies used the term "innovation" to elaborate the concepts of "invention." For example, several important studies used numbers of granted patents, R&D intensity, and patent citation to represent the term "innovation outcomes" (Ahuja, 2000a; Hitt, Hoskisson, Johnson, & Moesel, 1996; Shan, Walker, & Kogut, 1994; Stuart, 2000). Comparing the variables used by

these studies with Schumpeter's innovation definitions, I suggest that the scholars label their dependent variables as "invention outcomes" rather than "innovation outcomes."

Replacing the term "invention" with "innovation" in their studies, scholars in prior studies limited the scope of study to focus solely on Schumpeter's term of invention activities or, at most, the early stage of commercialization activities. By using innovation activities alone, scholars completely left out commercialization and adoption activities. It is even more surprising that there appears to be only a few empirical studies aimed at understanding the impact of interorganizational networks on commercialization activities. Whereas several studies in interorganizational relationships discussed related variables for "adoption" (Davis, 1991; Leblebici, Salancik, Copay, & King, 1991), there were only two qualitative case studies in management that explained factors associated with successful commercialization activities (Hargadon & Douglas, 2001; Hargadon & Sutton, 1997). One may argue that perhaps the knowledge of commercialization belongs to the marketing field; however, commercialization is one of the most crucial innovation activities that generate needed resources for firms to survive and thrive. In fact, successful commercialization activities feed a focal firm its invention activities and receive like response in return.

In recognition of the limitations of innovation definitions in the field of management, this study addresses the terminological issues of innovation thoroughly. Establishing and clarifying the constructs of innovation importantly allow the theoretical development in this particular area to proceed (Pfeffer, 1993). Therefore, this study proposes to use the term "invention" to represent the act of creating or developing a new product or process; "commercialization" to represent the process of creating a commercial product from an invention; and "adoption" as the process of imitation of innovation by similar firms. Accordingly, in this present study, the term "innovation" covers three sequential and

interdependent activities, beginning with invention activities, commercialization activities, and adoption activities.

Further, this study follows Wejnert's (2002) concept of "public consequence" to narrow the scope of the study to cover only invention and commercialization activities. Wejnert (2002) explained that unlike private consequences that affect the well-being of either individuals or small collective entities such as organizations, peer groups, and rural communities, public consequences deal with the inventions leading to historical breakthroughs that impact total societies (i.e., laws protecting civil rights, welfare policy, patent laws, or international regulation protecting the natural environment). Following the concepts of public and private consequences, this study elaborates the differences between "process" and "product" innovations to clarify the stages of innovation in the section of innovation studies. Product innovation generates public consequence because it primarily deals with commercialization activities, unlike process innovation which is more likely to produce private consequence from adoption activities.

Focusing on the concept of product innovation (Greve, 2003), the premise is that innovation research will be enriched if more studies integrate invention and commercialization activities. This will culminate in an understanding of the innovation development process as a whole. Please note that the study examines sequential and interdependent innovation activities, aiming to advance knowledge of an integrated innovation performance (i.e. product innovation). The main thesis of this paper suggests that the linkages between activities must hold simultaneously to provide support for relationships between invention and commercialization performance. Therefore, success or failure in product innovation is derived by the performance of both invention and commercialization activities.

Although a stream of product innovation studies in the field of interorganizational network often becomes increasingly popular, prior studies rarely have incorporated invention and commercialization activities in tandem to advance knowledge of the product innovation process. One exception is a study published in Strategic Management Journal, offering a comprehensive framework to elaborate interorganizational networks of biotechnology firms and product innovation processes (Rothaermel & Deeds, 2004). Moreover, two studies used dependent variables reflecting the concepts of invention and commercialization (i.e., innovation speed and patent renewals) (Kessler, Bierly, & Gopalakrishnan, 2000; Spencer, 2003). In addition to these particular studies, this study will review other important studies in this area in Chapter 3.

To foreshadow the structure of this study, Chapter 2 provides an empirical context of this study, explaining the scope of the biopharmaceutical industry. The biopharmaceutical industry represents a testing ground because the unique characteristics of the industry lend nearly perfect conditions for outcomes in terms of interorganizational networks and product innovation activities. Past studies focused on how biotechnology firms interacted with research oriented institutions and chemical-based pharmaceutical companies to achieve patentable inventions (Shan et al., 1994; Wuyts, Dutta, & Stremersch, 2004). Rothaermel (2001) indicated that the biopharmaceutical industry is composed of traditional pharmaceutical companies, fully dedicated biotechnology firms, and nonprofit research institutions and universities that engage in biotechnology research.

The primary research question is to examine multiple dimensions of interorganizational network that promote sustainable performance in terms of the product innovation. Consequently, this study focuses on a center of the networking system—a biopharmaceutical firm. With the understanding that the biopharmaceutical firm represents a driving force of interorganizational innovation networks, thereby undertaking invention and

commercialization activities, all important factors of the firm's interorganizational networks will be examined. Several other sections in chapter 2 include the important characteristics of the biopharmaceutical industry, roles of the patent protection, collaborative environments among biopharmaceutical organizations, and potential sources of data in the industry.

Chapter 3 is the literature review of innovation studies. Starting with general knowledge of innovation, I discuss several academic perspectives of innovation (i.e. evolutionary, behavioral, economics, and sociological perspectives). Then, I review several important innovation studies both in organizational and interorganizational levels. Following the perspective of product innovation, I separate prior studies into two main sections—invention and commercialization. I also discuss several studies that incorporate invention and commercialization in their analyses. Then, several studies of product innovation in the field of interorganizational network are reviewed in detail. Last, I categorize several important innovation studies, identify dependent and independent variables and empirical findings, and list data sources.

Chapter 4 importantly deals with hypothesis development in the study. To indicate motivation for the hypotheses, I briefly summarize both theoretical concepts of organizational learning and institutional theories. Since a number of scholars believe that innovation is a phenomenon, it is important to incorporate the two theoretical concepts to provide framework for the study, which allows recognition of multiple dimensions of interorganizational variables as predictors of invention and commercialization outcomes in product innovation. Basically, firms engage in interorganizational networks to generate invention and commercialization outcomes a) by learning from internal and external environments, b) by gaining acceptance and institutional supports from the market, and c) through interfirm peers. Based on two theoretical perspectives, the study proposes six sets of hypotheses and one concluding hypothesis. Specifically, the study extends Ahuja's (2000a) concepts of direct

and indirect ties in order to understand focal firm performance in terms of invention and commercialization activities. In the subsequent sections, the study proposes several hypotheses to understand concepts of tie-strength (Granovetter, 1973, 1983) and structural holes (Burt, 1992; Coleman, 1988). This study avers that the first three dimensions of an interfirm network should be used to predict a focal firm's product innovation performance.

Next, the prominence of a focal firm's partners (Stuart, 2000) is hypothesized to predict the focal firm's invention and commercialization outcomes. Afterward, the concepts of network orientations (i.e., exploration and exploitation partners) are examined (March, 1991; Rothaermel et al., 2004), regardless of the position of focal firms. Last, the concepts of focal firms' horizontal and vertical alliances from Kotabe and Swan (1995) and Silverman and Baum (2002) are used to understand invention and commercialization.

From hypotheses 1 to 6, it is interesting to note that whereas multiple dimensions of interorganizational networks from the perspectives of organizational learning and institutional approach are predicted to foster invention activities, these dimensions are simultaneously predicted to harm commercialization activities, and vice versa. Thus, the last hypothesis predicts that, taking into account the stability of biopharmaceutical interfirm networks (Powell, Koput, & Smith-Doerr, 1996), negative relationships between invention and commercialization performances should be found for focal firms.

Chapter 5 deals with the methodologies of this study, elaborating on the primary data sources, BioScan Directory, COMPUSTAT, Drug@FDA, and LexisNexis. These four data sources offer comprehensive information regarding the publicly traded biopharmaceutical firms from 1977 to present, which permits the study to employ cross-sectional time series analyses. The next section of this chapter elaborates three dependent variables, six main predictors, and several control variables. In brief, the number of patents of a focal firm is

used to capture its invention performance each year. Additionally, the number of marketed drug applications and revenues are the two commercialization outcomes of the focal firm.

The first set of the interfirm predictors includes the number of direct and indirect ties of the focal firms. The social network software called "UCINET" facilitates the collecting process for this set of variables. UCINET generates the density measure and the brokerage measure of each focal firm's network. These two measures are used to capture the second predictor—levels of structural holes. Next, the strength of ties is the third interfirm predictor. I calculate the average tenures of a focal firm's relationships with direct partners to determine the strength of ties in a particular year. Next, the fourth predictor is the prominence of the direct partners. This predictor is measured by the frequencies of the direct partners' news articles appearing in LexisNexis. The frequencies are measured in the period of ten years prior to the study.

The fifth set of predictors includes the focal firm's exploration and exploitation partners. The alliances' propensities to invention and commercialization are determined in the period of ten years prior to the study. If a focal firm collaborates with a set of alliances that generate a high number of patents, the focal firm deals with exploration partners. Inversely, if a focal firm deals with a set of alliances that obtain a high number of drug applications issued at the FDA, the focal firm collaborates with exploitation partners.

The last set of interfirm predictors is more complicated than the previous set of variables, because it involves the positions of a focal firm and its alliances in the drug development process. Using the same scheme to determine exploration and exploitation types of focal firms, I compare the posture of a focal firm and its alliances to determine the position of the focal firm and its networks—upstream and downstream horizontal networks and the upstream and downstream vertical networks. After testing for the impacts of multiple dimensions of

interfirm networks on invention and commercialization, the study evaluates the directions of all predictors to test the seventh hypothesis.

In the last section of Chapter 5, the study addresses the control variables. According to previous studies, the invention and commercialization outcomes of a focal firm are determined by several external and internal variables that are independent to the interfirm factors. Therefore, this study controls for a focal firm's propensities to invention and commercialization and its status, measured by the focal firm's tenure as a public firm and the closing stock price. Equity financing events are also added to control for instantaneous effects on invention and commercialization. Additionally, the research controls for the diversification level and profitability levels of a focal firm. Size as captured by the number of employees is also another controlled variable. To control for a focal firm's internal source of innovativeness, the study focuses on the focal firm's R&D expense. Lastly, the study controls for differences in years and industries among focal firms.

Chapter 6 reports the analytical techniques and results of the study. The beginning of the chapter discusses the model specifications and estimations. An elaboration of the fixed-effects and random-effects models explains why the random-effects models are more appropriate in my study. The study also examines the basic characteristics of the dataset and proposes to use the panel negative binomial regression model, the panel zero-inflated binomial regression model, and the generalized least squares (GLS) estimator to test significant contributions of all proposed interfirm variables on the patenting rates, the number of marketed drug applications, and the revenues of focal firms, respectively.

In this chapter, the basic statistical information (i.e., the number of direct ties, the number of indirect ties) suggests that the biopharmaceutical industry approaches maturity. The focal firms collaborate with their alliances to achieve invention and commercialization performances. Some findings about the impacts of direct and indirect ties toward invention

are consistent with prior studies. In the commercialization activities, while the number of direct ties contributes to the revenue, the number of indirect ties deteriorates it. The density of a focal firm's network contributes negatively to the number of marketed drug applications. Likewise, the brokerage opportunities of a focal firm's network suggest negative revenue for the focal firm.

Next, the tenure of a focal firm's network negatively contributes to the patenting rate, yet increases the focal firm's revenue. The prominence of alliances increases the number of marketed drug applications. However, the prominence reduces the revenue of the focal firm. Additionally, while the exploration ties improve revenue, they reduce the number of marketed drug applications for a focal firm. For the last set of the predictors, the horizontal upstream network decreases revenues, whereas the downstream vertical network jeopardizes the number of patents of a focal firm. Because of the complementary effects generated by the two vertical networks—upstream and downstream vertical networks—the two networks improve the revenue for a focal firm.

Chapter 7 discusses the results and concludes the dissertation, revisiting all significant predictors, in an attempt to understand the discrepancies between the hypotheses and the significant findings. The study deploys theoretical perspectives from organizational learning and institutional theory to further explain the significant results. Stating the importance of the integrated framework of invention and commercialization allows an address of some effects not previously seen or examined in previous studies. The study discusses the external and internal validity of this study, as well as managerial implications, research implications, and limitations at the end of the final chapter.

CHAPTER 2: EMPIRICAL CONTEXT

In this chapter, the study provides details of the biopharmaceutical industry as the empirical setting. Beginning with the definition and scope of the industry, specific information examines characteristics of the industry, roles of patent protection in the industry, and collaborative environments among different types of organizations. Lastly, the study gathers all important studies and elaborates on empirical findings, as well as data sources used to study the particular industry.

2.1 The Scope of the Biopharmaceutical Industry

The term "biotechnology" was coined by a Hungarian farmer in 1917; however, its definition varies considerably across countries, as well as different periods in history (Stehr, 2004). Biotechnology comprises three main technologies: recombinant DNA, first discovered by Boyer and Cohen in 1973; monoclonal anti-body, first discovered by Kohler and Milstein in 1975; and protein engineering technology, developed in the 1980s. These three main technologies offer the "prospect of producing an array of highly valuable processes and products in areas such as human health, crop production and protection, chemical feedstock production and processing, food processing, and waste management" (Liebeskind, Oliver, Zucker, & Brewer, 1996).

Regarding the formal definition of biotechnology, the office of Technology Assessment of the United States Congress (dismantled in 1995) defined "biotechnology" as any specific technique that uses substance from living organisms to generate a product, to improve plants or animals, or to develop microorganisms for specific uses. Thus, formally defined, the scope of biotechnology may be so broad as to cover several areas of natural sciences, including cell and molecular biology, biochemistry, and engineering and computer science, to name only the major areas. Additionally, many applications of biotechnology include the production of

new and improved foods, industrial chemicals, pharmaceuticals, and livestock (Barnum, 2005).

Regarding the scope of its industry, Bergeron and Chan (2004) suggested that "at minimum, biotech is synonymous with the high-stakes pharmaceutical industry." However, because a number and range of stakeholders are involved in the biotech value chain, it is difficult to pinpoint the overlapped areas of the biotechnology industry and pharmaceutical industry. According to the authors, "bringing a drug into market involves equipment manufacturers, highly skilled research, a research and production facility, a fulfillment infrastructure, a score of legal personnel to handle patents and liability issues, a marketing and sales force, advertising agencies, journals, and other media outlets" (Bergeron & Chan, 2004). Therefore, due to the interdependency of the overlapped activities in the biotechnology industry of the pharmaceutical industry, it is reasonable to include all types of organizations in the biotech value chain into the same boundary.

To simplify the situation, the study adopts the term "the biopharmaceutical industry" (Rothaermel, 2001) to represent a boundary that combines the biotechnology industry with the pharmaceutical industry. The biopharmaceutical industry reflects "the industry composed of traditional pharmaceutical companies, such as Merck or Eli Lilly, that utilize biotechnology for drug discovery and development, as well as fully dedicated biotechnology firms, such as Amgen or Genentech, and nonprofit research institutions and universities engaged in biotechnology research" (Rothaermel, 2001).

In fact, the interdependence of the activities among biotechnology firms and pharmaceutical firms may be seen more clearly if the economy is divided into specific groups of industries. Before 1997, the standard industrial classification (SIC) represented an attempt of the US Bureau of the Census to classify differences among industries. Since then, SIC has been revised as the North American Industry Classification System (NAICS) to classify

different industries. According to NAICS, the manufacturing sector is section 31-33, while chemical manufacturing is specifically assigned to fall into section 325. Within chemical manufacturing, the section of NAICS 3254 is particularly assigned for industries of pharmaceuticals and medicines (i.e., NAICS 325411-325414). According to this classification, this is where firms in the biopharmaceutical industry operate. The NAICS codes and their details for the pharmaceutical industry are shown in Table 2.1.

Table 2.1 Pharmaceutical Industry 2001 (NAICS 3254)

NAICS	Product	Shipments $Billion	Value Added $Billion
3254	Pharmaceuticals and Medicines	140.66	101.93
325411	Medicinal and Botanicals	11.59	7.34
325412	Pharmaceutical preparations	113.99	83.56
325413	In vitro diagnostic substances	7.29	5.42
325414	Biological products (except diagnostic)	7.79	5.61

Source: Medicinal and Botanical Manufacturing, U.S. Census Bureau, December 2004.

The combined value of shipment is the total sales of all firms operating in the industry. The value added is defined as the value of shipments, less cost of raw materials and cost of manufacture. In other words, it is the additional value created by all firms in the industry. The products from the subsection of pharmaceutical preparations represent the largest total sales and the highest value added to the overall biopharmaceutical industry. Interestingly, despite the fact that *in vitro* diagnostic substances (NAICS 725413) are therapeutics used outside the human body and thus are supposedly being scrutinized less carefully than those of other *in vivo* therapeutics by the FDA, *in vitro* diagnostic substances accounted for only 2.6% of total shipments in the pharmaceutical industry.

2.2 Important Characteristics of the Biopharmaceutical Industry

In the mid-1970s, the development of the U.S. biotechnology industry included the founding of large numbers of new biotechnology firms, dedicated to the commercialization of scientific developments in genetic engineering. Rothaermel et al. wrote: “the emergence of the biotechnology industry can be interpreted as a radical process of innovation that broke the

barriers of entry into the pharmaceutical industry, among other industries" (2004: 208). Lacking biotechnology knowledge, established pharmaceutical firms engaged in biotechnology research by forming alliances with the new biotech firms through long-term contracts or by forming joint ventures.

In turn, the new biotech firms entered into long-term relationships with established firms to obtain such complementary assets as product testing, production, marketing and distribution capabilities that the new biotech firms lacked at the outset of their development. Thus, the first and the most important characteristic of the biopharmaceutical industry was its network structure of interorganizational alliances that govern the exchange of complementary assets among the biotech firms, scientists, and established pharmaceutical firms (Liebeskind et al., 1996). According to Lerner et al. (2003), numerous small research-intensive firms in the biopharmaceutical industry finance primarily through public financing by entering into strategic alliances with pharmaceutical companies. Because of a unique tendency toward strategic alliances, the biopharmaceutical industry is identified as the industry with the highest alliance frequency among several other industries (Hagedoorn, 1993). The study discusses collaborative environmental details of the biopharmaceutical industry in the next section.

Second, similar to the pharmaceutical industry, the business model of the biopharmaceutical industry is recognized as a blockbuster. Regarding the model, Bergeron and Chan (2004) explained that the blockbuster business model of firms in the pharmaceutical industry generally reflects firm behaviors in the biopharmaceutical industry. They indicated that, in tandem to companies in movie and book-publishing industries, pharmaceutical companies live or die based on the success of one or two blockbusters every year or so. Particularly in the pharmaceutical industry, a blockbuster drug may earn as much as $1 billion or more in annual revenue.

Drugs such as SmithKline's Tagmet®, Glaxo's Zantac®, Syntex's Naprosyn®, and Bristol-Meyers' Capoten® provide examples of blockbuster drugs. The blockbuster business model draws biopharmaceutical firms to rely on huge revenue from one or two drugs to cover their expenses. It is more difficult for the firms to develop biotechnological drugs that target special or niche markets to fetch high levels of income. Thus, the firms tend to pursue cheap and general medicines for a larger mass of population. As a result, this action draws the biopharmaceutical industry to produce, market, and distribute mass-produced medicine for a larger group of people, rather than the more expensive biotechnological medicines that potentially offer fewer side effects and greater efficacy.

Third, despite a previous speculation by investors toward biotech, like that in dot-coms, statistical records suggest that biotech products represent less than 10 percent of the pharmaceutical market. For instance, pharmaceuticals created using biotechnology, despite all hype, represent only about $35 billion of the quarter-trillion dollar pharmaceutical market. Due to the expensive, marked-up prices, most people in developing countries, the large global market for medicine, can not afford biotechnological products (Bergeron et al., 2004). The limitation in terms of market restriction weakens the significant expectations of biotechnology in the pharmaceutical industry, especially in the eyes of multiple investors.

Fourth, the hype has gone for the biotech industry after 2000, and there exists tough processes of the clinical trials imposed by regulatory agencies. The tougher trials not only pose significant threats to all firms in the biopharmaceutical industry, but also prevent numerous biotech drugs delivered through pipelines from to reach the marketplace. Because of this market environment, drugs successfully reaching the marketplace tend to be significantly more expensive than traditional pharmaceuticals (Bergeron et al., 2004). This fact contributes substantially to the potentiality of biotechnology in the pharmaceutical

industry, by proving that although new technologies are necessary, such technology is not sufficient for commercial success.

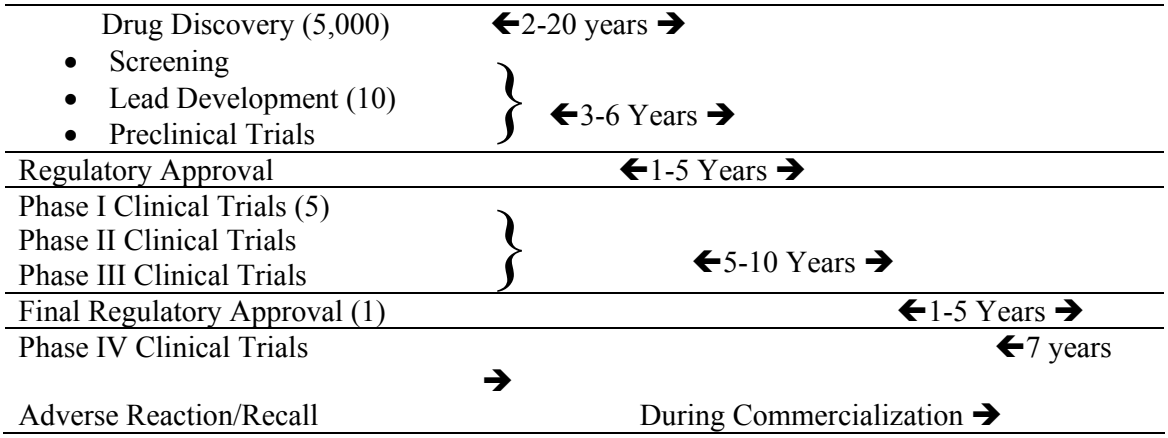
One study in strategic management suggested important strategies for small-and medium-sized enterprises in the biotechnology industry. The authors indicated that small-and-medium biotech firms should adopt an innovator strategy and invest considerably in R&D activity to establish and maintain their first-mover advantages. Since these smaller firms generally suffer size constraints and in turn, consequent resource shortages, the firms must concentrate limited resources on particular market niches in the pursuit of an innovator strategy. Additionally, the traditional belief that high risks can lead to high returns also may apply for large firms, yet that belief fails to apply for small-and-medium sized firms in the biotechnology industry (Qian & Li, 2003).

This particular research indicated that independent small-and-medium size firms, as opposed to corporate-sponsored counterparts and large firms, will carry a higher propensity to fail rather than to be successful, due to both disadvantage of their sizes and market jolts caused by frequent product obsolescence and unpredictable technological breakthroughs. Given risky situations in the biopharmaceutical industry, it is important to elaborate on the drug development process to illustrate why the developmental process significantly contributes to the success or failure of biopharmaceutical firms. Additionally, understanding the drug development process explains the necessity of collaborations among firms in this particular industry.

2.2.1 Drug Development Process

Derived from Bergeron and Chan (2004), Figure 2.1 provides information in regard to the modern drug development process as practiced by typical pharmaceutical firms in the United States. The figure illustrates that the first stage, involving drug discovery, pursues opportunities to bring natural plants or raw materials to the laboratory. During the drug

discovery stage, firms may gather or collect thousands of candidate drugs. Therefore, the process could take from 2 to 20 years to randomly explore and regard the complex logistic processes required to obtain and import the materials. The next three to six years after the drug discovery process include screening and lead development stages for identifying candidate drugs that have a desired effect *in vitro* or in the laboratory using test tubes.



Sources: Bergeron and Chan (2004); Figures in parentheses are the number of candidate drugs, indicating the high failure rate of the process.

Figure 2.1: The Modern Drug Development Process

Elaborating on the *in vitro and in vivo*, Rothaermel and Deeds (2004) mentioned that *in vivo* represents therapeutics placed inside the human body, whereas *in vitro* represents therapeutics used outside the human body. The candidate drugs that meet laboratory requirements, in this case *in vivo*, initiate with preclinical trials involving mice, rabbits, or other live subjects. With data from these preclinical trials, a proposal is made to the Federal Drug Administration (FDA), requesting to clinically test the candidate drugs with human beings. At this stage the regulatory approval from FDA may take from one to five years, depending on the results of the preclinical trials. Typically, at this stage, only five drugs of 5,000 candidate drugs, or 0.1 percent, are approved to proceed to the clinical trials.

Next, the following clinical trial stage uses three phases, with an increasing number of subjects in each phase. While Phase I may involve dozens of volunteers, Phase II involves hundreds of them. The effectiveness and side effects of the drugs are documented during one

to three years of both phases. Phase III, the final phase for the clinical trial, involves thousands of volunteers for periods of two years or more. Because Phase III is the largest and most comprehensive phase, Bergeron and Chan (2004) mentioned that this phase could account for 75% or more of a $200 to $800 million drug development budget. With satisfactory results in terms of safety, efficacy, and clinical value of a drug from Phase III, a pharmaceutical firm may issue a final application to the FDA, requesting approval to commercialize the candidate drug. Depending on the strength of clinical trials and circumstances, a drug with the potential to cure a previously untreatable, deadly disease may garner an approval process by exceptional FDA fast tracking. At this stage, Bergeron and Chan (2004) indicated that a typical period without fast tracking by the FDA extended to approximately 13 months in 2002; this period, however, was reduced substantially from the past, i.e., 33 months in 1989.

During the final regulatory approval process, the pharmaceutical company typically engages in expensive marketing campaigns of the drugs, spending tens of millions of dollars to introduce the upcoming products to the market. Soon after the approval by the FDA, the drug is released to the marketplace. Then, the pharmaceutical company is responsible for the next stage of the modern drug development—Phase IV of clinical trials process. Phase IV extends for as long as the drug is on the market, especially while the drug is patented-protected and unavailable in generic form. Within the final stage, if things should go wrong for the drug, a recall in this stage would be extremely costly for the firms. This is because not only must the commercial firms deal with patient litigations, but also the monies invested in marketing campaigns are lost; in addition, the firms' image may be tarnished (Bergeron et al., 2004).

2.2.2 Roles of Biotechnology in the Drug Development Process

Figure 2.1 shows that the typical drug development process inclusive of basic research, clinical trials, regulatory approval processes, and commercialization activities, covers from 10 to 20 years. Although the FDA has reduced the approval period of new drugs to the market, the process of modern drug development is still lengthy, extremely expensive, and fraught with risk. During the earlier stages of discovery and invention, pharmaceutical firms spend millions of dollars for uncertain results. During the later stages in commercialization, pharmaceutical firms also spend millions of dollar to introduce and educate people in the market to acknowledge the information regarding the active drug ingredients. Although the amount of money spent on the later stages may equal or exceed that spent on the earlier stages of the drug development process, the risks in the commercialization stage are relatively less than that of earlier stages, when the firms had to randomly exhaust resources for unknown results.

Biotechnology contributes to the pharmaceutical industry by significantly decreasing a candidate drug's time to market, thereby minimizing the likelihood of adverse reactions with a possible recall in Phase IV clinical trials. Rather than randomly hunt for plants or natural materials that may affect a specific type of disease, researchers use computer modeling to determine the molecular structure of the drug that will most likely interfere with the metabolism of the disease. Additionally, the profile of novel synthetic compounds that serve as candidate drugs may be stored in expansive libraries for future references and uses. This process offers a potential for shortening the process of development during the drug discovery stage. Thus, a challenge to the biopharmaceutical industry involves new approaches to drug development that are short enough to permit pharmaceutical companies to initiate favorable action before the patent protection expires, as well as being safe enough to avoid Phase IV adverse reaction and recall. Research and development expenditures have

increased since the early 1980s, while the number of drugs approved for market has not increased in proportion to the total investment (Kermani & Bonacossa, 2003). Consequently, proponents of biotech contend that the best way for pharmaceutical firms to survive and thrive is to leverage their opportunities in biotechnology and thus exploit this unique method in the drug development process (Bergeron & Chan, 2004).

2.3 Roles of Patent Protection in the Biopharmaceutical Industry

The overview of biotechnology and the pharmaceutical industry from the previous section suggested that research-based pharmaceutical companies with few other interests, such as Merck and Bayer, could easily spend 10-25% of sales on their research and development projects (Wittcoff, Reuben, & Plotkin, 2004). Further, for the dedicated biotechnology companies, this ratio can be considerably higher. Between 1990 and 2000, biotechnology R&D expenditure increased by 262 percent, whereas that for pharmaceutical rose by 121 percent over the corresponding period (Kermani et al., 2003). However, the high ratios of R&D to sales of those firms do not guarantee success in the commercialization of new drugs in the industry. Given the risky situation in terms of the modern drug development process in biotechnology and the pharmaceutical industry, it is pivoted to understand why and how firms in this particular industry willingly spend several million dollars to engage in uncertain drug development processes.

According to an article in a legal newspaper (Good, 2000), an important driving force in the biopharmaceutical economy is the need for an effective system of patent protection. Regarding their information, a top manager in a biopharmaceutical firm dramatically mentioned that "without patents, the biotechnology industry of today would not exist, and there would be no progress in development of new pharmaceutical products." Consistent with the previous argument, Bergeron and Chan (2004) indicated the importance of patent protection in biotech industry. They mentioned that without patent protection,

"pharmaceutical companies would be averse to spend upwards of $800 million to develop a new drug for the market." Furthermore, universities and research institutes would have less economic incentive toward investing years of effort to complete important basic research.

Kermani and Bonacossa (2003) reported a 1988 study of 12 industries conducted by the University of Pennsylvania; the study estimated that "around 60 percent of pharmaceutical products would not have been introduced without adequate patent protection." The authors explained that the existing environment for intellectual property protection can influence the investment behavior of companies. Specifically, for biopharmaceutical firms, strong patent laws are important; not only do the patent laws allow the firms a chance to recoup huge investments in R&D, but also the laws allow the firms to reward shareholders who have shown commitment and faith in the companies by investing from an early stage.

In fact, the effective system of patent protection in the U.S. allows the business of successful biopharmaceutical firms to become profitable. Although the ratio of successful drugs to candidate drugs is extremely low (i.e., only one percent of the compounds examined in the pre-clinical stage reach the stage of human testing), pharmaceuticals ranked first in profits in the 1999 list of Fortune 500 global companies (Carbone, 2003). Overall, patent protection has been essential to the high risk/high profit business structure of the biopharmaceutical industry. Success stories of the biopharmaceutical firms illustrate the importance of the patent system in motivating private investment in research and development. Thus, firms in this particular industry consistently outrank other industries in terms of patent-sensitivity and R&D expenditures.

2.3.1 Basic Patent Law Concepts

A patent is a legal grant by a government to encourage innovation, technical development, and ultimately economic prosperity (Khight, 2001). Patents are a device in which government grants inventors the sole right for a limited period of time to exploit their

inventions for commercialization (Wittcoff et al., 2004). To obtain a patent, the inventor must show that the invention is novel and non-obvious. Since the novel requirement in a patent law is difficult to meet for many innovators, it tends to hinder future inventions. Thus, the patent system incorporates non-obviousness as an additional requirement for patentability, using non-obvious characteristics determined by a skilled person to help fine tune the novelty requirement for promotion of incremental inventions in the market. Although the standard for non-obviousness is especially difficult to apply in the chemical and biotechnological fields, it is worth remembering in the high technology era where most innovation occurs incrementally (Ducor, 1998).

The innovator must show that the invention is useful or has utility, in addition to being novel and non-obvious. This usefulness or utility is a requirement that the invention has industrial use or value. Recently, courts require a higher standard of usefulness, however. In fact, patents dealing with advances in genetic technology receive even more stringent requirements in terms of usefulness. According to Knight (2001), many patent offices on a world wide basis now require that patents on certain genetic material display 'real-world' utility, or a clearly expressed use. In a practical standpoint, this means that, in their patent applications, innovators are required to illustrate an example of how the invention will make one become better. Further, the last patent requirement is that innovators must pay not only a fee to file the application, but also a fee to have the patent issued. In most countries, maintenance fees are required on a regular basis throughout the term of the patent or patent application, to keep the patent in force or the application pending (Knight, 2001).

After meeting all patentability requirements, the inventor must teach how to use and make the invention. By publicly disclosing technical information of an invention, others may learn from the invention by paying processing fees. Additionally, the government will grant the inventor the right to exclude others from utilizing the invention for a specific period. So far,

the patent system has grown rapidly. In the United States, Wittcoff et al. (2004) reported that whereas it took about 200 years to amass four million patents (until 1976), it took only 15 more years, to 1991, to accumulate one million more patents. Regarding a unique aspect of patent protection in the biopharmaceutical industry, Carbone (2003) indicated that "unlike innovations in information technology, which are often obsolete in a few years, best selling pharmaceuticals may generate blockbuster profits over the entire life of the patent." Wittcoff et al. (2004) wrote that as a result of the GATT (General Agreement on Tariffs and Trade) negotiations, the United States extended the period of patent protection for 20 years; however the protection period starts from the date of application instead of issuance (Wittcoff et al., 2004).

2.3.2 Specific Issues of Patents in the Biopharmaceutical Industry

According to the USPTO, there are three broad categories of patents: utility, design, and plant. An article in Drug Discovery & Development reported that among these types, most biotechnology patents fall under the category of utility patent. Particularly, there are two broad categories of utility patent: provisional and nonprovisional. According to an intellectual property attorney in the same article, innovators can file "a provisional application before the full application as long as the full application is filed within one year of the provisional and the provisional contains a full description of the invention, the date at which the novelty of the invention is to be decided will be the date of filing the provisional and the date from which the 20-year term starts will be the date of filling the 'full application'" (Terry, 2004). Regarding the extension of the patent protection period, the same attorney reported that patents subject to regulation under the Food Drug and Cosmetic Act can be extended. The period of extension relies on different circumstances, but the main reason for the extension relates to the length of the FDA approval process and represents an attempt to make up for lost time due to the lag period.

Although the drug inventors require FDA approval to commercialize drugs, there is no need for the drug inventors to meet the FDA's safe and effective requirements to apply for their patents (Terry, 2004). In fact, inventors can apply for their patents as soon as they believe they have created patentable inventions and want to protect the inventions. As soon as the scientists find that a discovery or invention has the potential to become a new treatment or a successful drug that will improve life for a million people, scientists should immediately contact lawyers if they work in a pharmaceutical or biotechnology company. Otherwise, those who work for universities should contact the Office of Technology Transfer. According to the article, the Office of Technology Transfer moves technology at the university to the market place as effectively as possible either by licensing commercializable technology to industry or by patenting the technology (Terry, 2004).

While patenting processes are similar across industries, it is important to note that the patent system for drugs in the biopharmaceutical industry carries unique characteristics. Comparing implications of patent systems for the biopharmaceutical and information technology industries, Carbone (2003) explained that whereas firms in the information technology industry typically require the rights of many patented components to produce a product, drug companies are more likely to depend on a small number of successful patents to develop a drug. Biopharmaceutical firms are more likely to avoid investment in research that may be similar to patent rights held by other companies. Further, firms are more likely to aggressively enforce rights they possess (Carbone, 2003). This suggests that the extent to which biotech innovators depend on others' technology to generate their inventions is less than that of their counterparts in the information technology industry.

Specifically, Carbone (2003) explained that patents in biotechnology tend to be more valuable than patents issued for traditional pharmaceutical firms. Whereas the traditional drug companies targeted small molecule chemicals with effects the drug companies

understood and that were relatively easy to design, biotech companies focused on a relatively small number of large molecules, reproducing in purified form proteins that were often already in use. The biotech firms subsequently isolated the relevant gene sequence and used the recombinant DNA approach to produce an almost limitless supply. Because the biotech mechanism producing the desired results is less well understood than that of the traditional drug firms, biotech firms were awarded by the patent authority with broader and more valuable patents than those of the chemical patents. As a result, Carbone (2003) reported that "patents on products like insulin or growth hormone earned billions of dollars in profits."

However, one major criticism regarding the broad-based patents acquired by biopharmaceutical firms is that the patents may block the next generation of biotechnological discoveries. The broad-based patents reflect unfair practices of right distribution, and they are major obstacles to greater innovation in the industry (Carbone, 2003). Given the fact that the biopharmaceutical industry is maturing (Wittcoff et al., 2004) and that there are many broad-based patents in the industry, it is difficult for new biotech inventors to develop new drugs without incurring additional expenditures. The additional expenditures that the new inventors must spend to acquire and incorporate the broad-based patented technologies into their work potentially increase the cost of typically expensive biopharmaceutical developments. This process leads to the extremely high prices of new drugs, preventing patients' access to the new medicines on a global scale. This fact validates critics who say that patents in the biopharmaceutical industry help companies put "profits" before "lives" (Kermani et al., 2003).

2.4 Collaborative Environments in the Biopharmaceutical Industry

Information about the blockbuster business model among major pharmaceutical firms and the patent process within the particular industry from the previous section indicated that the firms rely on the success of one or two drugs every year or two to survive in the industry.

Using the revenues from the blockbuster drugs to fill the regulatory pipeline with new drugs, the firms find indications for drugs already on the market, develop new formulations of proven blockbuster drugs, and maneuver around a variety of laws and regulations to exploit proprietary technology. In addition to tactics and strategies to survive the competition in the biopharmaceutical industry, Bergeron and Chan (2004) indicated that "another popular way to acquire a continuous stream of revenue from blockbuster drugs is for the pharmaceutical firm to merge with a pharmaceutical company with an existing blockbuster drug in its pipeline." Because of their massive economic impact on the industry and national economy, several types of collaborative agreements among firms in the biopharmaceutical industry warranted front-page coverage in the popular press, as well as special attention from the various antitrust regulatory agencies (Bergeron et al., 2004). The numerous collaborative agreements of firms in the biotechnology industry reported in the popular press suggest that secondary data on interfirm agreements between pharmaceutical firms and biotechnology firms in the United States should be available to collect and analyze. This fact drew attentions of researchers in areas of strategic alliances to conduct several studies (i.e., during 1994 – 2004), using the biopharmaceutical industry as a testing ground.

Regarding the mergers and acquisitions of pharmaceutical firms, Bergeron and Chan (2004) indicated that such practices are so popular that a pharmaceutical firm that has not been acquired or that is not acquiring another firm is the exception rather than the rule. From the news in 2002, Pfizer, a major pharmaceutical firm was planning to buy Pharmacia, a major competitor who commercializes Celebrex, the blockbuster arthritis therapy (McKenna, 2002). According to another article regarding Pfizer and Pharmacia after the merger, Pfizer blockbusters would combine its own blockbusters, Lipitor, Norvacs, Zoloft, and Viagra with those of Pharmacia including Celeblex, Xalatan, Detorl and Camptosar. The article mentioned that although "most likely to be known simply as Pfizer, the new company

contains the ghosts not only of Warner-Lambert and Pharmacia, but also of Pharmacia's past: Upjohn, Monsanto, and JD Searle" (Sellers, 2002). Figure 2.2 illustrates the mergers and acquisitions (i.e., horizontal integrations) of marketing-based firms, such as Pfizer and Pharmacia. The two headed arrows represent collaborative efforts and mutually interdependent patterns in terms of information and resource flows among several types of organizations in the biopharmaceutical industry.

Regarding the vertical integration, Rothaermel (2001) explained that pharmaceutical companies used interfirm cooperative strategies to adapt themselves to radical technological changes in the industry. During the technological breakthrough, the chemical-based pharmaceutical companies transformed themselves into biopharmaceutical companies by collaborating with new biotechnology entrants (i.e., upward vertical integration). In turn, the biotechnology startups engaged in downward vertical integrations utilizing their collaborative alliances to commercialize their biotechnology (Shan et al., 1994). To illustrate the case in point, another study indicated the collaboration of Eli Lilly, an established pharmaceutical firm, with Genentech, a biotechnology firm, in acquiring Genentech's Humulin, a human insulin based on recombinant DNA technology (Rothaermel, 2000). Rather than the destruction of existing pharmaceutical companies (which could not compete due to disruptive technologies) and the struggle of biotech startups (to commercialize inventions), the firms experienced mutual benefits from strategic alliances. The two firms withnessed complementary and collaborative efforts, which were subsequently introduced to current biopharmaceutical environment in exploitation alliances.

As illustrated by Rothaermel (2001), exploitation alliances are market-oriented alliances that focus on clinical trials (i.e., phase IV), FDA regulatory management, and marketing and sales, whereas exploration alliances are technology-oriented alliances that focus on drug discovery and development, as well as clinical and commercial manufacturing.

Collaborations between exploitation alliances and exploration alliances result in a successful commercialization of biotechnology. The argument that established pharmaceutical firms tend to engage in complementary collaborations, confirmed in a study by Kermani and Bonacossa (2003), reported that biopharmaceutical companies increasingly seek vertical collaborations with outsourcers such as contract research organizations (CROs).

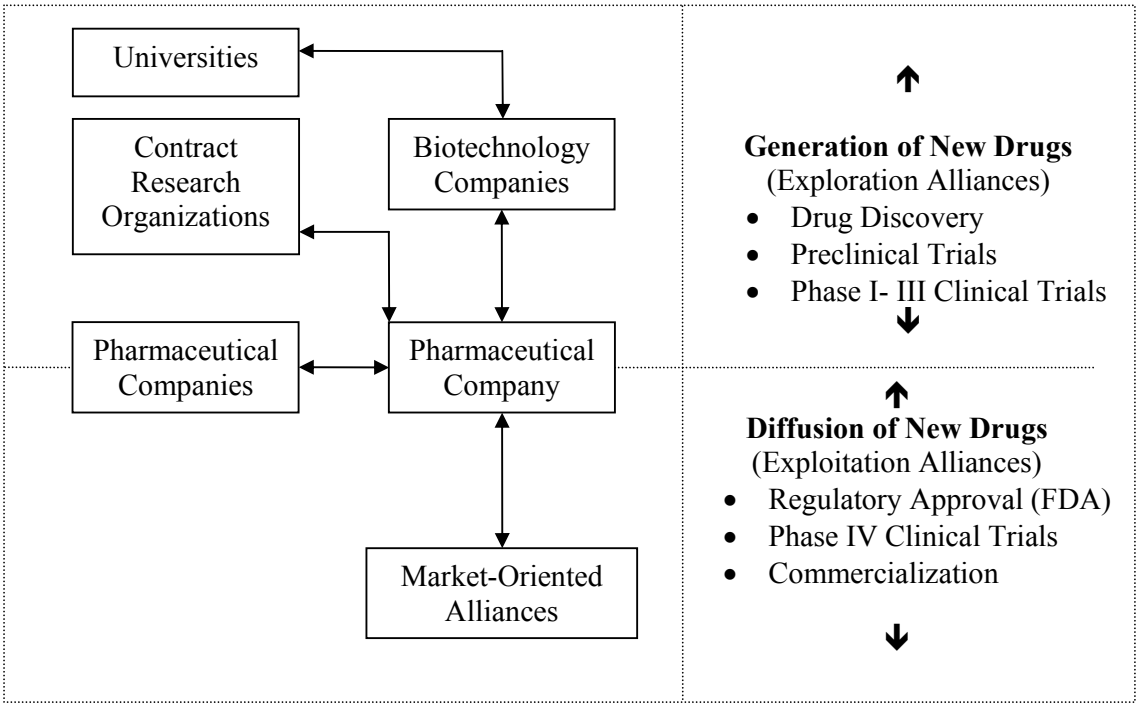


Figure 2.2 Collaborative Environments in the Biopharmaceutical Industry

In fact, the authors indicated that in 2001, biopharmaceutical companies outsourced around 60 percent of clinical work to CROs. Use of CROs possessing extensive experience in running large scale international trials should substantially expedite the clinical development process for pharmaceutical firms.

Another study indicated that "it was not uncommon for a single pharmaceutical firm to initiate alliances with competing biotechnology laboratories" (Vassolo, Anand, & Folta, 2004). Specifically, the larger pharmaceutical companies exchange financial support and established organizational capabilities in clinical research, regulatory affairs, manufacturing, and marketing for the expertise and patents of the biotech startups. A new environment

emerged by the end of the 1990s, drastically reshaping the traditional pharmaceutical industry from that of the seventies.

Figure 2.2 also elaborates the roles of universities and contract research institutes as upstream partners for biotechnology and pharmaceutical firms. Several studies addressed the importance of universities and research institutes as organizational partner, contributing to the tremendous success of biotechnology firms (Liebeskind et al., 1996; Silverman & Baum, 2002). Specifically, Liebeskind et al. (1996) indicated that "although the number of biotechnology scientists has increased rapidly, only a few 'star' researchers have made numerous commercially valuable discoveries, and many of these stars work in universities." The relationship between universities and biopharmaceutical firms may be illustrated by examining the founding history of Velcura Therapeutics, Inc.—a leading biotechnology firm in the treatment of bone-related injuries and bone disorders. The company spun from the University of Michigan not long after Michael Long, a professor in the pediatrics department, filed his first patent entitled "A method and composition of matter patent on the isolation of bone precursor cell." Dr. Long, current CEO of the company, mentioned that "the university was very helpful in marshaling resources to start the company. But once the company incorporated, it became a separate entity and had to negotiate for the right to the technology, just like any other company" (Terry, 2004).

Velcura Therapeutics, Inc. is just one of many biotechnology firms that spun from universities and later established strong relationships with those same universities. Liebeskind et al. (1996) suggested that biotechnology firms that want to glean cutting edge technologies, must set up a "university-like" organizational context in order to encourage firm scientists to work on publications with university scientists. In so doing, the social networks play an important role in promoting organizational learning and in fostering organizational flexibility in the biotech firms. In turn, collaborations with biotech firms

provide several important benefits to scientists at the universities. First, working with firms supports basic research in terms of funding. Second, industrial involvement in university research addresses the issues that are industrially relevant problems, and allows a focus on those problems with the greatest potential for industrial payoffs. Third, industrial involvement in the research program improves the capabilities of technology transfer by converting basic research results into products and services. Last, collaborating with industrial partners promotes employment opportunities for graduate students and researchers who seek to work in the corporate research environment (Lechtenberg, 1989).

2.5 Data Sources in the Biopharmaceutical Industry

Previous sections in this chapter elaborated on the general scope, general characteristics, roles of patent protection, collaborative environments, and current knowledge developed, using the biopharmaceutical industry as a testing ground. For instance, several studies in strategic management contributed to knowledge of strategic alliances in the biopharmaceutical industry. After the emergence of the biopharmaceutical industry in the mid–1970s (Lerner, Shane, & Tsai, 2003), information about the biopharmaceutical industry has become increasingly publicized and available to researchers who wish to observe the phenomenon and to develop and test hypotheses, using the industry as a testing ground. Table 2.2 attempts to list important sources of data in the biopharmaceutical industry used by several important studies during 1994–2004.

The information from Table 2.2 indicates that academicians have used several data sources to understand phenomenon related to the biopharmaceutical industry. Interestingly, many researchers have used more than one source of database to crosscheck validity and reliability. The three most popular sources in the industry are BioScan, Recombinant Capital Database, and Canadian Biotechnology Handbook. First, "BioScan" has been used at least by 13 studies in management. Walker, Kogut and Shan (1997) mentioned that BioScan is "a

commercial directory of biotechnology firms, published and updated quarterly by ORYX Press, Inc." The authors also commented that BioScan has generally been considered the most comprehensive compendium of information on relationships among biotechnology firms in the industry. According to BioScan website, the database source of information on covers more than 1,800 international companies involved in biotech product research and development activities. BioScan also provides a directory service containing detailed company profiles, inclusive of inside information on strategic alliances, mergers, product acquisitions, new products in development and coming to market, licensing and R&D agreements, and principal investors.

Likewise, multiple studies have used the Recombinant Capital database to collect data on strategic alliances of biopharmaceutical firms. Recombinant Capital is a San Francisco-based consulting firm specializing in tracking the biotechnology industry (Lerner et al., 2003). According to its website, the database of Recombinant Capital provides information regarding alliances and clinical trial progress of drug developments. The alliances database contains 19,303 high-level summaries of biotech alliances commenced since 1973 and currently tracks the progression of 1,619 clinical trials in which a biotech company is involved in the compound's development and/or commercialization.

Next is Canadian Biotechnology—the most comprehensive historical listing of Canadian biotechnology firms and their products, performance, and alliances (Silverman et al., 2002). The Canadian Biotechnology Handbook provides information for a more restricted set of "core" Canadian biotechnology firms. Interestingly, while the database is comprehensive, only Baum, Silverman, and Calabress have used this data source in their studies.

From Table 2.2, it is important to note that several data sources of the biotechnology industry are located in the state of North Carolina. These data sources include the University of North Carolina's Database on Biotech Alliances, the North Carolina Center for

Biotechnology Information, the North Carolina Biotechnology Industry Database, and the North Carolina Biotechnology Center (NCBC) Actions Database. Additionally, while many researchers used direct data source in the biopharmaceutical industry, Kotabe and Swan (1995) used 905 articles from the Wall Street Journal over a 5-year period in their study. The authors conducted a content analysis to test their hypotheses regarding the role of strategic alliances in a high-tech product development. They used three independent judges consisting of a technology researcher with a PhD degree, a product designer with an MBA degree, and a product engineer with a graduate engineering degree, to code their data; the effects produced 92 percent inter-reliability.

Table 2.2 Sources of the Biopharmaceutical Industry and Its Studies in Management

Biopharmaceutical Sources	Authors and Years
BioScan	(Folta & D., 2002; Gulati & Higgins, 2003; Nicholls-Nixon & Woo, 2003; Owen-Smith & Powell, 2004; Powell et al., 1996; Qian et al., 2003; Reuer, Zollo, & Singh, 2002; Rothaermel, 2001; Rothaermel et al., 2004; Shan et al., 1994; Vassolo et al., 2004; Walker, Kogut, & Shan, 1997; Zollo, Reuer, & Singh, 2002)
Recombinant Capital Database	(Gulati et al., 2003; Lerner et al., 2003; Wuyts et al., 2004)
Canadian Biotechnology & The Canadian Biotechnology Handbook	(Baum, Calabrese, & Silverman, 2000; Silverman et al., 2002)
The University of North Carolina's Database on Biotech Alliances	(Reuer et al., 2002; Zollo et al., 2002)
The North Carolina Center for Biotechnology Information	(Gulati et al., 2003)
The North Carolina Biotechnology Industry Database	(Vassolo et al., 2004)
The North Carolina Biotechnology Center (NCBC) Actions Database	(Folta et al., 2002; Walker et al., 1997)
The Institute for Biotechnology Information (IBI) database	(Gulati et al., 2003)
Biotechnology Guide USA	(Gulati et al., 2003)
Wall Street Journal (Articles)	(Kotabe & Swan, 1995)

Of all data sources, BioScan potentially offers the most data sources in regard to all types of collaboration among firms in the biopharmaceutical industry. For instance, the database

offers basic characteristics of biopharmaceutical firms including key personnel, numbers of employees, company history, facilities, information about ownership structure, and financial information. In terms of company history, the database includes an established date, a history of mergers and acquisitions, and name changes. Regarding the strategic alliances, names of alliances, collaborative prod ucts, types of agreements including equity and non-equity collaborations, and dates of agreement are specified. Additionally, the database suggests the names of all products in different development stages (i.e., in preclinicals, in phase II clinicals). While BioScan provides information regarding interorganizational networks of biopharmaceutical firms and their invention and commercialization activities, additional data sources are needed to supplement the specific aspects of data (i.e., financial outcomes) to address variables from particular hypotheses.

CHAPTER 3: INNOVATION STUDIES

The objective of this chapter is to review literature relevant to innovation studies. In the beginning of this chapter, innovation perspectives are separated into two concepts—one is accompanied with an uncontrollable outcome; the other is with a controllable outcome. Focusing on the controllable innovation perspectives, this study explains the concepts of "product" and "process" innovations. Following the concepts of product innovation, the study considers several articles in the areas to review invention and commercialization, the two important activities determining success or failure of typical firms. Then, in the following section, the study details the attempts to explain the relationships between interorganizational linkages and integrated innovation performance (i.e., invention and commercialization performance). At the end of this chapter, the study considers several important scholarly examinations of innovation and identifies the empirical findings and data sources.

3.1 Several Theoretical Perspectives in Innovation Studies

Schumpeter asserted that entrepreneurship is a process of "creative destruction" through which existing products or methods of production are destroyed and replaced with new ones (1934). McDaniel (2005) provided a contemporary view of Schumpeter's theory of the entrepreneur, noting that Schumpeter described the entrepreneur as an innovator who creates innovation. Schumpeter also regarded innovation as the commercialization of an invention. In fact, Schumpeter stressed the importance of the entrepreneur as a person who carries out new combinations, and who leads the means of production into new channels, possibly reaping an entrepreneurial profit (McDaniel, 2005). Nelson and Winter (1982) explained that the concept of innovation from Schumpeter's perspective is a broad framework, covering all innovative ideas and market practices. The authors quoted Schumpeter's five identified cases to identifying his concepts of innovation as: 1) "carrying out new combinations, 2) The

introduction of a new good . . ., 3) The introduction of a new method of production . . ., 4) The opening of a new market . . ., 5) The opening of a new source of supply . . ., 6) The carrying out of the new organization of any industry, like the creation of a monopoly position" (Schumpeter, 1934: 66).

Based on this knowledge, both practitioners and scholars in the field of strategic management have recognized "perpetual innovation"—a term used to describe how quickly and consistently new technologies replace older ones. For most organizations, innovation is a substantial influence on competitive dynamics since it mainly affects the strategic actions and responses of all firms competing for limited resources within slow-cycle, fast-cycle, or standard-cycle markets. Accordingly, most organizations are required to possess resources and capabilities in order to generate and exploit innovation.

In terms of theoretical development, innovation studies began over three decades ago. However, both researchers and practitioners do not understand much about how they can control and influence the innovation processes and outcomes. Like strategic management, innovation theory also appears to derive from practical rather than theoretical concerns (Drazin & Schoonhoven, 1996). This means that firms recognize the importance of innovation, but they have little idea on how to deal with its uncertainty. At its core, however, scholars in areas of innovation management have proposed three basic assumptions: 1) innovation is universally desirable for organizations, 2) once an organization increases its size beyond a critical mass, it becomes more inert, less capable of meaningful organizational change, and unsuitable for future innovation, and 3) certain structures and practices can overcome inertia and increase the generation rate of innovation (Drazin et al., 1996).

Whereas the three assumptions indicate relationships between organizations and innovation outcomes, innovation strategies are still relatively unknown and fraught with risk. Both academicians and practitioners do not know much about innovation process and how to

influence the innovation outcomes. Organizations generate innovations, the vast majority of which are worth little to themselves; however, some are extremely important and valuable (Greve, 2003). A study in management indicated that "despite continued scholarly efforts in the past three decades to understand the innovation process and the conditions under which innovation is facilitated, current empirically developed theories of organizational innovation are not adequately encompassing" (Damanpour, 1996: 693) Drazin and Schoonhoven (1996) confirmed that innovation theory relatively models a less developed paradigm. The author wrote:

> Unlike other evolving fields or organizational inquiry, such as organizational economics, contingency theory, organizational ecology, and institutional theory, innovation research demonstrates little in the way of common theoretical underpinnings to guide its development (1996: 1065).

The arguments regarding the less developed paradigm of innovation theory are comparable to Pfeffer's (1993) call for developing the paradigm of organizational science. Like organizational science, innovation knowledge is continuously developed and scrutinized by different academic perspectives including management, economics, sociology, and even a scientific field like engineering. In the following pages, this paper illustrates several important perspectives: evolutionary, economics, behavioral, and sociological perspectives. The objective is to briefly review current academic knowledge of innovation.

In the broadest perspective, the innovation process can be understood by an evolutionary approach (Aldrich, 1999; Nelson & Winter, 1982). According to Aldrich (1999: 21), "evolution results from the operation of four generic processes: variation, selection, retention and diffusion, and struggle over scare resources." According to the general concepts of evolutionary perspectives, firms differ in terms of unique routines and competencies or what Aldrich (1998) termed as "genes," the particular structures developed through an internal

problematic search, founding of new organization by outsiders, and mistakes or misunderstandings in their business practices. The variations produce unequal performances and different abilities among firms to survive the competitive environments. Those firms that successfully deal with market forces and conform to institutionalized norms as well as additional pressures from internal factors are selected and preserved within the environments. Overtime, the successful structures or genes are duplicated or reproduced by others. Because similar firms compete against one another for limited resources in the competitive environment, the process after variation, selection, retention, and diffusion represents the struggle among themselves.

Nelson and Winter (1982) followed the concepts of Schumpeterian competition to explain why some firms track emerging technological opportunities (i.e., innovation) with greater success than other firms. The authors indicated that Schumpeter (1950) stressed the advantage for innovation for a large firm size. Further, his concept implied that a market structure could be another factor influencing the opportunities in which firms could exploit and earn abnormal profit from their innovation. Specifically, Schumpeter declared that perfect competition is an incompatible market structure for innovation, suggesting that the competitive environment in the market encourages a spur to innovation. On the contrary, the monopolistic and/or oligopolistic markets reflect weak competition and thus encourage a permissive environment for an activity like Research and Development (R&D). Further, whereas most analyses of the relationship between market structure and innovation indicate a one-way causation from market structure to innovation, under Schumpeterian competition, there is a reverse flow of the causation as well. Schumpeter (1950) for example, argued that successful innovators who are second movers may invest their profit and grow in relation to their competitors. Similarly, effective "fast second" firms may come ultimately to dominate

others once they successfully acquire substantial resources in their industries (Nelson et al., 1982; Schumpeter, 1950; Setzer, 1974).

Applying the evolutionary approach to Schumpeter's concept of innovation, Nelson and Winter (1982) claimed that they offer a model that permits firms to differ in their emphasis on innovation and imitation. Specifically, the authors suggested that firms differ in terms of their policies toward two techniques of production: "by doing R&D that draws on a general fund of relevant technical knowledge [innovation] or by imitating the production processes of other firms [imitation]" (1982: 282) Ultimately, the authors argued that the evolutionary approach is better than orthodox theory to understand the innovation process as a phenomenon. Unlike the orthodox theory, which tends to relatively ignore genuine novelties, the evolutionary approach has the merit of placing issues of change at center stage. The evolutionary approach views innovation process as dynamic activities of variation, selection, retention and diffusion, and the struggle over scarce resources, as well as the interdependent processes that explain the success and failure of innovation and organizations.

Whereas the evolution approach may be so broad that it covers an international level of technological progresses and successful growth of nations (Nelson & Winter, 1982), economics perspectives offer narrower concepts and more specific knowledge about innovation. For instance, economics applies concepts of agency theory in comparing the conflicts of interest between agents and principal relationships with the conflicts of managers and their shareholders in terms of implementing innovation strategy. Using agency theory, one study in management found a negative relationship between diversification strategy and R&D investment (Baysinger & Hoskisson, 1989).

Because an investment in R&D tends to associate with a higher level of risk, managers who are typically risk-averse are reluctant to engage in innovative activities, resulting in a loss of competitiveness and lower performance in firms (Hoskisson, Hitt, & Hill, 1993). The

findings from this study suggest that a) managers (agents) will be likely to avoid innovation strategies because the strategies are too risky, and b) without innovation strategies and outcomes, firms will lose competitiveness and performance in the long term. Further, a more recent study in strategy found that institutional ownership (as a governance device) is positively related to firms' innovation (Kochhar & David, 1996). Because the institutional owners prefer a higher level of risk pattern than managers, institutional owners tend to promote innovation activities as ways to enhance the value of organizations. This particular study also confirms that ownership structure is one of the significant factors determining levels of corporate innovation.

According to behavioral perspectives, several learning theorists suggested necessary factors and conditions in which firms can learn and create innovation outcomes (Cohen & Levinthal, 1990; Kim, 1998; Van De Ven & Polley, 1992). Drawing from learning theory, Cohen and Levinthal argued that organizations need prior related knowledge to better identify, assimilate, and use new knowledge (1990). The prior related knowledge is an important condition for firms to create incremental innovations (i.e., competency-enhancing innovations). Using concepts of prior related knowledge, Hill and Rothaermel (2003) suggested that if incumbent firms possess a high level of prior knowledge, yet such knowledge is irrelevant, the firms will be less likely to create radical innovations (i.e., competency-destructive innovations). Likewise, Kim (1998) indicated that effective organizational learning and absorptive capacity require two major elements—prior knowledge base and intensity of efforts. Using Hyundai Motor as a case study, Kim (1998) also detailed three stages of learning orientation—duplicative imitation, creative imitation, and innovation—which occur subsequently for Hyundai Motor.

While economics and behavioral perspectives reveal us innovation strategies that fall within organizations, sociological perspectives explain innovation strategies that fall outside

organizations. In particular, population ecologists offered a concept of organizational inertia that constrains firms' reactions toward innovations, while the institutionalization of market values and environments provides an important framework for consumers to understand innovation (Selznick, 1996). Combining concepts from these perspectives, economics and behavioral scholars regard innovation as a controllable outcome while sociologists believe that innovation is an uncontrollable outcome. In the following section, this paper reviews several studies to understand the position of innovation as an uncontrollable outcome.

3.2 Innovation as an Uncontrollable Outcome

From an analysis of the past innovation research, three factors of innovation are located outside of management's control. Drawing from studies of sociologists, the first factor is organizational inertia. Organizational ecologists asserted that organizations have an inertia which hinders or prevents radical changes in strategies and structures (Hannan & Freeman, 1984). Accordingly, organizational inertia is an important condition that hampers generations of innovation within organizations (Drazin et al., 1996; Hill & Rothaermel, 2003). As indicated by Hannan and Freeman (1984), sources of organizational inertia consist of both internal and external factors. Whereas managers influence such internal factors as sunk costs and the dynamics of political coalitions, managers rarely influence such external factors of inertia as temporal patterns of opportunities and threats in relevant environments (i.e., other competitors, technological environments).

The next aspect of innovation which falls outside management's influence is the occurrences and outcomes of technological breakthrough (Hargadon et al., 2001). Specifically, two types of innovations occur after the technological breakthroughs—competency-enhancing and competency-destroying innovation. The former innovation builds on know-how embodied in the technology that it replaces. These competency-enhancing innovations introduce "a new technical order, with a vastly enhanced performance

frontier, while building on the existing technical order rather than making it obsolete" (Hargadon et al., 2001).

The latter innovation provides new knowledge which entirely replaces existing technology (Anderson & Tushman, 1990). Conversely, the concepts of competency-destroying innovation are comparable to the concepts of discontinuous technologies, in that both represent price-performance improvements over existing technologies so significant that "no increase in scale, efficiency, or design can make older technologies competitive with the new technology" (Tushman & Anderson, 1986). Because technological breakthroughs from the competency-destroying innovation are more radical, less predictable and less manageable than those breakthroughs from the competency-enhancing innovation, the breakthroughs from competency-destroying innovation are more likely to be another factor falling outside managerial control in terms of occurrences and innovation outcomes (Tushman et al., 1986).

The last factors related to innovation strategies that fall out of managerial control are institutional and market dynamics, which constitute an acceptable framework for constituents to evaluate innovation. These factors, important for innovation strategies, seek to successfully diffuse generated innovation and to gain acceptance by public. Hargadon and Douglas (2001) compared constituents in institutional perspectives with social actors in the market (i.e., consumers, dealers). In the market, social actors or consumers interpret the meanings of innovative products using current understandings located within institutional framework. If the concepts or appearances of innovation fall outside the default framework, consumers will not understand such concepts or appearance. Thus, they will not support or accept the innovation. Recently, several studies mentioned that innovators may influence the market and technological framework (Spencer, 2003; Zahra & Nielsen, 2002). However, in so doing, the innovators need support from interorganizational linkages.

3.3 Innovation as a Controllable Outcome

After elaborating the important aspects of innovation that fall outside of management's control, it is important to discuss what managers can do to compensate for those factors. Although managers cannot directly influence external uncertainties (i.e., they cannot change the general environment), they can directly influence their strategies (Nohria & Gulati, 1996), organizational structures (Damanpour, 1996), and behaviors (Dougherty & Hardy, 1996) to achieve innovation outcomes. In fact, given the evidence that some firms continuously and successfully generate and exploit innovations, whereas many others fail to do so, several researchers in innovation areas attempted to understand the influence of managers in determining the innovation outcomes.

Drazin and Schoonhoven (1996) indicated the importance of innovation studies by reviewing several important works on innovation. The authors suggested that because of the importance of innovation, Administrative Science Quarterly (Tushman & Nelson, 1990), Strategic Management Journal (Guth & Ginsburg, 1990), and Academy of Management Journal (Drazin et al., 1996) publications in the genre devote special issues to understanding the concepts of innovation. The authors claimed that "it is clear that the study of the generation of innovation is central to the study of organizations and organizational theory." Despite the fact that the previous statement was made almost a decade ago, organizational factors, if clearly understood, should explain the complexity and uncertainty of innovation.

Regardless of the popularity of innovation studies to uncover the length and complexity of innovation activities, the terminological concepts of innovation remain unorganized and unkempt. For instance, several articles on management (Damanpour, 1996; Nohria et al., 1996) applied the term "innovation" to represent the term of "invention" as initiated by Schumpeter (1934). Additionally, others used the term "adoption" and "diffusion" interchangeably to represent Schumpeter's term "imitation" (Davis, 1991; Goes & Park,

1997). Consequently, despite Schumpeter's development of a categorization of innovation activities in 1934, few scholars have seriously followed a consistent use of the terms.

Particularly, Schumpeter (1934) indicated three important and distinctive activities in innovation processes—invention, innovation, and imitation. The author noted that 1) invention represents the act of creating or developing a new product or process; 2) innovation represents the process of creating a commercial product from an invention; and 3) imitation represents the adoption of an innovation by similar firms. The fact that Schumpeter used "innovation" to involve three types of innovation activity simultaneously confused several scholars from the beginning. As a result, few scholars applied Schumpeter's terms in following studies. To clarify and categorize different activities of innovation and to honor Schumpeter's work (1934), this study matched several terms used in various studies that applied Schumpeter's categorizations of three innovation activities. These terms are presented in Table 3.1. As illustrated by the table, the comparable concepts in later studies confirm that three existing sequential stages of innovation proposed by Schumpeter (1934) are valid and deserve recognition by other scholars in the field of innovation.

Drawing from Schumpter's (1934) terms of innovation activities, this paper suggests that invention and the combination of innovation and imitation are similar to exploration and exploitation as initiated by March (1991). According to March, exploration activities capture such terms as "search, variation, risk taking, experimentation, play, flexibility, discovery, innovation." Additionally, the exploitation activities include such terms as "refinement, choice, production, efficiency, selection, implementation, execution." During exploration, firms engage a generating process to create new products and processes. Once successful in terms of invention, the same firms then commercialize the new products and processes during the exploitation period.

Given Schumpeter's definition of imitation, a view of March's concept of exploitation also reflects behaviors of firms in the selection, refinement, and implementation of new products or processes derived from external partners. These behaviors clearly reflect the concept of imitation coined by Schumpeter (1934). Therefore, the study includes imitation activities in the concept of exploitation.

Table 3.1 Innovation Concepts

Original Innovation Concepts	**Innovation Activities**		
(Schumpeter, 1934)	Invention	Innovation	Imitation
(March, 1991)	Exploration	Exploitation	
(Davis, 1991; Leblebici et al., 1991)	N/A	N/A	Innovation Adoptions
(Rogers, 1995)	Innovation and Technology	Diffusion of Innovation	
(Wejnert, 2002)	Innovation	Public Consequence	Private Consequence
(Kelm, Narayanan, & Pinches, 1995)	Innovation	Commercialization	N/A
(Greve, 2003)	Developing Innovation	Launching Innovation	N/A
Proposed Terms of Innovation*	**Invention**	**Commercialization**	**Adoption**

Leblebici et al. (1991) studied the imitating process in which established firms adopted new practices from peripheral firms in the radio industry. The authors used an institutional approach to explain the establishment of an innovative field by acceptance of central players in the radio industry. Davis (1991) examined the adoption of innovative organizational practices among corporations during a specific period. The author found that specific, innovative, organizational practices such as golden parachutes and poison pills were adopted by several organizations through networks of executives. In sum, the two studies suggested that by means of interorganizational linkages, established firms adopted new practices (innovations) into their organizations; further, adoption process is comparable to March's exploitation activities.

Next, to specify the scope of diffusion of innovation, this paper refers the previous work of a prominent sociologist, Rogers (1995) who asserts that "an innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption." In his book—Diffusion of Innovation—Rogers analyzed technological innovation, using the terms "innovation" and "technology" interchangeably (Rogers, 1995). According to the analytical scope, it was apparent that Rogers regarded innovation as a new technological improvement in the broadest sense (i.e., including commercialized activities of the new technology). Therefore, according to Rogers, a diffusion of innovation is "a process by which an innovation is communicated through certain channels over time among the members of a social system" (1995).

Although innovation diffusion (Rogers, 1995) and innovation adoption involve transfers of new knowledge or practices from innovators or diffusing units to recipients of knowledge or adopters, these dual concepts are not necessarily the same. Whereas the innovation adoptions primarily occur within an organizational level as a recipient organization attempts to imitate or copy the legitimate structures or forms of superior organizations (Deephouse, 1996), the broader concept of innovation diffusions involves all levels of recipients (i.e., from organizations to individuals or from individuals to individuals). Wejnert (2002) described the two impacts of an innovation's diffusion, involving both public and private actors. For those innovations that carry public consequences, the adoption of innovations often leads to reforms that are historical breakthroughs. The authors mentioned further that such breakthroughs include laws protecting civil rights, welfare policy, patent laws, or international regulations protecting the natural environment.

For innovations with private consequences, the diffusion should affect the well-being of adopters that are either individuals or small collective entities such as organizations, peer groups, and rural communities (Wejnert, 2002). Following the concepts of Wejnert (2002),

this paper suggests that the diffusion of inventions from organizations to market (i.e., commercialization process) should have scope at the public consequences, rather than the private consequences. On the other hand, the diffusion of inventions that creates the private consequences should be regarded as the adoption process.

While several articles in management primarily focus interest on the factors related to invention and the private consequence (i.e., innovation adoption), relatively few scholars elaborate invention and its public consequence (i.e., commercialization.) Drawing from perspectives of the prior research of innovation, Greve (2003) noted that innovation involved two processes: a development stage leading to an innovation and a decision-making stage that launches a product that incorporates the innovation. These two distinct processes have caused research on innovation to be split into two traditions. Unfortunately, since only a few studies integrated the two processes of innovation, the author proposed that innovation research would be enriched if more studies would consider the distinct difference between developing and launching innovation (Greve, 2003).

Whereas the integration of the two innovation processes in innovation studies are rare, Kelm, Narayanan, and Pinches (1995) illustrated a remarkable study of integration. The authors specified that their innovation version consisted of two different stages—innovation and commercialization—which contributed to differring organizational performances (see table 2.1). In their study, the scholars specifically studied perceptions of shareholders as reflected by stock prices of the firms during the two different stages of innovation. They gathered two types of announcements in categories of biotechnology, new products, science and research, and technology from the Wall Street Journal Index from 1977 through 1989. The authors viewed the firms' announcements of positive progress of projects as innovation (i.e., generation of innovation), together with the firms' announcements of new product introductions as commercialization (i.e., diffusion of innovation). By integrating the two

processes of innovation, Kelm et al. (1994) successfully captured an aspect of knowledge in terms of generating and diffusing innovation. The study suggests that invention and commercialization contribute differently toward organizational successes (i.e., increasing stock prices).

In the following, this study will review literature to represent the roles of managerial factors and innovation outcomes based on Schumpeter's invention and commercialization (1934). It is important to note that this paper strictly follows the proposed terms of innovation according to Table 3.1 in categorization of the following studies. Therefore, hereafter, the term "innovation" is used to represent all types of activities involving invention, commercialization, and adoption. The term "invention" is used to represent the first stage of innovation (when inventors convert ideas into existence). "Commercialization" is used when inventors or firms attempt to introduce an invention into market (converting new beings into well-known and useful products), resulting in the public consequence (Wejnert, 2002). Last, "adoption" is used to represent activities involving firms that imitate or adopt invention from other successful firms, resulting in the private consequence (Wejnert, 2002).

3.3.1 Product and Process Innovations

From the earlier section, it is obvious that successful invention activities normally precede commercialization activities. However, this relationship may not always be true for all types of innovation. As Wejnert (2002) elaborates, for instance, innovation activities with private consequences begin with invention activities and then are followed by adoption activities. Therefore, invention activities may not always link directly to commercialization activities. A firm inventing a new process or an innovative method to increase the internal efficiency and effectiveness of its manufacturing procedures may not or will not commercialize the new process or the method to the public. Instead, it may want to keep the

invention as a trade secret to use internally to increase its competitiveness against competitors. Instead of commercializing its invention, the same firm may want to transfer or diffuse the trade secret to another factory, new strategic business units, and even its strategic alliances to improve its competitive positions in the market. This diffusion activity of the particular invention exclusively deals with adoption activity. Thus, it has nothing to do with commercialization activity.

Generally, the innovation activities mentioned earlier are termed "process" innovation. Unlike the "product" innovation in which the invention activities are normally followed by commercialization activities, the "process" innovation includes all changes in the manufacturing methods and equipment used to produce typical goods or services in the market, or in office procedures and sequencing in work routines. This process innovation usually is followed by adoption activities. Whereas product innovations are often seen as the cutting edge in the market-place, process innovations play equally important a strategic role contributing to a powerful source of advantage—"being able to make something no one else can, or to do so in ways which are better than anyone else" (Tidd, Bessant, & Pavitt, 1997). Recognizing this fact, several scholars in management have focused their attention to the generation and diffusion of not only product innovations but also process innovations (Leblebici et al., 1991; Davis, 1991; and Goes & Park, 1997).

From traditional perspectives, concepts of "product" and "process" innovation can sometimes be confusing (Tidd et al., 1997). For example, the issuance of a credit card by financial institutes to facilitate their customers in terms of financial transactions was a combination of product and process innovation. Therefore, using only traditional concepts to distinguish between the two types of innovation reflects a somewhat blurred dividing line. Using the concepts of invention, commercialization, and adoption, this paper suggests that the concepts of product and process innovation should be clarified before the advancement of

theoretical knowledge in the innovation areas can proceed. Particularly, if an innovation process involves commercialization activities, the innovation should be regarded as product innovation. On the contrary, if the commercialization activities are absent in an innovation process, the innovation is a process innovation.

Because the concepts of innovation in this present study involve commercialization activities, innovation concepts from the following sections directly apply to the context of product innovation. In general, the scope of the present study basically aims to cover invention and commercialization activities, as integrated innovation activities that generate substantial values for innovators. In the pharmaceutical industry, specifically, the commercialization of new drugs means success or failure for pharmaceutical firms. For instance, by commercializing its Prozac in the period of six months, Eli Lilly could generate as much as $800 million in profit. In contrast, a significant saving in manufacturing or accounting costs would have much less impact on the firm's financial results. In this particular case, a 25 percent reduction in the manufacturing costs of Prozac would have saved only $60 million per year (Rochin, 2006).

Because of the significant contribution of product innovation, this paper focuses its attention on two important innovation activities (invention and commercialization). The outcomes of process innovation may be internally recognized as firms could effectively and efficiently arrange and exploit their resources to produce goods and services. However, the outcomes of product innovation reflect higher market values of the firms, for firms could invent and commercialize new products and, thereby acquiring acceptance and support from the constituents. Thus, one distinct advantage of studying product innovation is the obvious direct and causal relationship of focal firms' successful product innovation and revenue growth. In the following sections, this paper will explain the current knowledge of invention and commercialization as main innovation activities of product innovation.

3.3.2 Invention

Hitt, Hoskisson, Johnson, and Mosel (1996) studied the ability of different organizational contexts to invent. These scholars provided theoretical perspectives and empirical findings to explain why and how specific corporate strategies—mergers, acquisitions, and divestitures—as strategic choices are harmful to firms' ability to generate innovative outcomes (Hitt et al., 1996). According to the study, firms are more likely to use financial controls rather than strategic controls to manage business units as the firms engage in specific corporate strategies; the emphasis on financial controls tends to drive out internal innovation, fostering a short time horizon. Empirically, the authors concluded that different organizational strategies could contribute to different innovative outcomes.

Damanpour (1996) discussed organizational size and complexity as important contextual factors to foster or to inhibit invention. The authors explained that while several studies suggested that large organizations have more potential, flexible structures, and slack resources to handle innovative challenges, other studies indicated that large organizations are typically more formalized, standardized, and highly inert and thus are said to be less innovative than smaller organizations. Nohria and Gulati (1996) proposed that there is an inverse U-shaped relationship between the degree of organizational slack available to organizational subunits and the extent of innovation these units produce. Whereas "slack allows for experimentation, provides resources to meet environmental uncertainty, promotes chance discovery, and frees managerial attention to support innovation," it also can lead to promotions of pet projects and inefficiency (Nohria et al., 1996). As both perspectives are valid, it is possible to see a predicted inverse U-shaped relationship between slack and innovation (i.e., invention, commercialization, and adoption).

Dougherty and Hardy (1996) conducted a longitudinal study of 40 new product development efforts. From the findings, they indicated that there are three generic innovation

problems in their study: 1) resource flows and mechanisms to sustain resource flows were absent; 2) the organizations possessed little in the way of collaborative structures to develop innovations across functional departments; and 3) strategic support for innovations was absent—the data suggest that senior managers in the organizations studied either never supported the projects or did so only temporarily (Dougherty et al., 1996). From the generic innovation problems, it is clear that senior managers can implement their innovation strategies to influence several organizational contexts, to resolve the generic innovation problems, and to create innovation outcomes.

The review of studies relating to invention indicates that the current stream of studies use the two terms of "innovation" and "invention" interchangeably. This section of the chapter will indicate that from methodology perspectives, these studies have captured several measures (i.e., R&D intensity, patents, and new product development) to use in their studies. Such measures only use the term "invention," defined as the capability to generate new and patentable products or processes to the market. The measures did not address commercialization and adoption, which subsequently are the important innovation activities suggested by Schumpeter (1934).

3.3.3 Commercialization

The second process of product innovation is commercialization. One study in management suggests that "commercializing knowledge involves transfer from discovering scientists to those who will develop it commercially" (Zucker, Darby, & Armstrong, 2002). Because commercialization falls into the concepts of information distribution or knowledge diffusion, the reviews of diffusion elaborate on basic ideas of how innovators communicate information about their innovations. In other words, the concepts of diffusion should suggest how innovators might sell their innovations to the market. Using concepts of Rogers (1995), Cool, Dierickx, and Szulanski (1997) studied diffusion of innovations within an organization.

The authors compared the explanatory power of factors emphasized by the traditional diffusion perspective (i.e., Rogers, 1995), with factors deemphasized or neglected by that perspective. The comparisons suggest that the traditional perspective (i.e., Roger, 1995) may not apply exactly within the organizational context because factors other than those traditionally emphasized seem to play an important role in the diffusion of innovation within organization (Cool, Dierickx, & Szulanski, 1997).

Specifically, Cool et al. (1997) found that before critical mass (adoption of the invention by 25% of the decision units) is reached, supply factors, i.e., contents of innovation and technology, are dominant in the diffusion process. However, after critical mass is reached, demand factors (i.e., innovation adopters, opinion leaders) are dominant, which is when advice derived from the traditional perspective applies best. The findings suggest that within the organizational context and before the critical mass is reached, supply-related factors are more likely to accelerate the process of diffusion than are demand-related factors emphasized by the traditional perspective (Cool et al., 1997).

Regarding commercialization, Hargadon and Douglas (2001) introduced the concepts of product design as innovation strategies to explain the successful diffusion of innovation in the market. They conducted a case study analysis to understand how Thomas Edison's design strategy enabled his organization to successfully gain acceptance for an invention that would ultimately displace the existing institutions of the gas industry. According to Hargadon et al. (2001), managers need to develop competencies in the design process to create a "robust design"[1] and/or a "dominant design."[2] They wrote that "while innovations must appear novel to draw attention and suggest an advantage, entrepreneurs must initially present the meaning and value of their innovations, including their novel features, in the language of existing

[1] The robust design is an adoption of innovators' ideas by designing the concrete details of their embodiment to embed them within rather than distinguish them from the established social system that they seek to change.
[2] Dominant design is a single architecture that establishes dominance in a product class Anderson, P., & Tushman, M. L. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. ***Administrative Science Quarterly***, 35(4): 604-633.

institutions by giving them the appearance of familiar ideas. . . . Purely novel actions and ideas cannot register because no established logics exist to describe them" (2001: 478). The previous quotation indicates that managers need to pay attention to the design, which is the particular arrangement of concrete details that embodies an innovation and provides the means to mediate between innovation and institutions. If managers neglect the importance of product designs, they will find their products being ignored by customers in the market. Hargadon and Douglas (2001) suggested that the design process is important for successful diffusion of innovation because it grounds a particular innovation in its particular time and place by providing it with a set of meanings and values that are embedded in the existing institutional environment.

3.4 Interorganizational Networks and Innovation Activities

Whereas prior innovation studies already examined several organizational factors, a current stream of research mainly switches to innovation outcomes generated by interorganizational networks. Since all firms operate in an open system, it is important to involve examinations of interorganizational contexts to improve our knowledge of innovation outcomes. Participating in interorganizational linkages, organizational innovators have a better chance to influence several uncontrollable factors of innovation in the external environment (Spencer, 2003). In fact, Powell, Koput, and Smith-Doerr (1996: 116) suggested that "the locus of innovation will be found in networks of learning, rather than in individual firms." To provide an overview of the relationships of interorganizational linkages and innovation outcomes, this paper will explain fundamental concepts in an area of interorganizational networks and then report the current development of this area in terms of innovation outcomes.

The period after Granovetter's (1973) seminal work, "Strength of Weak Ties," saw interfirm network researchers begin to apply the concept of ties to understand relationships

among and between organizations. According to Poldony and Page (1998), the definition of a network form of organization includes a wide array of joint ventures, strategic alliances, business groups, franchises, research consortia, relational contracts, and outsourcing agreements. In particular, the interorganizational networks of firms significantly reflect embedded ties as "strong enduring relationships between trustworthy partners with no shadow of a future to ensure cooperation in the present" (Podolny & Page, 1998; Uzzi, 1997).

In fact, research in different areas attempted to explain why organizations need alliances. For example, a study in sociology indicated that organizations collaborate to stabilize environmental uncertainty and to satisfy their resource needs (Gulati & Gargiulo, 1999). Stuart (1998) investigated strategic alliance in a high-tech industry and asserted that organizations in crowded positions and those with high prestige are most likely to form alliances. The author mentioned that the concepts of crowded positions and high prestige confirmed the importance of relationship positions among partners and reputations of firms as factors in determining whether or not focal firms would engage in cooperative strategies (Stuart, 1998).

In line with studies in sociology, Kenis and Knoke (2002) explained that organizations collaborate because of socio-economic factors—interdependency, prior mutual relationship, mutual centrality, and reciprocity. These four socio-economic factors are comparable with inducement and opportunity, the two important factors that maintain interorganizational networks (Kenis & Knoke, 2002). While inducement is the economic incentive causing inter-firm partners to collaborate, the opportunity reflects the prior network positions shaping future collaborations among previous network members (Ahuja, 2000b).

Further, the formation of interorganizational relationships and their implications have been investigated in the context of institutional linkages (Ahuja, 2000b; Baum & Oliver, 1991) and alliance networks (Baum et al., 2000; Doz, 1996; Gulati, 1995; Gulati et al., 1999;

Hamel, 1991). Additionally, network scholars have found that interorganizational ties can support organizational change, and enhance organizational survival chances (Miner, Amburgey, & Stearns, 1990). Using interorganizational linkages to understand innovation or new product development, several scholars have studied the direct relationships between firms' strategic alliances and their innovative outputs (Ahuja, 2000a; Almeida & Phene, 2004; Kotabe et al., 1995; Shan et al., 1994; Stuart, 2000; Wuyts et al., 2004).

Whereas our understanding of the impact of interorganizational linkages on invention are clearly evident in contemporary contexts, researchers offer limited knowledge regarding integrated frameworks that comprehensively address the issues of invention and commercialization (Rothaermel et al., 2004; Spencer, 2003; Wuyts et al., 2004). Because most generated inventions fail after the commercialization process, it is important to understand the importance of the interdependent pattern between the two processes simultaneously (Rothaermel et al., 2004). Accordingly, this paper follows Greve's (2003) call for researchers to integrate important activities of innovation to understand contributions of interorganizational linkages on overall innovation performance. However, due to the traditional aspects of innovation research in the interorganizational area that separated two innovation activities—invention and commercialization—this paper will separately elaborate on studies in the two areas to provide a review of current knowledge within the field. Afterward, this paper will discuss in detail the few existing studies that integrate the two innovation processes in order to understand the roles of interorganizational linkages and innovation outcomes.

3.4.1 Interorganizational Networks as Invention Generators

Regarding the roles of interfirm networks toward generated innovation outputs (i.e., invention), Shan, Walker, and Kogut (1994) examined the association between interfirm cooperation and the invention outcomes of startup firms in the biotechnology industry. Using

a commercial directory of biotechnology firms (BioScan), the authors gathered data relating to cooperative agreements between startups and established firms. They measured the number of patents granted to startups as results of the cooperative agreement. From the findings, the authors indicated that "startup innovation [invention] output does not attract large firm relationships, but rather depends on them" (1994: 393). They also summarized that "a startup's size, access to public equity markets, and position in the network of agreements have important direct or ancillary effects on innovation [invention]" (Shan et al., 1994: 393). The attempt of Shan et al. (1994) may be recognized as one of the earliest studies to understand why firms need alliances to achieve better outcomes of invention.

Next, Kotabe and Swan (1995) reported the role of strategic alliances in a high-technology product development. The authors used the announcement of a new product introduction from The Wall Street Journal to capture the ability of a focal firm to invent. Their study indicated that several characteristics of alliances, including horizontal linkages and small firms, generate more innovative products. Unlike vertical linkages which tend to be more concerned with cost economizing, horizontal linkages that include R&D consortia, patent swaps, technology transfers, and joint ventures are more likely to supplement the internal technology base. As for the role of size, the authors reported that large firms are more efficient innovators than small firms because of their more diverse resources and skills, better developed marketing channels, and economies of scale. Therefore, in order to compete with larger competitors, small firms must be highly innovative to attract customers. In the context of interorganizational linkages, a mixture of large and small firms was supported as most conductive to generate inventions (Powell et al., 1996).

Further, Ahuja (2000) examined empirical relationships among collaborative networks, structural holes, and focal firms' invention in the chemical industry. Using the number of successful patent applications, or granted patents, as a measure of innovative output in focal

firms, Ahuja (2000) regarded the number of direct partners (i.e., joint ventures) of the focal firms and the number of indirect partners as the number of direct and indirect ties determining the innovative outputs of focal firms. Following Burt (1991), Ahuja (2000) also measured the magnitudes of interfirm structural holes (i.e., a high index reflecting richness in structural holes). Ahuja (2000) found that increasing levels of structural holes or the magnitudes of disconnections among partners in the collaboration networks decrease innovative outputs. He also indicated that while both direct and indirect ties influence innovative outputs positively, the impact of indirect ties is moderated by the firm's level of direct ties. Interestingly, Ahuja (2000) did not address how relationships among collaborative networks and their structural holes determine the ability of the focal firms to commercialize inventions.

Recently, Wuyts et al. (2004) examined portfolios of interfirm agreements in technology-intensive markets to understand the consequences for product development and profitability. The authors argued that firms can monitor and manage their portfolios of agreement to achieve their objectives. Similar to Ahuja's (2000a) suggestion that different types of networks provide different benefits, Wuyts et al. recommended: "firms that have the end objective of radical innovation invest in a technologically diverse portfolio to gain access to a diverse knowledge base in which it repeatedly contracts with the same partners to facilitate complex knowledge transfer" (2004: 98). Since the authors used the new drugs classified by the FDA as a measurement of radical innovation, they focus on the firms' capability to invent (Schumpeter, 1934) rather than to commercialize or to adopt.

Further, Wuyts et al. (2004) mentioned that frequent cooperation with the same partners operating in a diverse technology facilitates the transfer of tacit knowledge, an important knowledge for successful inventions. The authors explained that the implications of the diversity of technologies allow a focal firm to access a non-redundant knowledge and to

enhance its radical inventions. However, the downside is that access to diverse or non-redundant knowledge requires high investment costs, and firms often have a difficult time recouping their initial investments. To confirm Wuyts et al.'s (2004) concepts that collaborations with the same partners facilitate invention outcomes for focal firms, a study in economics indicated that focal firms participating in the advance technology program tend to issue higher patents (Darby, Zucker, & Wang, 2004). The authors followed the sociological concepts of social embeddedness to explain how particular focal firms exploit knowledge benefits from their member partners. They suggested that the program promotes institution-building, by encouraging partners to establish new organizational structures that facilitate innovation and capture of inventions in technologically advanced commercial products. In sum, the findings of both Wutys et al. (2004) and Darby et al. (2004) not only confirm Ahuja's (2000a) assertion of the roles of direct-tie partners, but also suggest the importance of qualitative relationships between partners during generation of inventions.

Further, Almeida and Phene (2004) examined a different type of interorganizational relationship between subsidiaries and multinational corporations (MNCs). The authors used patent citation data to measure the usefulness of inventions by foreign subsidiaries of U.S. semiconductor firms to test the hypotheses. They found that the technological richness of the MNCs, the subsidiary's knowledge linkage to host country firms, and the technological diversity within the host country have a positive impact on capabilities to generate patentable inventions. According to the findings, the authors explained that subsidiaries did not directly absorb the technological richness of the MNC, yet the subsidiaries did internalize the underlying organizing principles, systems, and processes that permit subsidiaries to generate useful inventions.

Additionally, subsidiaries did not directly benefit from the host country richness, but they tended to exploit the country's technological diversity through knowledge linkages, seeking

to learn from a much narrower subset of firms in a specific region. The authors suggested that in order to generate successful inventions, the MNC should require that certain subsidiaries play unique roles that may not require knowledge integration with the rest of the firm, but serve the MNC in terms of technological exploration through linkages within specialized regions and countries (Almeida et al., 2004).

Taking the important findings of all previous studies, several conclusions can be made to report the current knowledge of how and why interorganizational linkages facilitate a focal firm to generate patentable inventions. First, when a small startup collaborates with large organizational members in the network, it tends to generate higher levels of patentable inventions. Stuart (2000) confirmed that startups benefited from large and innovative strategic alliance partners. In the situation in which growth and innovation rates are critical for survival, large firms in particular act as endorsements for the startups by building public confidence in the value of their organizational products and services while helping them to attract customers and other corporate partners (Stuart, 2000).

Second, Kotabe and Swan (1995: 631) indicated that "communication, coordination, and a multidisciplinary effort between and within firms are a key to building trust and superior performance." Accordingly, startups and established members in interorganizational networks need a balance between technology and strategy to generate numbers of new products to the market. To explain the previous point, Li and Atuahene-Gima (2001) studied the product innovation strategy and the performance of new technology ventures in China. The authors indicated that support from government institutions plays a significant role in enhancing the effectiveness of a new technology venture's product innovation strategy. They surprisingly found that the relationship-based strategies do not enhance the effectiveness of a new technology venture's product innovation strategy. Accordingly, if firms place too much

importance on strategy as opposed to technology, they are less likely to achieve an innovation strategy.

In the study, political networking with high status officials appeared to play no role in terms of increasing product innovation performance, particularly in transitional economies. The authors explained that it is possible that difficulties in relationships between alliance partners (i.e., Chinese officials and authorities) and new technology ventures may divert limited managerial resources and attention away from core product innovation strategies. To be successful in generating new and innovative products to the market, startups need to find the equilibrium point between the competing demand from their institutional partners and invention processes. Without this equilibrium, startups tend to fail in terms of either establishing necessary relationships or generating product innovations. The study of Li and Atuahene-gima (2001) therefore suggested that in a specific circumstance (i.e., in China), strategic alliances or interfirm networking strategies to collaborate with high status partners (i.e., Chinese officials) may not always yield successful innovative results.

Last, during the invention period, startups need more direct ties to support a technological base and knowledge management structure (i.e., how to manage technological richness). Regarding the relationships between focal firms and established members, Ahuja (2000) explained that because direct ties primarily benefit resource-sharing (over-information spill benefit), focal firms intending to accomplish innovative generation should gain benefits from interfirm networks with higher numbers of direct ties, rather than the networks with higher numbers of indirect ties.

3.4.2 Interfirm Networks as Diffusion Drivers

Traditionally, researchers in marketing have focused on commercialization activities while the economics and management literature have presented a rich exploration of product innovativeness (Kotabe et al., 1995). Comparing concepts of product innovativeness and

those of invention activities, this study found that a current trend of innovation studies expands its scope to offer broader activities. For instance, a stream of research in interorganizational networks addressed the role of an interorganizational network, as a predictor of an organizational adoption of inventions (i.e., products and processes). Recently, studies in interorganizational network also attempt to elaborate relationships between interfirm networks and commercialization activities.

Before reviewing the studies in diffusion, it is important to repeat the distinction between commercialization and adoption. Commercialization includes subsequent activities occurring after invention activities (Kelm et al., 1995) and targets public consequences (Wejnert, 2002). Adoption, on the other hand, involves imitating activities of the organizational inventors. These activities are conducted by the adopters of inventions (i.e., process innovations) to copy new structures, practices, or strategies to achieve benefits in terms of effectiveness and efficiency (Davis, 1991). The adoption also creates only private consequences (Wejnert, 2002). Accordingly, commercialization involves a diffusion of inventions (i.e., products or processes) aiming to gain market acceptance, whereas adoption most likely refers to a diffusion of new practices or organizational processes between organizations seeking to improve existing practices or the process of adopting organizations' routines. Next, I will review the following studies to understand the current knowledge of adoption. Subsequently, studies of commercialization will be discussed.

Using institutional perspectives to examine the adoption process, Leblebici, Salancik, Copay, and King (1991) examined how inventions emerged and diffused over time in an interorganizational field, using the historical context of the U.S. radio broadcasting industry. The study is fairly parallel to the study of Christensen and Bower (1996) who considered the emergence of disruptive technologies and their impact on the failure of leading firms. While both studies described the adoption of new products and practices among organizations

operating in different industries (i.e., the U.S. radio broadcasting and the disk drive industries), the studies also addressed similar theoretical puzzles: How do the inventors diffuse their inventions and justify the new and useful ideas? And why do those who owe their positions of power to prevailing institutions willingly adopt these ideas?

According to the studies, the adoption process of inventions began when small and less dominant firms introduced new products and services (i.e., disruptive technologies) in the emerging or peripheral markets in order to compete with existing products and services offered by established firms. At that time, the new products and services were not accepted because of deviation from standard practices or performance. Since the dominant or established players had vested their interests in the institutionalized conventions (i.e., established technologies), these dominants players used their resources to maintain the status quo or introduce only practices and/or products that confirmed established conventions and satisfied their main customers (Christensen & Bower, 1996; Leblebici et al., 1991). The two studies explained further that once the new products or services (i.e. innovation) offered a better performance than that of the existing practices and/or products in the markets, established firms accepted and replaced their established products or services with the invention. With the acceptance of established firms in the industry, the invention initiated by new players was successfully endorsed and diffused to the public. At this stage, invention became fully recognized as innovation.

The studies of Leblebici et al. (1991) and Christensen and Bower (1996) described the introduction of invention by startups, the reactions of established players, and the diffusions of invention as a way to achieve better performance and to gain acceptance by customers and/or other constituents in the markets. Whereas the two studies considered how established organizations willingly change their technologies to adopt invention, the authors did not suggest the roles of interorganizational relationships in the process.

To illustrate further in terms of innovation adoption or imitation, Goes and Park (1997) studied interfirm linkages—several types of links among 400 hospitals over ten years—as channels of innovation diffusion. The authors investigated the effects of four distinct types of interorganizational links on a service innovation in hospitals and found considerable support for the relationship between several types of interorganizational linkages (i.e., structural links, administrative links, institutional links, and resource links) and the adoption of innovative services and technologies. Unlike Roger (1995), who concentrated his studies on diffusion of innovation within communities, and Cool et al (1997), who studied diffusion of innovation within organizations, Goes and Park (1997) offered perspectives of interfirm networks as channels for a focal organization to adopt innovative services and technologies from organizational peers. Additionally, Goes and Park (1997) illustrated that adoption activities do not necessarily involve interactions between established firms and peripheral firms. Rather, the adoption of interorganizational networks reflects transfers of any practices, processes, or inventions that were considered new between organizations.

Whereas studies of adoption activities are common in management literature, a few studies discuss commercialization activities. In the followings, this paper will describe two studies that addressed the importance of commercialization activities of innovation. A study of Hargadon and Sutton (1997) provides a good illustration of how a product design firm—IDEO—successfully commercialized inventions. The authors blend the concepts of social network and organizational memory perspectives in a model of technology brokering that explains how IDEO develops innovative products. IDEO acquires knowledge from its external network, stores the knowledge in the organization's memory, and then retrieves that knowledge to successfully commercialize new innovations. The study of Hargadon and Sutton (1997) illustrates the importance in interfirm networks diffusing invention. The diffuse of invention comes combining structural holes (Burt, 1992, 1997) and organizational memory

perspectives (Walsh & Ungson, 1991) to enhance technology brokering and innovation in a product development firm. Unfortunately, because Hargadon and Sutton (1997) used the case study approach to singularly explore factors contributing to successful commercialization, they could not generalize and validate their findings.

Recently, Zahra and Nielson (2002) conducted a study to understand sources of capabilities, integration, and technology commercialization. The authors used four indicators to represent technology commercialization in the study, noting that technology commercialization should 1) develop and introduce a large number of product and process technologies; 2) create radically new products; 3) expedite the introduction of these new products to the market; and 4) create new knowledge. Further, the study offered interesting findings about a firm's use of external sources to pursue competitive advantage through the effective and timely commercialization of new technology. From the findings, the authors reported that whereas a firm's use of external resources tends to increase its product introductions and the speed of introductions, the products tend to draw negative associations with technology radicalness and patents. The authors explained that "outsourcing and other external sources adversely influence the development of tacit and firm-specific knowledge necessary for radical innovation that yields new knowledge" (Zahra et al., 2002: 393). On the other hand, external sources encourage higher frequency and speed of product introduction and process of innovation for new and less radical innovation.

The previous studies of adoption and commercialization offered current knowledge in areas of interorganizational networks. First, while the startups normally generate and introduce inventions in the industry, it was the adoptions of such inventions by established firms and public constituents that accomplished the transformation of inventions into innovations. Powell et al. (1996) mentioned that rather than use external relations as a temporary mechanism to compensate for unmastered capabilities, firms use collaborations to

expand all their competencies. Accordingly, successes or failures for the startups and established firms strongly rely on how the firms exploit new practices in the external environments. In the current competitive landscape, both startups and established firms rely on one another. The startups provide new practices, and established firms endorse and justify the practices.

Second, as suggested by several studies, when inventions are more controversial in nature, low-status and peripherally located innovators, as opposed to high-status and centrally located actors, tend to generate new practices and introduce practices to be adopted (Christensen et al., 1996; Leblebici et al., 1991). Empirical evidences also confirmed that the low-status (or startup) innovators become more successful than the high-status (or established) ones when it comes to the context of radical innovations (Christensen et al., 1996). Third, whereas interorganizational linkages may be effective resources facilitating focal firms to successfully diffuse inventions, relying too much on external linkages can harm focal firms' internal capability to generate new and radical technologies (Zahra et al., 2002).

In reference to the previous point, the question remains as to what extent firms should rely on external sources in order to successfully diffuse innovation while maintaining generating capabilities of internal radicalness and patents. Powell et al. (1996) reported that although biotechnology firms expanded interorganizational relationships (i.e., degree of centrality), the firms tended to maintain a number of ties and partners. According to Powell et al., "this suggests that firms are not 'promiscuous' in their use of ties; rather, they are deepening their connectedness without adding substantial numbers of new ties" (1996: 134). The fact that interorganizational relationships of innovation network are quite stable underscores the importance of using an integrated framework of invention, commercialization, and adoption in order to understand the overall innovation performance. This argument introduces the following section, which examines the framework of

interorganizational networks and overall innovation performance (i.e., invention, commercialization, and adoption activities).

3.4.3 Integrated Framework of Interfirm Linkages and Innovation Activities

Several arguments supported an integrative framework to fully understand how interorganizational linkages could impact product innovation activities (i.e., invention and commercialization) (Greve, 2003; Rothaermel et al., 2004). Since empirical research consistently claims that the process of interorganizational partner selection represents a partial function of inertia force (Li & Rowley, 2002), firms do not and cannot easily change interfirm networks (Powell et al., 1996). Yet, interorganizational linkages are empirically stable (Powell et al., 1996), the integrative framework of innovation processes should enrich our understanding about the roles of interorganizational linkage and focal firms' innovation performance (Greve, 2003). To report the current knowledge in the area, this paper will review several articles that use the integrative framework of innovation process.

Rothaermel and Deeds (2004) offered the most comprehensive framework to discuss the interorganizational networks of biotechnology firms and innovation processes. In the study, the authors developed a comprehensive framework of sequential activities in innovation activities—generating and diffusing innovations—and matched the activities with two types of alliances—exploration and exploitation alliances. Using concepts from organizational learning, the authors found that "exploration alliances predict products in development, which in turn predict exploitation alliances, and that exploitation alliances predict product on the market" (2004: 216).

During one period of invention, firms sought help from exploration alliances to enhance technological knowledge and capability to transform ideas into products. Once the firms achieved their primary objectives in terms of new product development, they acquired exploitation firms to commercialize the products into market. The authors mentioned that on

an average, new technology ventures that use an exploration-exploitation strategy tend to be more successful in terms of having more products in development and in the market (Rothaermel et al., 2004).

Additionally, Rothaermel et al. (2004) asserted that the size of focal firms can moderate any propensity to engage in alliances. Using the concepts of transaction cost economics and the "pecking order" hypothesis of the optimal capital structure model, the authors explained that once a firm has sufficient internal resources to handle innovation activities, the firm must compare the costs and benefits of engaging in alliances with those of using its own internal resources in the product development process. Because the commercialization activities in the biopharmaceutical industry are more certain than invention activities, biotechnology firms tend to withdraw from exploitation alliances while sticking with exploration alliances (Koza & Lewin, 1999). The study of Rothaermel et al. (2004) illustrated that as firms grow larger, they will integrate vertically by terminating exploitation alliances first, and then exploration alliances.

Unlike Shan et al.'s (1994) finding that alliances predict the number of focal firms' patents, Rothaermel et al. (2004) indicated that the study extends knowledge by showing that although patents explain alliances, patents address a specific and particular type of alliance—an exploitation alliance. In other words, firms with large numbers of patents induce a high number of exploitation partners. Whereas Rothaermel et al. (2004) indicated the process in which different types of partners in interorganizational linkages contribute to innovation performance, Spencer (2003) illustrated that focal firms engage in the strategies to share knowledge with an innovation system, seeking to increase innovation performance. Spencer argued that "firms that shared relevant knowledge with their innovation system earned higher innovative performance than firms that did not share knowledge" (2003: 217). Although Spencer (2003) indicated that her paper focuses only on the relationship between a firm's

knowledge-sharing strategy and its innovative performance during the pre-commercial phase of industry emergence, this section includes the study because the knowledge-sharing strategy substantially influences the success and failure of invention and commercialization activities. By indicating that firms can shape an institutional environment during the early period of generating innovation (Spencer, 2003), this study also provides concepts which fall in line with the concept that robust designs shape institutional framework and market dynamics of diffusing innovation (Hargadon et al., 2001).

According to the findings, Spencer (2003) indicated that by sharing technological knowledge with external researchers in terms of publications or basic research, a firm can influence the institutional environment in at least two ways. First, firms can shape technological and environmental standards by sharing a portion of their own knowledge with the technological community, thus directing an industry-wide conversation toward advances in technology. Second, by attracting other innovators to a technological trajectory, firms form a critical mass of alliances with a mutual interest in the success of the technology (Spencer, 2003). Interestingly, concepts of critical mass indicated by Spencer (2003) during the generating innovation period is comparable to Roger's (1995) concepts of opinion leaders and the critical mass, which influence the successful diffusion networks. The "critical mass" refers to an important referent stage occurring at the point where enough individuals have adopted an innovation so that the innovation's further rate of adoption becomes self-sustaining. According to Rogers (1995), opinion leaders are individuals who lead in influencing opinion about innovations. The number of opinion leaders positively relates to the critical mass.

Spencer (2003), by addressing the importance of having a critical mass of competitors on the same technology trajectory, extends the understandings of interorganizational linkages with alliances in networked industries. Importantly, firms should acquire opinion leaders—

externally individual researchers, organizations, and even competitors—to develop evaluation standards that favor the firms' product designs and build a strong industry infrastructure. In this regard, firms should focus attention to all possibly important knowledge contributors in the broadest environment. Specifically, in the flat panel display industry, the author mentioned that firms need to implement strategies to influence not only the national innovation system, but also a global innovation system to achieve high innovative performance. The author defined "an innovation system" as one that consists of resources and institutions, built through interactions among universities, research institutes, and innovating firms, which a company can harness to successfully commercialize innovations" (2003: 217). Spencer wrote: "Firms that interacted with their global innovation system earned higher innovation performance than firms that interacted with only their national innovation system" (Spencer, 2003: 217). Overall, this particular study contributes to the knowledge of relationships between interorganizational linkages and innovation outcomes by including the implications of innovation systems on both national and global levels.

The last research that integrates the two innovation activities used innovation speed as its dependent variable to reflect the period from the onset of generating innovation to the end of diffusing innovation (Kessler et al., 2000). In this study, Kessler et al. (2000) used three relative measures (speed relative to schedule, speed relative to similar, previously completed projects, and speed relative to similar projects of competitors) to represent innovation speed of several projects in organizations. The authors asked respondents to check off one of 13 boxes describing projects as relatively faster, slower, or equal in speed to schedules, past projects, or competitor projects. According to previous research by Kessler et al., the concepts of "innovation speed" are referred to as "the time elapsed between a) initial development, including the conception and definition of an innovation, and b) ultimate commercialization, which is the introduction of a new product into the market place" (1996:

1144). Thus, in Kessler et al. (2000), innovation speed represents an integrative framework to understand the speed at which firms convert ideas into commercialization.

Using innovation speed as their dependent variable, the authors found that a specific type of interfirm network (i.e., external sourcing partners) was not only associated with lower competitive success, but also related to slower innovation speed. The authors reasoned that the integration of external and internal knowledge could be very difficult and problematic, especially during the idea generation stage. Additionally, knowledge from external sources faces more organizational barriers than internally developed knowledge. Last, because an idea is initiated from an outside organization, or external source, it is unlikely that the project champion will motivate employees and push along the project. According to the findings of Kessler et al. (2000), external learning by an outsourcing approach harms generating innovations, and will subsequently determine unsuccessful results in diffusing innovation. These negative outcomes from the strategy of outsourcings were demonstrated by lower competitive success and slower innovation speed. For the researchers, the outcomes from this study underline the necessity of examining innovation process in distinct phases, particularly when attempting to understand the contributions of interfirm networks toward innovation outcomes.

3.5 Summarizing Innovation Studies

The previous sections explained several important innovation studies. At the end of this chapter, Table 3.2 summarizes how these studies assess and measure the performance of innovation activities. Drawing on concepts of invention activities from Schumpeter (1934), as well as several scholars in innovation areas, this paper gathers several important innovation studies in the pre-commercial stage (Spencer, 2003) and commercialization stage. The first ten studies explained how firms generate inventions from both organizational and interorganizational perspectives. Interestingly, scholars use different indicators to capture

dimensions of invention performance in the pre-commercial stage. The most common variables in the invention stage, however, are the number of granted patents (Ahuja, 2000a; Almeida et al., 2004; Shan et al., 1994). Additionally, the most popular source of data was from the United States Patent Trademark Office (USPTO).

Stuart (2000), particularly, used patent citations to determine the innovativeness of a firm. He mentioned that firms are required to list citations to all previously-granted patents which made technological claims similar to those claimed in their applications. Accordingly, the patent citations trace all technological ancestries. Assuming that the most important patented inventions are those highly cited in later patents, Stuart (2000) indicated that the most innovative firms are those that developed a significant fraction of the highly-cited patents.

Next, seven studies used several different measurements to capture commercialization activities. Most studies in this area followed a methodology of case study analysis to examine factors relating to diffusion activities. For example, Hargadon and Douglas (2001) examined the successful strategy of Thomas Edison to commercialize innovations, whereas Leblebici et al. (1991) used the radio industry to illustrate the diffusion process of innovation. Regarding the studies of diffusion, a singular study attempted to empirically measure commercialization. In this particular study, Zahra and Nielson (2002) used a survey method to understand capabilities and technology commercialization (TC). The authors used numbers of new products, technology commercialization speed, radicalness of the products, and number of patents as their dependent variables. Interestingly, Zahra and Nielson's TC is so broad that it covers several dimensions of innovation.

Rogers (1995) specified that diffusion of innovation is a process by which an innovation is communicated through certain channels over time among the members of a social system (1995). Consequently, several studies examined the process to understand the adoption of innovation. This paper includes several studies of the adoption process in Table 3.2 to

illustrate relevant variables and measurements. At least three studies in this area empirically examine the adoption of innovations (Christensen et al., 1996; Davis, 1991; Goes et al., 1997). Using results from interviews in a case study of the world disk-drive industry, Christensen et al. (1996) suggested how leading firms fail to adopt disruptive technologies. Within the article, the authors indirectly illustrate influential factors of technology diffusion. The authors noted the model: established firms invest chunks of their resources in existing technologies, but ignore the potentially new technologies; thus, fail to compete with the startups who allocate resources and efforts to develop their own new technologies. Later, when the new technologies are accepted and supported by consumers and the performance of the new technologies is found to exceed the established firms' existing technologies, the adoption pattern is clearly witnessed.

Further, using empirical analyses of the proxy statements of focal firms and the annual hospital disclosure reports as main sources of information, Davis (1991) and Goes and Park (1997), respectively, explained factors affecting firms' decisions to adopt innovations into their organizational practices. In sum, these two studies suggested that different interorganizational linkages are responsible for successful innovation adoptions among hospitals who implemented the new technologies.

The last segment of Table 3.2 includes innovation studies that examined performance of the integrated innovation activities (the interorganizational innovation system). Two aspects of innovation studies fall into this section. The first aspect involves studies that integrate invention activities and diffusion activities into a single framework; the second aspect involves studies that use dependent variables to capture the total effect of innovation development (i.e., innovation speed and patent renewals). For the first aspect, at the organizational level, Kelm et al. (1994) and Greve (2003) illustrated the importance of

integrating invention and diffusion studies to understand comprehensive framework and consequences of innovation processes.

It is surprising that few studies offered an integrated framework to study overall innovation processes. As Kelm et al. (1995) indicated, announcements of biotech inventions and their product commercialization (diffusing innovation) engender different, but sequential outcomes to the values of firms, thus, analyzation of either one of the two continuous activities is incomplete. Rothaermel and Deed (2004) also confirmed that a link exists between different alliances participating in the different innovation processes, beginning with generating and ending with commercializing products on the market.

Thus, in order to understand the processes of how interorganizational linkages contribute to innovation development, Rothaermel and Deed (2004) offered an integrative framework to examine the early stage of invention (i.e., drug discovery, preclinical trials) to the latter stages of diffusion of new products on the market (i.e., clinical trials, FDA approvals, and commercialization). With the integrative framework, the scholars successfully captured the fact that different sets of alliance partners determine the number of products in developments, as well as the number of products in the market.

For the second aspect, Spencer (2003) and Kessler et al. (2000) offered interesting variables as proxies that captured abilities of firms to generate and diffuse innovation outputs. Following innovative methods from studies in economics, Spencer (2003) used patent renewal methods as an estimate of patent portfolio value to capture the value of a firm's patented innovations. The author mentioned that in some European countries, inventors must pay a significant annual fee to maintain intellectual property protection for their patented technology.

Table 3.2 Summaries of Empirical Innovation Studies between 1991 and 2004

		Authors (Year)	Related Variables	Invention Variables	Findings	Data/Method
Organization	1	Hitt et al. (1996)	- Acquisition strategies, divestitures, financial controls (IV)	- R&D intensity; New product intensity (DV)	- Negative	- Survey & COMPUSTAT
	2	Damanpour (1996)	- Structural complexity, organizational size (IV)	- Number of innovation initiated or implemented (DV)	- Positive - Moderator	- Meta-analysis
	3	Nohria and Gulati (1996)	- Organizational slack (IV)	- Total economic impact from innovation (DV)	- Inverse U	- Survey
	4	Dougherty and Hardy (1996)	- Management and organizational resources, processes, and strategy (IV)	- New product development (DV)	- Positive	- Interview
Inter-organization	5	Shan et al. (1994)	- Interfirm cooperation, startups' size, access to public equity market, and position in the network of agreement (IV)	- Number of granted patents (DV)	- Positive	- BioScan and USPTO
	6	Kotabe and Swan (1995)	- Small firms and horizontal linkages (IV)	- Announcements of new product introductions (DV)	- Positive	- WSJ
	7	Ahuja (2000a)	- Direct and indirect ties, low levels of structural holes (IV)	- Number of granted patents (DV)	- Positive	- USPTO
	8	Stuart (2000)	- Large and innovative alliances (IV)	- Patent citations (DV)	- Positive	- USPTO
	9	Wuyts et al. (2004)	- Diverse tech and repeated interfirm agreements (IV)	- New drugs classified by FDA (DV)	- Positive	- FDA, COMPUSTAT USPTO
	10	Almeida and Phene (2004)	- Technological richness, Technological diversity, Knowledge linkages (IV)	- Number of successful semiconductor patents (DV)	- Positive	- USPTO, Dataquest, Integrated Circuit Engineers

Table 3.2 (Continued)

		Authors (Year)	Related Variables	Diffusion Variables	Findings	Data/Method
Organization	11	Cool et al. (1997)	- Supply and demand factor, critical mass (IV)	- The ratio of annual change in the number of electronic switches for each subunit (DV)	- Positive	- Several archives;
	12	Hargadon and Douglas (2001)	- Robust design (IV)	- Acceptance by the market (DV)	- Positive	- Historical case study;
Inter-organization	13	Leblebici et al. (1991)	- Acceptance by the central and established players (IV)	- The organization of a field (DV)	- Positive	- A case study;
	14	Davis (1991)	- Fragmented ownership structure, interlock network centrality, small-size firms, institutional ownership (IV)	- Adoptions of poison pills (DV)	- Positive	- The Investor Responsibility Research Center (IRRC), Proxy Statements;
	15	Christensen and Bower (1996)	- Rate of the technical progress, performance demanded in a market (IV)	- Adoption of disruptive technology (DV)	- Negative	- Case study, interviews;
	16	Goes and Park (1997)	- Structural links, institutional links, resource-based links (IV)	- Adoption of service innovation in a hospital (DV)	- Positive	- Annual reports and other archives;
	17	Zahra and Nielson (2002)	- Internal human and technological resources (IV)	- Frequency; speed; radicalness; and patents (DV)	- Positive	- Survey;

Table 3.2 (Continued)

		Authors (Year)	Related Variables	Product Innovation Variables	Findings	Data/Method
Organization	18	Kelm et al. (1994)	- Shareholder value (DV), technology and market related factors (IV)	- Announcement of product invention; announcement of product commercialization	- Positive - Moderator	- WSJ Index, COMPUSTAT;
	19	Greve (2003)	- Performance variables (ROA, ROS, ROE), low slack variables (i.e., ratio of quick asset to liabilities) (IV)	- R&D intensity; number of innovations made by a firm (DV)	- Negative	- Nikkei NEEDS database, Journals New Technology Japan and Techno Japan;
Inter-organization	20	Kessler et al. (2000)	- External technology sourcing strategies at later stage of technology development (IV)	- Innovation speed (relative to schedule, relative to acceleration, relative to competitive speed) (DV)	- Negative	- Survey;
	21	Spencer (2003)	- Knowledge-sharing strategies, national innovation system, global innovation system (IV)	- Patent renewal from citation patterns (DV)	- Positive	- Unidentified Archives;
	22	Rothaermel and Deeds (2004)	- Exploration alliances, products in development, exploitation alliances (IV)	- Products in development, products on market (DV)	- Positive	- BioScan, USPTO, FDA;

*** IV** refers to an independent variable; **DV** is a dependent variable

Thus, "the patent renewal methodology assumes that firms will renew patents as long as they are useful for the firms, and allow unproductive patents to lapse" (Spencer, 2003). Drawing from this process, Spencer (2003) was able to capture the firms' capability to generate useful and valuable inventions. However, to some extent, patent renewal methods only indicated that particular inventions may be successfully commercialized in the inventors' perspective.

Kessler et al. (2000), applied an original variable, "innovation speed," to cover the period of firms from an early stage of generating innovation to the last stage of diffusing innovation to the market. Thus, the innovation speed as a variable reflects the capabilities of firms to deal with speeds of both generating and diffusing innovation. Because the innovation speed is an indicator designated to capture the sum of invention speed and commercialization speed, one may argue that the indicator does not elaborate on information regarding individual outcomes of invention and diffusion activities.

Taken together, studies in the integrated innovation performance section suggest several important implications. First, since Rothaermel et al. (2004) indicated the path dependence among four linking variables—exploration alliances, products in development, exploitation alliances, and products on the market—it is important for researchers to understand the nature of overall alliances to determine the consequences of invention activities and diffusion activities to understand overall innovation performance. Second, the inclusion of relevant organizational partners in the innovation system is a required methodology to understand specific types and characteristics of interorganizational linkages leading to successful innovation outcomes (Spencer, 2003).

Because all organizations operate in an open system, research should include relational contents and relational multiplexity in the study to deal with the complexity of interorganizational linkages. The relational contents involve complex issues of information

exchanges among organizations while the multiplexity exists when multiple and overlapping ties are in place between the nodes in a network. These two variables are important concepts in the interorganizational network research, because they enable researchers to consider various impacts from relevant factors in the system simultaneously (Zaheer & Usai, in press).

Last, the use of innovation speed or patent renewals as dependent variables seems to be appropriate when scholars intend to capture the total effect of innovation outcomes. However, according to several studies of innovation, focal firms change organizational networks to achieve current objectives (Ahuja, 2000a; Rothaermel et al., 2004; Wuyts et al., 2004). While a direct empirical study is still needed to explain the influence of the specific exploration-exploitation ratios on the focal firms' innovation performance (Rothaermel et al., 2004), the use of an integrative framework to understand the path-dependent processes of invention and commercialization activities is deemed to be necessary.

CHAPTER 4: THEORETICAL FRAMEWORK

The development of the biopharmaceutical industry described in the second chapter was a complex and fundamentally unique phenomenon. In general, the biopharmaceutical industry is a nearly perfect testing ground to combine academic concepts of interorganizational linkages and innovation theories. The industry consists of many strategic alliances collaborating to achieve innovation performance. Prevalent collaborations in various forms of agreement among pharmaceutical firms, biotechnology firms, research institutions, and universities have been witnessed throughout the past decades (Darby et al., 2004; Zucker, Darby, & Brewer, 1998).

Comments of biopharmaceutical experts consistently indicate the importance of a patent protection system that encourages collective efforts and collaborative environments of interorganizational networks. Since biopharmaceutical firms are confident with the patent law enforcement and the process of intellectual protection, they willingly share their developed proprietary technologies with alliance partners to further develop and commercialize new and potential drugs to the market. With this evidence, theorists have conducted a number of studies to understand organizational factors involved in strategic alliances and innovation outcomes since the 1980s.

Whereas prior studies successfully confirmed alliances as primary predictors of innovation performance, the studies seldom included several aspects of relational networks among alliances. Additionally, prior research generally ignored the fact that the innovation process (i.e., product innovation) is a path-dependent pattern with continuous and interdependent activities of invention and commercialization (Greve, 2003; Rothaermel et al., 2004). To fill the literature gap, an integrative framework warrants. Further, as the biopharmaceutical industry reaches a mature phase (Wittcoff et al., 2004), behaviors of relevant organizations and patterns of interorganizational linkages become increasingly

consistent and stable. One can argue that perhaps this specific period represents a better time to re-assess the relationships between strategic alliances and innovation outcomes in the particular industry.

BioScan, the most popular database used by many studies, details most collaborative types of the biopharmaceutical industry. The directory contains the content of agreements including R&D agreements, licensing agreements, clinical and contract research services, analytical and pharmaceutical formulation services, and feasibility studies. The same database also describes company history in terms of ownership structures (i.e., acquisitions and mergers). These collaborative efforts and environment reflect what Poldony and Page (1998) defined as the "network form of organizations," a wide array of collaboration including joint ventures, strategic alliances, business groups, franchises, research consortia, relational contracts, and outsourcing agreements.

Whereas several studies in interorganizational networks have already indicated motives and outcomes of collaborative efforts among firms, relatively few studies offer the comprehensive knowledge of how interorganizational networks could influence overall innovation activities. For instance, whereas Shan et al. (1994), Kotabe and Swan (1995), and Ahuja (2000a), and Darby et al. (2004) elaborated on the importance of interfirm networks in generating innovation, the scope of innovation only covered invention performance as measured by patentable inventions. This is surprising, given the fact that success or failure of invention activities (i.e., product innovation process) largely depends on performances of commercialization activities. Whereas some firms produce a number of inventions that have no market value, other firms produce fewer and much more profitable inventions. All firms want to be successful in both invention and commercialization; however, few have achieved both simultaneously. In academic literature, whereas several scholars contribute in terms of

invention, there is no empirical study to understand the commercialization activities among alliances.

4.1 Theoretical Backgrounds

From the review of innovation studies in Chapter 3, management scholars have used concepts of several theoretical frameworks to explain innovation processes (i.e., evolutionary economics, behavioral, and sociological perspectives). However, Drazin and Schoonhoven (1996) indicated that innovation studies are still less developed. The knowledge in those areas could not fully explain directions and causal relationships of factors relevant to invention and commercialization. Drawing upon several theoretical perspectives from the exhaustive literature review in chapter 3, most scholars used two important theoretical perspectives—organizational learning and institutional approaches—to understand the innovation phenomenon and to explain consequences of innovation related organizational behaviors. Before applying the two perspectives to develop the hypotheses in this chapter, this study will briefly review the main concepts of organizational learning and institutional approaches to highlight their current contributions toward innovation.

First, organizational learning focuses on issues of how organizations or groups within the organization recognize, acquire, and exploit information or knowledge to alter their fits with external environment (Aldrich, 1999; Cohen et al., 1990). The notable point of the approach is that some alterations may improve the organizational fit within the environment, whereas others may worsen it. March (1991) suggested that firms would be successful in the short-run through engagement in exploitation activities, but that the same firms would have difficulties in the long-run if there were no concentration on exploration activities. Thus, the concepts of organizational learning are relevant to the trade-off decisions, complicated processes, and activities that have no inherent link to success.

Aldrich (1999) suggested that research in organizational learning can be separated into two strands; the adaptive learning (Argote, 1993) and the knowledge development perspectives (Cyert & March, 1963). The former perspective treats organizations as goal-oriented activity, a system that learns from experience by repeating successful behaviors and discarding unsuccessful ones. Aldrich (1998) suggested that the adaptive learning perspectives are highly comparable to the concepts within evolutionary process, in which the variations of organizational structures and behaviors are selected, retained, and diffused among similar firms in the competitive environment. In the second strand of organizational learning, the knowledge development perspective, learning is not only about trials and errors, but also occurs as patterns of cognitive association and casual belief that are communicated and institutionalized. Therefore, learning can be inferential and vicarious, and organizations can generate new knowledge through experimentation and creativity (Aldrich, 1998).

With regard to institutional perspectives, the knowledge development perspective of learning approach and the concepts of institutional approach are highly overlapped (DiMaggio, 1991a). Firms learn from their environments and adjust themselves so that they are similar to other firms operating in the same industries. The similarity ensures that the firms conform to the institutionalized framework and that the firms survive the competition because they gain acceptance and support from the constituents. In the following, there will be a brief summarization of the main concepts of the institutional approach. Regarding this approach, Aldrich (1998) indicated that scholars have extended concepts of institutionalization into multiple dimensions. For instance, Parson (1956) argued that institutional patterns within organizations must be similar to the patterns of other organizations and social units within the same society. Further, Selznick (1957) offered another theme of institutional approach as a process of instilling values, by use of critical statements as presented by participants in organizational environments. Tolbert and Zucker

(1996) defined the process involved in the growth, coupled with deeply shared meanings among social actors as "habitualization" and "objectification." The authors described habitualization as the rise of patterned problem-solving behaviors, with objectification serving as the shared social meaning attached to these behaviors (Aldrich, 1998).

Applying the concepts of institutional approach in understanding of commercialization, Hargadon and Douglas (2001) proposed the implication of "robust design" as the practical approach of successful innovators, intended to draw attention and to convince public constituents or consumers to support the rise of innovation. In order to be successful in terms of commercialization, inventors must understand the institutionalized framework of the public, in a scope that allows people to commonly understand and accept the new technologies and innovative products. Inventors must balance the novelty of the products and the existing knowledge of the public to ensure that everyone in the public understands the occurrence, accepts the extension of technologies and products, and supports the inventions.

Incorporating the innovation concepts into several interorganizational network variables, the study uses the theoretical concepts of organizational learning and institutional approach to develop the hypotheses. The theoretical concepts of learning provide a framework for understanding the need of collaboration at the dual stages of product innovation process (i.e., invention and commercialization) (Rothaermel et al., 2004). Although, firms may alter their interfirm networks to fit the external environment, the new networks do not always guarantee success.

Additionally, learning provides concepts of exploration and exploitation activities (March, 1991). These activities are important factors in contributing to the formation of a focal firm's network to generate invention and commercialization. However, since there are several dimensions of the network, focal firms engaging in different dimensions of the network perform differently. During the early stage of the product innovation process, firms

engage in exploratory search involving invention activities and innovative capabilities to develop new knowledge, which subsequently generates additional value. Once the firms achieve performance from exploration activities, they turn to exploitation activities.

Rothaermel and Deed (2004) indicated that in reality, most firms engage in exploration and exploitation activities simultaneously because firms manage several concurrent projects at different stages in the product innovation process. However, from a learning perspective, the knowledge and capabilities currently exploited must have been explored at some earlier time.

Theoretical concepts of institutional perspectives primarily facilitate the understanding of the network formation during the commercialization process (Hargadon et al., 2001; Stuart, 2000). Institutional perspectives explain firm behaviors in gaining acceptance and legitimacy from the society. The formation of a focal firm's network to ensure the acceptance and legitimacy of its innovative products as well as acceptance into the social status of the focal firms reflects such behavior. For instance, Stuart (2000) recommended that startups collaborate with established firms to ensure survival and to increase revenue growth.

In the context of institutional perspective, a high status or prominent network enhances a focal firm's acceptance and legitimacy. However, the institutional perspective suggests that established partners tend to stick with default assumptions or an existing framework of technologies (Christensen et al., 1996; Tushman et al., 1986). It would be interesting to examine the impact of the established partners of the focal firm on invention performance.

Integrating the learning theory and institutional perspective, this chapter examines the implications of roles and collaborative structures of strategic alliances. The proposed model indicates how several dimensions of the interfirm network reflect the effective product innovation. Please refer to Figure 4.1 for the overall model of the study.

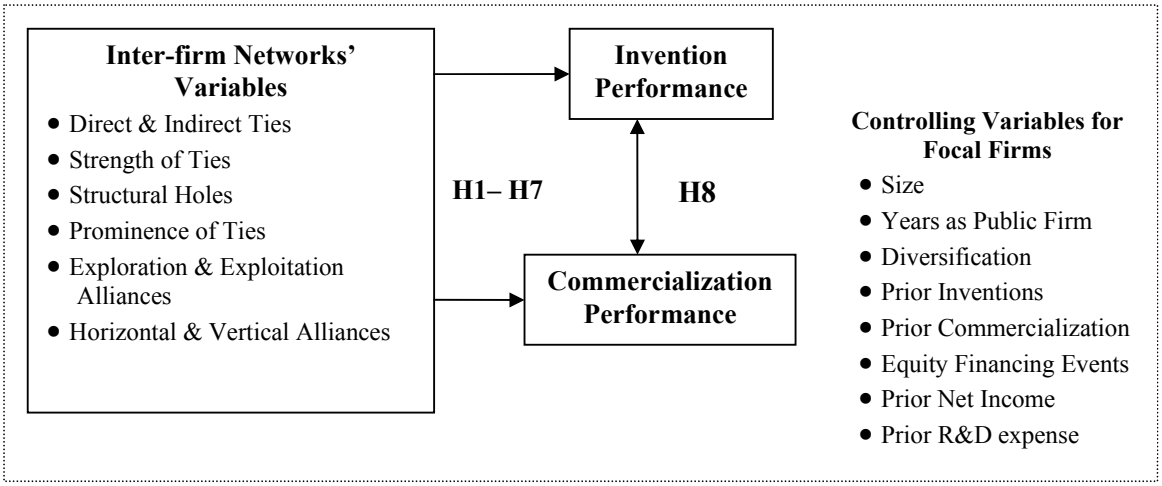


Figure 4.1: Interorganizational Networks for Product Innovation

4.2 Interorganizational Network Variables

In this section, the study will briefly summarize the six dimensions of the interfirm network variables and discuss the hypothetical relationship between invention and commercialization performances. Afterward, an elaboration on theoretical development will follow. Regarding the first dimension, direct and indirect ties, Ahuja (2000a) successfully indicated that these ties promote patentable inventions. The author, however, mentioned that the contents of ties that go through the networks were not directly examined. Additionally, because the dependent variable represented a number of successful patent applications, or granted patents, the author did not apply the concepts of direct and indirect ties toward an understanding of the performance of commercialization activities. The second and third dimensions of interorganizational variables involve two important concepts: the structural holes and the strength of ties. Prior studies in organizational learning offer knowledge regarding how the variables explain invention performance; this present study extends those concepts to understand how the levels of structural holes, weak ties and strong ties explain the outcomes of product innovation process (invention and commercialization activities).

The fourth characteristic of ties is a prestige of alliances in the focal firm's network. Studies of interorganizational networks and adoption suggest that high-status and low-status

focal firms in the networks perform differently in terms of invention and adoption capabilities (Christensen et al., 1996; Leblebici et al., 1991; Rochin, 2006). The studies also acknowledge that the adoptions of innovation process among organizations are facilitated by specific characteristics of interorganizational networks (Davis, 1991; Kraatz, 1998). Regarding this issue, institutional scholars suggested that the prestige or legitimacy of focal firms' linkages help them survive and thrive in the industry (Baum & Ingram, 1998; Baum et al., 1991). However, given the development of all the related knowledge in the area, the impact of the prestige in the focal firm's network on the integrated framework of invention and commercialization has been relatively ignored.

The fifth dimension deals with orientations of focal firms in integrated innovation networks. Rothaermel et al. (2004) categorizes two types of network orientations. The authors found that exploration partners help focal firms in terms of invention activities and that exploitation partners facilitate commercialization activities. However, the authors suggested that future research should examine the mix of exploration and exploitation and its contribution in terms of performance. The comprehensive framework of this present study provides a further analytical model regarding how different alliances simultaneously contribute to performances of product innovation.

The last dimension to be examined in this study is the position of focal firms in the alliance networks. This dimension offers a set of hypotheses that closely relates to the findings of Rothaermel et al. (2004). The hypotheses involve the relationships of focal firms and their horizontal and vertical alliances (i.e., downstream and upstream alliances) and the influences of those relationships on invention and commercialization performances. Whereas prior studies have found that types of alliances (exploration and exploitation alliances) determine the focal firms' invention and commercialization performances, this present study suggests that the findings may not always be straightforward. The hypotheses indicate that

the interaction effects of the orientation of the focal firms and their upstream and downstream alliances could moderate the influences of upstream and downstream alliances.

In the concluding hypothesis, the relationships between outcomes of invention and commercialization activities are examined. Using several concepts of organizational learning and institutional approach throughout the previous hypothesis development, the last hypothesis predicts that those focal firms aiming to exploit their interfirm networks to generate inventions are unlikely to be successful at commercialization activities. Conversely, the focal firms aiming to draw commercial benefits from their interfirm networks will be less successful at invention activities. In other words, because a particular focal firm's alliance network is particularly structured to achieve either invention performance or commercialization performance, the success of one activity is at the expense of the other activity.

4.2.1 Direct and Indirect Ties

Powell et al. suggested that "when the knowledge base of an industry is both complex and expanding, and the sources of expertise are widely dispersed, the locus of innovation will be found in a network of learning, rather than individual firms" (1996: 116) Regarding the importance of the network of learning, Tsai (2001) examined knowledge transfer in organizational networks. The author indicated that a central network position of business units works with units' absorptive capacity to generate innovation and improve business performance. The central network position of business units reflects the external knowledge access, while the units' absorptive capacity facilitates the ability of the units to assimilate new external knowledge and the ability to apply such knowledge to commercial ends, and thus create the opportunity for profit (Cohen et al., 1990; Tsai, 2001). Whereas the absorptive capacity is a specific characteristic within a focal firm, a central network position deals largely with numbers of direct and indirect ties associated with the focal firms. If the

central network position could be measured by the number of direct and indirect ties of a focal firm, the study of Tsai (2001) should support the argument that the high numbers of ties for the focal firm accelerate its innovation activities and performance.

Several studies indicated the importance of social networks (i.e., direct and indirect ties) as sources of knowledge and learning capabilities in firms (Nahapiet & Ghoshal, 1998; Smith, Collins, & Clark, 2005). However, Ahuja (2000a) specifically elaborated on the contributing benefits of direct and indirect ties toward patentable inventions. The researcher indicated that direct ties bring three main benefits: knowledge sharing among partners, complementary skills among partners, and scale economies in research and development programs (see further details in Ahuja, 2000a). A firm's partners not only bring knowledge, experience, assistance, and rare resources to the focal firms, but also transfer additional information received by the interactions with other partners to the focal firm, and vice versa. Thus, drawing from the prior studies and their arguments on organizational learning perspectives, direct and indirect ties reflect linkages to knowledge held by the focal firm's partner and the knowledge held by its partner's partners (Gulati et al., 1999; Smith et al., 2005).

4.2.1.1 Direct and Indirect Ties and Invention Activities

Empirically, Ahuja (2000) found that direct and indirect ties of collaborative networks among firms in the chemical industry significantly contributed to the invention performance of focal firms. The author indicated that the impact of indirect ties on a firm's invention performance will be moderated by the level of the firm's direct ties. Because the relative addition to knowledge through indirect ties is less for firms with many direct ties than for those with few direct ties, the focal firms with many direct and indirect ties will receive only a marginal increment of knowledge to generate inventions from indirect ties. Additionally, if a focal firm's partners have many connections, the information that reaches the focal firm

through the network also reaches the other partners of its partners. A large number of indirect ties mean that there is more competition among the focal firm and its partners' partners. This competition of knowledge from the common partners produces more constraint in a focal firm's ability to absorb new information or respond to it as effectively as a firm with a few direct ties (Ahuja, 2000a).

Further, because Ahuja (2000a) asserted that direct ties serve as sources of resources and information necessary for invention activities, a focal firm seeking resource-sharing benefits to improve its invention activities should prefer direct ties to indirect ties. Because the magnitude of the benefits provided by direct ties is significantly different from those provided by indirect ties, focal firms need direct ties to gain resource-sharing benefits rather than indirect ties to gain information-spill over benefits. To illustrate the previous point, a biopharmaceutical firm should improve its productive capabilities in terms of invention activities if it has many direct ties with universities, research institutes, and chemical-based pharmaceutical firms. With many direct ties, the focal firms no longer need a high number of indirect ties because the necessary knowledge and important information have already been received from the direct ties. Thus, the direct ties moderate the contributions of indirect ties as sources of information to generate patentable inventions.

4.2.1.2 Direct and Indirect Ties and Commercialization Activities

Regarding benefits of direct and indirect ties on commercialization activities, it is reasonable to assume that a focal firm with many direct and indirect marketing and consumer networks should perform successfully in the activities. Specifically, under the institutional approach, a successful commercialization depends largely on the acceptance and support of constituents or consumers (Hargadon et al., 2001). Unlike the focal firms, in the case of invention activities that seek to acquire benefits from their partners in terms of resource sharing (and, to some degree, information spillovers), the focal firms in the case of

commercialization activities require direct and indirect partners to communicate and introduce their inventions to the market. Therefore, in addition to receiving important information, the focal firms use their ties to send messages about their inventions to the public.

Rogers (1995) indicated that "critical mass" and "opinion leaders" are very important factors determining the successful commercialization activities. In a successful commercialization network, the larger numbers of direct and indirect ties of a focal firm represent multiple channels of communication with a plethora of opinion leaders. These critical leaders serve to generate the critical mass, an important referent stage occurring at the point in which enough individuals adopt an innovation, resulting in the innovation's further rate of adoption becoming self-sustaining (Rogers, 1995).

Spencer (2003), addressing the importance of having a critical mass of competitors on the same technology trajectory, extends the understanding of interorganizational linkages to alliances in networked industries. According to Spencer, it is more important that firms acquire opinion leaders—externally individual researchers, organizations, and even competitors—who will develop evaluation standards that favor the firms' product design, thus building a strong industry infrastructure. In this regard, firms should focus particular attention to all possible direct and indirect knowledge contributors in the broadest environment. Further, the interaction between the direct and indirect should provide positive outcomes in terms of commercialization. Drawing from the previous arguments, this study proposes the first set of hypotheses to understand the potential benefits of direct ties, indirect ties, and the interaction between direct and indirect ties toward invention and commercialization activities.

H1a (i): The more direct partners that a focal firm maintains, the greater the firm's invention performance.

H1b (i): The more indirect partners that a focal firm maintains, the greater the firm's invention performance.

H1c (i): The impact of indirect partners on a focal firm's invention performance will be moderated by the level of the firm's direct ties.

H1d (c): The more direct partners that a focal firm maintains, the greater the firm's commercialization performance.

H1e (c): The more indirect partners that a focal firm maintains, the greater the firm's commercialization performance.

H1f (c): The greater the number of both direct and indirect partners, the better commercialization performance for the focal firm.

4.2.2 Structural Holes

Burt (1997) related his argument of structural holes to define the benefits of a social network in terms of the information and control advantages of being the broker in relations between people otherwise disconnected in a social structure. The concepts of structural holes differ from those of strength of ties because the concept of strength of ties concerns the ties that span the chasm between two social clusters, while the concept of structural ties is about the chasm spanned that generates information benefits (Burt, 1992). For example, a focal firm may have a strong-tie network with immediate alliances, but the network may have plenty of holes among the members. On the other hand, another focal firm may have a weak-tie network with no structural hole at all.

Regarding the information benefits of structural holes, Burt (1992) suggested that the benefits include access, timing, and referrals. Access represents the positions from which a manager can obtain additionally useful information from his or her network; timing involves getting information and acting beyond that information to acquire an advantageous business position; referrals are transferring processes which filter information to the manager so that the information is direct, concentrated, and legitimate (Burt, 1992).

According to Burt (1997), the more holes spanned mean richer information benefits from the network for a focal firm, because unconnected members in a network tend to bridge more

non-redundant information from more clusters. Burt suggested that each cluster of contacts forms a single source of information, because people connected to one another tend to share common backgrounds and information. Thus, these individuals in a cluster usually know the same things at about the same time. If one can bridge the two clusters, he or she would have gained not only the information benefits but the control benefit of structural holes. The position of members in social networks who create structural bridges between disconnected cliques determines whose interests are served by the bridge (Burt, 1997). Therefore, it is a social network position that determines who has power to allow the focal actors to get thing done and achieve their goals.

4.2.2.1 Structural Holes and Invention Performance

Using the concepts of structural holes to understand the inventions of interorganizational networks, Ahuja (2000) found that high magnitudes of disconnections among partners in the collaborative networks decreased patentable inventions of focal firms. Ahuja explained that because the context of his study dealt with collaboration and resource sharing among networks of competitors, it required the benefits of closed networks. Thus, a low level of structural holes within interorganizational networks helps a focal firm to overcome opportunism among competitive members. The author suggested that for the other collaborative context in which the key principle is information brokerage, a high level of structural holes among interorganizational networks should help focal firms to bridge structural holes between the two unconnected clusters. For instance, if the focal firm is a product-development consulting firm that bridges structural holes between clients in different industries, a high level of structural holes should satisfy the demands of the focal firm's customers (Hargadon et al., 1997). In sum, according to Ahuja: "whether structural holes are good, bad, or irrelevant is liable to be a function of the context. When developing a collaborative milieu and overcoming opportunism are essential to success, closed networks

are likely to be more beneficial. When speedy access to diverse information is essential, structural holes are likely to be advantageous" (2000: 451).

In the context of the biopharmaceutical industry, traditional pharmaceutical firms that engage in relationships with isolated biotechnology firms (i.e., a possibly high level of structural holes) or disconnected research contract organizations should be more likely to generate a lower level of inventions. It is more likely that the interorganizational relationship with a high level of structural holes should prevent the development of trust and effective communications among partners. This effect obviously harms the invention development of the focal firms. In the context of invention activities, Walker, Koput and Shan (1997) indicated that biotechnology firms reproduced their network structures according to social capital, not structural holes. They found that biotechnology startups followed the logic of social capital to form their strategic alliances, because the relationship in the biotechnology network lasts a long time. In this case, trust and commitment in resource-sharing activities received by closed networks are more important for a focal firm and its collaborative agreements than non-redundant knowledge and opportunities. Thus, following concepts of Ahuja (2000a) and Walker et al., (1997), this study proposes that a focal firm collaborating in a low level structural-holes network should perform well in terms of inventions.

4.2.2.2 Structural Holes and Commercialization Performance

Since innovation is a socially driven phenomenon, an effective position of a focal firm in a society should accelerate the speed in which the focal firm can successfully introduce and diffuse new products and services. Hargadon and Sutton (1997) conducted a case study analysis of IDEO, a successful product design firm. In their study, the authors blended the concepts of network and organizational memory perspectives (Walsh et al., 1991) in a model of technology brokering explaining how IDEO developed and successfully commercialized innovative products. The authors indicated that IDEO, as a successful organization, acquires

knowledge from external ties, stores it in the organization's memory, and retrieves that knowledge to generate new innovations.

In the context of the biopharmaceutical industry, Walker, Kogut and Shan (1997) indicated that the structural holes theory may apply more to networks of market transactions than to networks of cooperative relationships. Several mergers and acquisitions of market-based pharmaceutical firms reflected attempts of the focal firms to generate structural holes and acquire market power in the biopharmaceutical industry. The Federal Trade Commission had to work harder to supervise the transactions because the horizontal mergers and acquisitions of these market-based competitors could create a monopoly situation in the particular industry. Since the networks of market transactions require a speedy access to diverse information and it is important for biopharmaceutical firms to control clusters with non-redundant information, the firms that seek success at commercialization activities tend to operate in a network with a high level of structural holes.

Whereas several studies in this section did not explicitly mention concepts of learning and institutional approaches when explaining the different benefits of high and low levels of structural holes in collaborative networks of the biopharmaceutical industry, the following arguments are plausible. Since an environment of interfirm relationships in the low-level structural holes facilitates interfirm learning of complex and technical knowledge, a focal firm should be successful in receiving and transferring knowledge that promotes its invention. Meanwhile, knowing peers from different and various industries as represented in the high-level structural holes, the focal firms better their understanding of the institutional framework of the market. Thus, the focal firms are more likely to be successful in commercializing their inventions. I propose the following hypotheses, using concepts of structural holes to predict the outcomes of invention and commercialization activities.

H2 (i): The number of structural holes among a focal firm's direct and indirect partners is negatively associated with the focal firm's invention performance.

H2 (c): The number of structural holes among a focal firm's direct and indirect partners is positively associated with the focal firm's commercialization performance.

4.2.3 Strength of Ties

Whereas the previous concepts of direct and indirect ties deal with the quantitative numbers of direct and indirect ties of a focal firm, the next concept, strength of ties, deals with the qualitative aspects of the direct ties for a focal firm. Actually, the concept of strength of ties began when Granovetter (1973) regarded the strength of ties as a construct with the following dimensions: amount of time, emotional intensity, intimacy, and reciprocal services that characterize the relationships. Analyzing the multiple dimensions of the strength of ties, it seems impossible for any empirical theorists to capture the four dimensions of tie strength at once. Empirically, none of the studies has simultaneously used the four dimensions suggested by Granovetter (1973). Despite the weak methodological concept of strength of ties in the early period, several network theorists continued to develop theoretical concepts in network research. The theorists introduced several technical methods to measure characteristics of relational variables, including lines, paths, density comparisons, connectedness, centrality, cliques, and cluster (Scott, 1991).

Regarding the benefits of tie strengths, Granovetter asserted that a major benefit of a weak-tie network is the non-redundant information shared by weak-tie members (1973). Unlike strong ties that are dense and comprise redundant information in the networks, weak ties combine people with arm's length relationships (Granovetter, 1973). The arm's length relationships combine people with different backgrounds and non-redundant information. A study in management indicated that one of the special characteristics of weak ties is large-size networks (Uhl-Bien, Graen, & Scandura, 2000). The authors of this study mentioned further that because of loose relationships, members in the weak-tie networks maintain relationships

with others at relatively lower costs. Because weak-tie networks have larger internal networks and more arm's length connections, people in these particular networks are more likely to benefit from networks in terms of job advancement (Podolny & Baron, 1997).

Whereas some scholars are paying attention to weak-tie relationships in a social network, others researchers focus their research interest on strong-tie relationships. Strong ties, dense and redundant, foster a) clear and consistent sets of expectations and values among members, and b) trust and support from others, allow members to access certain crucial resources and to implement strategic initiatives (Podolny et al., 1997). Hansen (1999) found that a weak-tie relationship between sub-units speeds up projects when knowledge is not complex, yet slows down projects with highly complex knowledge. Whereas weak ties may be good channels for information transfers, strong ties could be better information channels when information is complex, socio-emotional, and technical (Hansen, 1999; Sparrowe, Liden, & Kraimer, 2001).

Hansen (1999) studied the strength of ties that facilitates knowledge transfer between teams within an organization, but another study examined the strength of the interfirm network that allows firms to survive the competition. When facing market uncertainty (i.e., uncertainty which is outside of a firm's control and shared across firms), firms reduce the uncertainty through interactions with existing and similar (i.e., strong-tie) partners. By solidifying the present network structure, firms feel secure, considering that strong-tie partners will deliver important resources and help deal with uncertain market conditions including consumer demand, industry-level technology trajectories and standards, and input costs (Beckman, Haunschild, & Phillips, 2004).

4.2.3.1 Strengths of Interfirm Networks and Invention Performance

From the literature review, several articles reported a positive relationship between the quality of alliance relationships and invention performance (please see Chapter 3). Silverman

and Baum suggested that biotech university scientists whose research efforts have a tremendous impact on biotechnology firms' success rarely transact with more than one firm at a time. Specifically, the authors mentioned that "the relative lack of scale and scope economies in an individual research project (i.e., as compared to marketing) imposes stark limits on the number of simultaneous alliances to which an upstream research player can commit its particular scientific or technological expertise" (2002: 793).

Liebeskind et al. (1996) noted the fact that 163 (77%) of 213 "star" researchers in the biopharmaceutical industry worked in universities, another 44 (21%) worked in other nonprofit research institutes, and only six "stars" (3%) worked in firms. While that particular information was introduced almost a decade ago, it still illustrates the fact that an important source of biopharmaceutical technology comes from scientists working at universities. Because biotechnology scientists rarely changed careers as professors at universities, this fact suggests immobility among intellectual resources and thus the need for biotechnology firms to maintain stable and strong interorganizational relationships with universities during the technological development period.

During the invention activities, biopharmaceutical firms established social capital with knowledge-based organizations (i.e., universities, biotechnology firms, and contract research organizations). Walker, Kogut and Shan (1997) examined the formation of network structure in the biotechnology industry and found that firms valued long-term benefits of interorganizational relationships over short-term benefits of brokering opportunities. Rothaermel et al. (2004) indicated that as biopharmaceutical firms grew larger, the firms tended to first withdraw from exploitation alliances before withdrawing from exploration alliances. Since exploitation alliances generally exhibited less uncertainty, the alliances required fewer resources to maintain than did exploration alliances. Therefore, focal firms'

relationships with exploration alliances should be stronger than those with exploitation alliances.

Drawing from perspectives of organizational learning, the focal firms seeking to generate invention require strength of ties to facilitate knowledge transfer from interorganizational partners. The established network of biotechnology firms seeking to generate inventions is thus relatively based on a strong-tie basis.

4.2.3.2 Strengths of Interfirm Networks and Commercialization Performance

As a strong-tie network is hypothesized to produce invention performance, it should not generate commercialization performance. Whereas strong-tie relationships facilitate all members to communicate and coordinate with complex and technical information and knowledge (Hansen, 1999) relatively, the members do not need strong-tie relationships to commercialize inventions. In fact, a recent study suggested that firms seeking to successfully complete new drug development projects should carefully assess alternative partners rather than merely turning to partners with whom the firms have had prior alliance experience (Hoang & Rothaermel, 2005).

Unlike inventing partners, marketing partners do not have to recognize specifically technical features associated with inventions in order to commercialize them in the market. This argument is in line with Zahra et al. (2002), asserting that by using external marketing-based partners, firms can improve their competitive advantage through effective and timely commercialization of new technology. Drawing on the concepts of the institutional approach, this paper suggests that focal firms need weak-tie alliances to diffuse information and to gain acceptance for their inventions that will ultimately displace the existing and established similar products. Because the number of arm's length partners is larger than the number of strong-tie partners (Uhl-Bien et al., 2000), the arm's length partners should be used as more effective channels of production innovation by the focal firms. Thus, if the focal firms can

convince numbers of their weak-tie alliances with arm's length relationships of product innovation, firms are more likely to be successful in terms of convincing and gaining acceptance and, thus obtaining support from consumers in the larger society.

The trade off between the two benefits of strong-tie and weak-tie alliances in terms of invention and commercialization performances should be observable in collaborative networks within the biopharmaceutical industry. Walker, Kogut & Shan (1997) indicated that although there is evidence indicating a relationship between interfirm cooperations and startups' patent activities, the network formation of biopharmaceutical firms does not necessarily lead to an optimal structure for both invention and commercialization activities. Given that other variables are constant, it is more likely on one hand that biopharmaceutical firms allocating their resources to establish weak-tie relationships with peers in the same industry should perform well in terms of commercialization activities. On the other hand, the firms that concentrate resources on strong-tie relationships with other biopharmaceutical firms should do well in terms of invention activities. This paper submits the following set of hypotheses:

H3 (i): The strength of a focal firm's immediate ties within the network is positively associated with the focal firm's invention performance.

H3 (c): The strength of a focal firm's immediate ties within the network is negatively associated with the focal firm's commercialization performance.

4.2.4 Prominence of Direct Partners

The next factor that characterizes ties is the prominence of the direct partners. Several studies in management, specifically using the institutional perspectives, indicate the importance of economic status and reputation of individual organizations and interorganizational networks as the determinants of innovation outcomes (Baum et al., 2000; Christensen et al., 1996; Leblebici et al., 1991; Rothaermel, 2001). Because of prior successes and highly invested costs sunk into existing technologies, the prominent firms are

inflexible and uncomfortable with new inventions available on the market. This inflexibility prevents the high-status firms from being able to allocate sufficient resources to develop potentially disruptive inventions (Christensen et al., 1996; Leblebici et al., 1991). In the interorganizational context, this inflexibility should also be held for the focal firms collaborating with predominantly prestigious partners. Having high-status or well-known partners in their networks limits the possibility of the focal firms to access and acquire radical and innovative resources to pursue disruptive technologies. This should not help the focal firms to develop their invention activities.

Since prominent firms are preoccupied with exploiting their prior technologies, Christensen et al. (1996) and Leblebici et al. (1991) indicated that startup firms alone normally introduce disruptive technologies or inventions to compete with existing products and services offered by the established firms. According to institutional perspectives, the startup firms do not have or need legitimacy or social supports from their interfirm partners to facilitate invention activities (Hargadon et al., 2001; Leblebici et al., 1991). Whereas the focal firms may not need the prominence of alliances in the development of invention, the firms may require technical knowledge and fresh perspectives of alliances. If a focal firm is among several startup alliances, it should gain mutual benefits in terms of disruptive technologies from its startup peers. In other words, it should acquire some radical knowledge (i.e., new knowledge or technologies that are not yet acceptable to the constituents) from its startup partners to develop inventions.

However, during commercialization activities, a study has shown that a startup firm seeks collaboration with high-status alliances so that the alliances may act as endorsements by building additional public confidence in the value of the startup focal firm's organizational products and services (Stuart, 2000). Further, the high-status alliances facilitate capabilities of a startup focal firm to attract its customers and other corporate partners. As some

institutional theorists (DiMaggio & Powell, 1983; Leblebici et al., 1991) noted, although low-status firms are the first to innovate, the prominence of a firm is important to the initiation of change in many organizational fields, particularly where prestige matters (Sherer & Lee, 2002). Hence, in the biopharmaceutical industry, it takes a radical knowledge of new and less prominent startup alliances to generate inventions, together with the reputations of prominent partners, to commercialize the inventions that have not been legitimized in the markets. Drawing from previous arguments on the learning and the institutional perspectives, the next hypotheses follow:

> **H4 (i): The prominence of a focal firm's immediate partners is negatively associated with the focal firm's invention performance.**
>
> **H4 (c): The prominence of a focal firm's immediate partners is positively associated with the focal firm's commercialization performance.**

4.2.5 Exploration vs. Exploitation Oriented Partners

Regarding the next dimension, two interfirm networks determine product innovation performance of focal firms. As previously reviewed in Chapter 3, the concepts of exploration and exploitation (March, 1991) are respectively comparable to invention and commercialization (Rothaermel et al., 2004). Specifically, drawing on the concepts of organizational learning, Rothaermel et al. (2004) indicated that focal firms work with their exploration partners to be successful in terms of invention activities. Additionally, firms work with exploitation partners to be successful in terms of commercialization activities. In the context of the biopharmaceutical industry, the exploration-oriented network includes a partner majority of that focuses on the upstream activities of the value chain (basic research and drug discovery and development), whereas the exploitation-oriented network includes a partner majority of that focuses on the downstream activities of the value chain (clinical trials, FDA regulatory process, and marketing and sales).

Whereas Rothaermel et al. (2004) successfully conducted a study indicating that a) the exploration alliances determine focal firms' products in development, that b) the products in development (as measured by patents and R&D projects) lead to focal firms' numbers of exploitation alliances, and that c) the exploitation alliances suggest the focal firms' products on the market, the authors did not relate specific exploration-exploitation ratios to firm performance. Incorporating the fact that focal firms engage in exploration and exploitation activities simultaneously with the fact reported by Powell et al. (1996) that interorganizational alliances are empirically stable among biopharmaceutical firms, the focal firms with high ratios of exploration alliances may perform better in their invention activities than in their commercialization activities. Conversely, the focal firms will perform relatively better in commercialization activities if they have high ratios of exploitation alliances. This paper offers the following hypotheses:

H5a (i): Focal firms whose networks have a greater preponderance of exploration-oriented relationship will have higher levels of invention performance.

H5b (i): Focal firms whose networks have a greater preponderance of exploitation-oriented relationship will have lower levels of invention performance.

H5c (c): Focal firms whose networks have a greater preponderance of exploration-oriented relationship will have lower levels of commercialization performance.

H5d (c): Focal firms whose networks have a greater preponderance of exploitation-oriented relationship will have higher levels of commercialization performance.

4.2.6 Horizontal and Vertical Networks

Empirically, prior studies suggested that exploration- and exploitation-oriented networks should help a focal firm to respectively accomplish invention and commercialization performances (Beckman et al., 2004; Rothaermel et al., 2004). However, given several conditions, these predicted relationships may not always be straightforward. Specifically, Rothaermel and Deed (2004) found a negative moderating effect of firm size toward the networks and performances. The authors suggested that as firms grow, the firms tend "to

withdraw from a product development path to discover, develop, and commercialize promising projects through vertical integration" (2004: 201). It is arguable that as firms grow, they move their positions in the value chain of the biotechnology industry from inventors to merchandisers (i.e., from exploration to exploitation). Thus, extending the finding of Rothaermel et al.'s, (2004) regarding a focal firm's size, this paper suggests that the focal firm's position in the product development path should influence the benefits of interfirm networks toward product innovation performance. In other words, whereas the previous findings examined types of partners in focal firms' networks, the findings did not acknowledge the types and contributions of focal firms in the networks. Drawing from the previous arguments, this paper examines impact of focal firms' orientations and complementary relationships with partners on subsequent product innovation performance.

4.2.6.1 Horizontal Alliances

Kotabe and Swan (1995) and Silverman and Baum (2002) examined horizontal and vertical linkages in the biopharmaceutical industry. The first study found that horizontal alliances involve high risk and high return situations. The authors reasoned that the horizontal alliances are difficult to manage and maintain because the alliances are often between direct competitors that consume and compete for similar resources within the same industry. The finding from Kotabe and Swan (1995) aligned with the finding of Silverman and Baum (2002), suggesting that horizontal alliances tend to be the most important alliances to increase a focal firm's exit rate.

Despite the high risk of the exit rate within the horizontal collaborations, evidence suggested that as the biopharmaceutical industry matures, consolidations among biotech firms become popular, legally possible, and frequent (Barrett, 2005; Sellers, 2002). Silver and Baum (2002) explained that the vertical alliances tend to be more concerned with cost economizing; however, the horizontal alliances collaborate in such activities as R&D

consortia, patent swaps, and technology transfer, in an attempt to supplement the internal technical base and to improve long-term product technology development.

Since the upstream horizontal network does not possess insightful perspectives regarding the improvement of commercialization performance, the network should not promote a focal firm's commercialization performance. Likewise, the focal firm collaborating with a downstream horizontal network does not gain special knowledge and additional information for invention activities; neither should the focal firm perform well in terms of invention. Based on these basic arguments, this paper proposes the next related hypotheses.

> **H6a (i): An upstream focal firm collaborating with a greater number of its horizontal alliances (i.e., an upstream horizontal network) is positively associated with invention performance.**
>
> **H6b (i): A downstream focal firm collaborating with a greater number of its horizontal alliances (i.e., a downstream horizontal network) is negatively associated with invention performance.**
>
> **H6c (c): An upstream focal firm collaborating with a greater number of its horizontal alliances (i.e., an upstream horizontal network) is negatively associated with commercialization performance.**
>
> **H6d (c): A downstream focal firm collaborating with a greater number of its horizontal alliances (i.e., a downstream horizontal network) is positively associated with commercialization performance.**

4.2.7.2 Vertical Alliances

In the context of the vertical networks—an upstream focal firm collaborating with downstream partners (an upstream vertical network) and a downstream focal firm collaborating with upstream partners (a downstream vertical network)—the objectives of the two vertical collaborations are primarily reciprocal, yet obviously different. For instance, whereas a downstream firm initiates collaborations with upstream alliances (i.e., exploration-oriented networks) to acquire resource-sharing benefits in terms of invention activities, an upstream firm starts its collaborations with downstream alliances (i.e., exploitation-oriented

networks) to exploit its technologies through commercialization activities (Rothaermel, 2001; Rothaermel et al., 2004).

In terms of risks in the vertical alliances, Silverman and Baum (2002) indicated that the upstream firms dealing with downstream partners face lower mortality rates than the downstream firms dealing with upstream alliances. The authors explained that because resources usually flow up, the upstream focal firms dealing with downstream alliances receive significant infusions of capital resources (i.e., licensing fees, patent purchases) that allow them to survive and continue their invention activities. On the other hand, because the downstream firms inject their significant resources to upstream alliances in exchange for licensing agreements or marketing contracts, the downstream firms risk survival by spending capital resources in another industry.

Rothaermel and Deed (2004) suggested that as long as the upstream firms possess proprietary inventions, the upstream firms will be attracted by downstream firms, i.e., the exploitation alliances. The authors further suggested that although the patents were non-significant in predicting the firms' products in development, the number of exploitation alliances significantly determines the greater number of the firm's products on the market. From previous findings, therefore, upstream firms dealing with a substantial number of downstream alliances should perform well in commercialization activities.

As the upstream firm generates a number of potential inventions and attracts the substantial number of exploitation partners, the firm also acquires sufficient resources to expand its operation (Rothaermel et al., 2004). A prior research empirically found that successful (full-grown) upstream startups tend to establish footholds in exploitation activities (Koza & Lewin, 1998). At this stage, the full-grown upstream firm rearranges its organizational structure by pulling resources from invention activities to infuse in commercialization activities. This process suggests that a full-grown upstream firm usually

moves from exploration orientation to exploitation orientation (March, 1991). Because of the trade-off situation in exploration and exploitation activities, the full-grown upstream focal firm should perform relatively poorer in its invention activities when compared with its past performance.

Regarding the downstream vertical network, a downstream firm usually takes an initial advantage in commercializing potential inventions generated by upstream alliances. Rothaermel and Deed (2004: 218) wrote:

> "While technology start-ups may have been penalized initially because the problem of asymmetric information in the market for know-how lowered prices of quality projects, larger more successful technology ventures may be able to take advantage of their positions by gaining a price premium for lower-quality projects."

If the downstream focal firms—usually larger and more successful technology ventures—could collaborate with the greater number of upstream alliances—usually the technology startups—the focal firms should always gain premium and perform successfully in terms of commercialization. Therefore, success of the focal firms in the downstream vertical network relies on their capabilities to maintain a great number of technology startups in their portfolios.

With regard to the invention activities of a downstream vertical network, several studies indicate that successful invention activities are generated by "star" researchers who work in universities or with particular organizations that have "university-like" environments (Liebeskind et al., 1996; Terry, 2004). Therefore, although the downstream firms could obtain a high number of upstream alliances, it is unlikely that the firms possessing substantial marketing expertise and operating in the established "business-like" environments would be succeeded in the invention activities. Accordingly, this paper proposes the following set of hypotheses.

H6e (i): An upstream focal firm collaborating with a greater number of downstream alliances (i.e., an upstream vertical network) is negatively associated with invention performance.

H6f (c): An upstream focal firm collaborating with a greater number of downstream alliances (i.e., an upstream vertical network) is positively associated with commercialization performance.

H6g (i): A downstream focal firm collaborating with a greater number of upstream alliances (i.e., a downstream vertical network) is negatively associated with invention performance.

H6h (c): A downstream focal firm collaborating with a greater number of upstream alliances (i.e., a downstream vertical network) is positively associated with commercialization performance.

4.2.7 Performance of the Invention and Commercialization Activities

Drawing from organizational learning and institutional perspectives, previous hypotheses indicated that several interfirm network variables could facilitate and/or hamper performances of specific innovation activities. Table 4.1 reviews all independent variables and their hypothetical associations with invention and commercialization performances. The table also supports several studies indicating that different structures or characteristics of interfirm networks suggest different benefits and outcomes (Ahuja, 2000a; Liebeskind et al., 1996). As several prior studies suggested (Greve, 2003; Rothaermel et al., 2004), the two sequential activities of invention and commercialization should be examined and tested in tandem to enrich knowledge of product innovation. This table primarily offers negative relationships of several interfirm variables that simultaneously influence invention and commercialization performances.

As discussed earlier in the literature review section (Chapter 3), concepts of interorganizational network inertia (Li et al., 2002) and social capital (Liebeskind et al., 1996) suggested that focal firms do not or cannot change interfirm networks for short-term or brokering benefits. Specifically, in the biopharmaceutical industry, focal firms tend to

maintain long-term relationships and gain social capital benefits with existing and repeated interfirm networks (Powell et al., 1996).

Table 4.1 Predicted Directions of Network Variables and Innovation Performances

Hypothesis #	Interfirm Variables	Invention Performance	Commercialization Performance
		Predicted Relationships	
1a (i) and 1d (c)	Direct Ties	+	+
1b (i) and 1e (c)	Indirect Ties	+	+
1c (i) and 1d (c)	Direct*Indirect Ties	-	+
2 (i) and 2 (c)	Structural Holes	-	+
3 (i) and 3 (c)	Strength of Ties	+	-
4 (i) and 4(c)	Prominence of Partners	-	+
5a (i) and 5c (c)	Exploration Partners	+	-
5b (i) and 5d (c)	Exploitation Partners	-	+
6a (i) and 6c (c)	Upstream Horizontal Ties	+	-
6b (i) and 6d (c)	Downstream Horizontal Ties	-	+
6e (i) and 6f (c)	Upstream Vertical Ties	-	+
6g (i) and 6h (c)	Downstream Vertical Ties	-	+

Following the evidence that focal firms rarely change their interfirm partners, it is reasonable to acknowledge that the negative relationship between invention and commercialization activities will be prevalent for the focal firms in product innovation networks. Perhaps this rationale explains why focal firms that are successful in terms of invention activities have limited success in commercialization activities and vice versa. Drawing on the two important theoretical concepts of organizational learning and institutional approach, this paper suggests that focal firms with stable interfirm networks will be relatively successful at either invention or commercialization activities. Unless focal firms possess special capabilities to simultaneously exploit dynamics for invention and commercialization activities, the firms will have to face a trade-off situation in which they must choose to perform relatively poorly or successfully in their invention or commercialization activities. Therefore, in this last hypothesis, the paper presents:

> **H7: Focal firms will face a trade-off relationship between invention and commercialization performance.**

CHAPTER 5: DATA AND MEASUREMENTS

5.1 Data and Sample

The biopharmaceutical firms are identified by matching a set of firms in the pharmaceutical industry and a set of firms involved in biotechnological product activities. Rothaermel et al. (2004) posited that BioScan is one of the most comprehensive directories covering the global biotechnology industry (please also see more details in Chapter 2). Therefore, BioScan is used as the primary source to identify biotechnological firms. Because BioScan has recorded all available biotechnological agreements for the focal firms since the 1970s, the sets of biotechnological firms include both active and inactive statuses. This approach prevents the potential problem of survival bias among the focal firms in the study.

Ahuja and Katila (2001) indicated that examining a single industry over a common period controls for industry and period effects. This study examined the public firms that have engaged in biotechnological activities and operated in the pharmaceutical industry between1986 and 2003. The public firms that generate pharmaceuticals and medicines in the market are listed in NAICS 3254; the products consist of medicinal and botanicals (NAICS 325411), pharmaceutical preparations (NAICS 325412), in *vitro* diagnostic substances (NAICS 325413), and biological products (except for diagnostics) (NAICS 325414). By comparing organizations from two sources, one may identify the focal firms that generate and commercialize pharmaceutical products and are involved in biotech product research and development, commonly specified and depicted by COMPUSTAT and BioScan. This process yielded a population of 262 publicly traded biopharmaceutical firms in the U.S. stock market.

The focus of this study on publicly traded biopharmaceutical firms is because several studies have already examined the relationships of startups and their networks toward innovation performances (Baum et al., 2000; Shan et al., 1994). Yet, according to Baum et

al., (2000), one of the primary reasons for nascent firms to associate with established firms was to increase their legitimacy in the public. Therefore, invention and commercialization outcomes may not necessarily be the primary objectives of the particular startups in the collaborations. Unlike nascent firms, the publicly traded firms have achieved legitimacy and reputation from the public. Accordingly, the publicly traded firms primarily collaborate with their interfirm partners to gain benefits in terms of inventions and commercialization.

Because the objective of the study is to examine a focal firm's product innovation—invention and commercialization performance—as influenced by the biopharmaceutical interfirm network, it is important to include all biotechnological agreements between the focal firm and its partners. BioScan provides coverage information regarding biotechnological alliances of the focal firms in its database. Although BioScan offers comprehensive information on all 1,752 biotechnological organizations (February, 2005), the database does not offer complete data of many other biotechnological firms appearing in the database (i.e., as alliances or shareholders). For example, BioScan might offer nearly complete information on a focal firm's important strategic alliances, but it does not feature profiles of all of the focal firm's partners in the database.

This limitation potentially contributes to the bias associated with the data collection and analytical process. From interviews with the database editor, BioScan acquires information on a cooperative and available basis. Thus, to some extent, it does not necessarily update the actual data. Despite the limitation, the BioScan database is still the most comprehensive data source, reporting more collaborative agreements than any other data sources (Powell et al., 1996; Rothaermel et al., 2004; Shan et al., 1994).

In addition to BioScan, the study used COMPUSTAT to provide financial data of the focal firms and their partners including sales, net incomes, stock prices, R&D expenses, and the number of employees during the study period. The study also obtained information from

the United State Patent and Trademark Office (USPTO) to determine the number of patents assigned to focal firms and their partners. These numbers correspond with their invention performances during the study period. The USPTO patent full-text and image database offers reliable and comprehensive information regarding patents from 1976 to present.

The next data source to be used in the study is a public database called "Drugs@FDA" published by the United States Food and Drug Association (FDA). Information regarding all approved drugs is publicly available to download at the FDA's website. The Drugs@FDA database contains prescription and over-the-counter human drugs currently approved for sales in the United States. The database not only provides information regarding approved drug names, the companies that sponsored applications for approvals, and FDA action dates, but it also gives the marketing status (prescription, over-the-counter, or discontinued) of the commercial drugs in the U.S. Regarding the market status of discontinued drugs, the database provides information regarding the drugs that have been removed from the market in the United States for reasons other than safety or effectiveness.

Further, because one drug usually has more than one application if it has different dosage forms, the study gathered all relevant information regarding applications and document types (i.e., there are more than 50 document types) that require approvals by the FDA. As a result, those successful applications are regarded as important indicators of commercializing performances achieved by focal firms. The last data source used to gather information about the status of the focal firms' alliances is LexisNexis Academic database. The search engine at LexisNexis allowed a search of the frequencies in which the particular partners of the focal firms appeared in articles from newspaper, magazines, journals, wires, and transcripts (i.e., the Business Wire, the Cancer Journal, and the Chemical Week).

5.2 Measures

The main research questions in this study consider which dimensions of the interfirm network directly contribute to focal firms' invention and commercialization performance, as well as how these multiple dimensions influence the activities. To answer the questions, the study focuses on a group of publicly traded biopharmaceutical firms. Specifically, the dependent variables include a focal firm's number of successful patents (invention performance) and a focal firm's number of marketed drug applications and revenues (commercialization performance).

Following Poldony and Page's (1998) definition of a network form of organizations, a network includes a wide array of joint ventures, strategic alliances, business groups, franchises, research consortia, relational contracts, and outsourcing agreements. Further, this study examines the characteristics of an overall focal firm's network, rather than a dyadic relationship. The definition of interfirm network may be assumed from several network scholars such as Shan et al., (1994), Ahuja (2000), Wuyts (2004), and Kotabe and Swan (1995). All collaborations (both contractual and non-contractual ones) of a focal firm are counted as an interfirm network. For instance, while direct ties have contractual relationships with focal firms, indirect ties have no written contracts with focal firms. These indirect ties link the focal firms through their direct ties (as identified by the written contracts between them).

Since there are several levels (direct and indirect ties) and aspects (upstream and downstream activities, more prominent and less prominent partners) of collaborations, my study examines multiple dimensions of the interfirm network in detail (i.e., how each dimension contributes to invention and commercialization performance). The multiple dimensions of interfirm networks consist of a) the number of direct and indirect ties, b) the level of structural holes, c) the strength of the network, d) the prominence of the network, e)

exploration and exploitation networks, and f) upstream and downstream horizontal networks and upstream and downstream vertical networks as the predictors. In the following discussion, measurements of all variables along with the control variables are considered.

5.2.1 Invention Performance of the Focal Firms

As Chapter 3 noted in detail, several studies have provided guidelines on the measurement of invention performance. For instance, the number of successful patent applications is commonly used to determine the invention performance of a focal firm (Ahuja, 2000a; Ahuja & Katila, 2001; Almeida et al., 2004; Darby et al., 2004; Rothaermel et al., 2004; Shan et al., 1994). Patents are a device in which government grants inventors the sole right for a limited period to exploit their inventions for commercialization, individual and organizational inventors—especially in the biopharmaceutical industry. Consequently, inventors patent inventions to protect their investments (Wittcoff et al., 2004). In order to successfully get a patent, however, the inventors' inventions must meet several important requirements (i.e., novelty, non-obviousness, and utility).

The use of patents as a measure of invention performance has some limitations. Ahuja (2000a) reported that for some firms, not all inventions are patentable and still other inventions are not patented for strategic reasons. Further, not only firm-level factors, but also several industry-level factors may influence the focal firms' propensity to differ in patenting activity (Cohen & Levin, 1989; Levin, Klevorick, Nelson, & Winter, 1987). Because the set of focal firms in this study is from the biopharmaceutical industry, the variance in patenting propensity across industries is controlled and minimized. However, firms may differ in patenting and commercializing propensity within an industry. Therefore, the study controlled the propensity by using dummy variables of NAICS.

In this study, the numbers of granted patents for each focal firm are collected during a specific period (1986-2003) from the USPTO patent full-text and image database. To reflect

the invention performance associated with the interfirm networks, the study collected the number of successful patent applications before and during the period in which the focal firms actively engaged in collaborative agreements of the dataset. Using the successful patent application date permits consistency in the treatment of all patents and controls for differences in delays that may occur in granting patents after the application is filed (Ahuja et al., 2001; Trajenberg, 1990). Note that the patent count for the dependent variable was based on the patents of the focal firms obtained each year from 1986 to 2003. These patent counts are dissimilar from the patent counts used to measure the independent and control variables. The independent and control variables, as explained below, were based on the number of patents obtained by the focal firms and their direct partners in a specific period (10 years) before the year of observation.

5.2.2 Commercialization Performance of the Focal Firms

Commercialization performance suggests a substantial challenge in terms of empirical measurement. In general, commercialization performance should reflect the extent to which both the market and consumers accept and respond to inventions (Hargadon et al., 2001). As mentioned previously, scholars have used several measures to capture commercialization performance. For instance, Zahra and Nielson (2002) used four different indicators to reflect the meanings of technology commercialization. The authors mentioned that technology commercialization should 1) develop and introduce a large number of product and process technologies; 2) create radically new products; 3) expedite the introduction of these new products to the market; and 4) create new knowledge. An analyzation of Zahra and Nielson's (2002) definition finds that the scope of technology commercialization has so many dimensions that to some extent, the broadness overlaps the scope of product invention.

As discussed earlier, the biopharmaceutical industry is comprised of high-tech organizations, collaborating to accomplish invention and commercialization activities. The

commercialization activities include such activities as the application processes at the FDA, manufacturing the drugs, quality controls, packaging processes, advertisements, post-clinical trials, and managing the image and reputation of drugs on the market.

This study captured focal firms' commercialization performance using two main dimensions. The first dimension is the successful drug applications that are still on the market. As did Zahra and Nielson (2002) and Rothaermel et al. (2004), the study accumulated the number of drug applications of focal firms that were successfully approved by the FDA over seventeen years. The Drugs@FDA database provides information relating to all drugs available in the U.S. market, including several types of successful applications. According to the FDA's website (2005), "the approval history is a chronological list of all FDA actions involving one drug having a particular FDA application number (NDA). There are over 50 kinds of approval actions including changes in the labeling, a new route of administration, and a new patient population for a drug product." The frequencies of these successful approval activities should reflect focal firms' capability to convince the FDA and to market their inventions.

To make the number of successful drug applications more meaningful in terms of commercialization, the study gathered the number of drug applications no longer available in the market. The "market status" of drugs—an important aspect of marketing information offered by the Drugs@FDA database—suggests the current portfolio of focal firms' marketed drug applications (prescription, over-the-counter, and discontinued). The FDA lists the drugs that fall into the "discontinued" category due to reasons other than safety and effectiveness of the drugs.

According to FDA's website (2005), "when the sponsor of the innovator drug product has obtained exclusivity or patent protection for a new aspect of product labeling and has removed the previous unprotected labeling for reasons other than safety or effectiveness," the

sponsor is required to submit a discontinued label for the listed drug. In theory, because the innovator could delay generic competition by continuing to make minor—but protectable—changes to the drug and removing unprotected labeling, the FDA's requirement for the sponsor is to report the discontinued labeling for the new drugs in order to make safe and effective generic drug products available to the public as promptly as possible when relevant market protection has expired.

Drug applicant holders are requested (not mandated) to inform the FDA when products are no longer marketed. However, products may also be added to the discontinued section if annual reports of the applicant holders indicate that the product is no longer marketed. While there is no empirical study that examines what factors contribute to the discontinued labels, one possible explanation for the discontinued labels may be a lack of marketing capabilities. If the drugs are successfully commercialized, the sponsor of those drugs rarely removes or changes them. Focal firms can launch many drugs approved by the FDA into the market. However, if they must modify the drugs to satisfy the demand in the market, these firms fail in commercialization activities. Thus, the number of discontinued labels may in several ways represent unsuccessful commercialization of the active ingredients or even dosages (i.e., technologies and inventions).

To reflect the overall commercialization performance of the focal firms in terms of marketed drug applications, the study subtracted the number of drug applications available in the market with a number of particular applications labeled as "discontinued" in a particular year. After the subtraction, the dependent variable to measure commercialization performance becomes a number of marketed drug applications—the total products available in the market for the focal firms. Please note again that this number reflects the current portfolios of a focal firm's drugs in the market or its commercialization capability. Obviously, if a focal firm has a high number of marketed drug applications, the focal firm

should possess a high capability to generate revenue by converting its invention performance to commercialization performance.

Whereas the number of marketed drug applications is likely to be a good proxy of revenue for a focal firm, a focal firm's revenue may not necessarily reflect that number of marketed drug applications. Therefore, the second dependent variable in this study is the focal firms' annual revenue. Wuyts et al. suggested that "innovations are often credited for generating sales growth and thereby aiding profitability" (2004: 90). Bergeron and Chan (2004) indicated that pharmaceutical firms look forward to their blockbuster drugs every year or two. The blockbuster drug is a drug that can earn $1 billion or more in annual revenue. Therefore, if the focal firms successfully commercialize the new blockbuster drugs, revenues should substantially increase in the following years.

On the contrary, if there are substantial declines in the focal firms' revenues, one could infer that the focal firms are possibly having some troubles with their commercialization activities. Therefore, the sales figures of all focal firms are regarded as a proxy of commercialization performance. It is important to note that the revenues of focal firms will be analyzed in tandem with the other dependent variable to interpret the results. All the information regarding the revenues and the successfully marketed drug applications in the market are available at COMPUSTAT and Drugs@FDA.

5.2.3 Direct and Indirect Ties

To obtain the number of direct and indirect ties in a focal firm's network, the study primarily used data from BioScan to track the collaborative biotech agreements between the focal firm and its direct alliances. All direct alliances that engage in non-equity agreements with the focal firm in BioScan are counted as direct ties for a focal firm. Since the non-equity contracts as specified by the BioScan directory include universities, private

organizations, and governmental entities, all entities counted as the direct ties of a focal firm's network. There was no control for the differences in organizational types.

The study particularly regarded only non-equity agreements as direct ties, because acquisition events will be regarded as the control variable in this study. For the number of indirect ties to a focal firm, I counted the number of direct ties' partners of each focal firm. It is important to note that whereas BioScan provides comprehensive information of agreements between focal firms and their direct alliances, the database does not offer the comprehensive information of agreements between the focal firms' partners and their alliances (i.e., the focal firms' indirect partners). Therefore, the data might not be complete in providing the total picture of the focal firm's indirect tie networks.

To account for the number of active direct and indirect ties, the study accumulated all agreements recorded for the focal firms in three-year, seven-year, and ten-year periods prior to the observation year. The study also led the variables for one year to allow the direct and indirect ties to generate an impact on each dependent variable. For instance, the measure of direct ties of Firm A in 2000 is included in the regression model to test for the dependent variables in 2001. The number of direct ties is the accumulated number from 1991 to 2000 (the ten-year period), from 1994 to 2000 (the seven-year period), and from 1997 to 2000 (the three-year period). The reason for using a cumulative number, rather than a yearly number, is that once the focal firms begin biotech collaborations with their alliances, the direct ties should have been activated and continued. Thus, the channels of knowledge and information flows from the ties should have been established and active for several years (i.e., drug development process takes as long as 5 to 10 years).

Figure 5.1 illustrates the hypothetical numbers of direct and indirect ties of Elan Corporation in 1995 and 1999, based on the real data. In 1995, Elan Corporation had only five direct ties, with no indirect ties. In 1999, the company increased its direct and indirect

ties to 12 and 4 respectively. Notice that H, G, M, and L were counted as indirect ties, even though H and G were already direct ties for Elan in 1999.

Further, M was only counted once as an indirect partner of Elan, although it has common links with both G and K, the two direct partners.

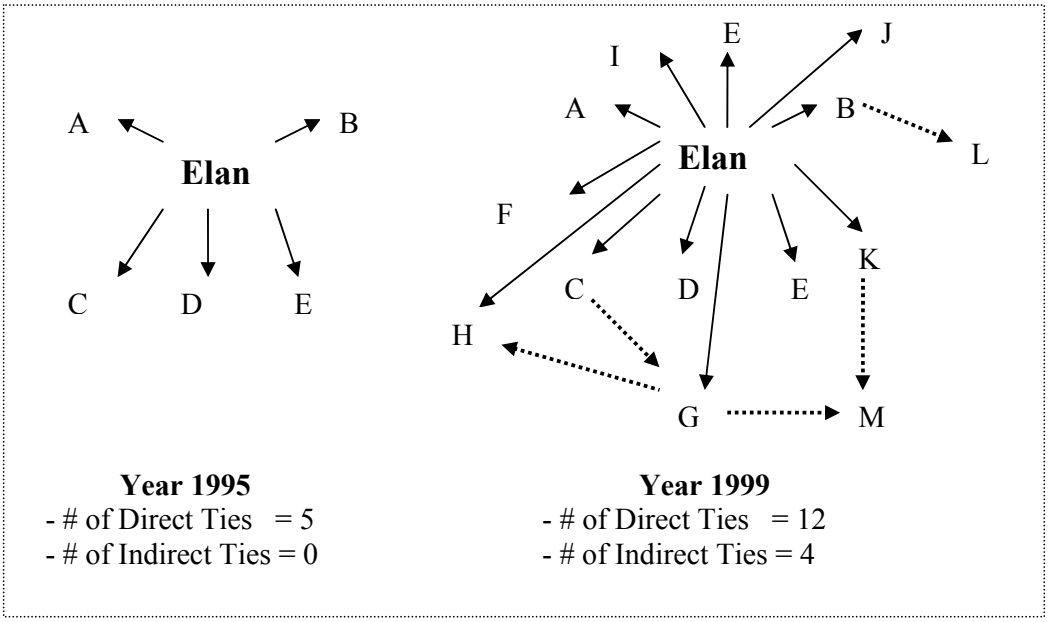


Figure 5.1 Hypothetical Number and Positions of Direct and Indirect Ties

Since Ahuja (2000a) found the significant interaction effect between direct and indirect ties of the focal firms, the study multiplied direct and indirect ties to generate another independent variable to test for the interaction effects of direct and indirect ties on invention and commercialization performances.

5.2.4 Structural Holes

To facilitate the collecting and analytical process to distinguish the structural holes, the study used the UCINET software to derive several social network measures (Borgatti, Everett, & Freeman, 2002; Hanneman & Riddle, 2005). Specifically, a focal firm that shares partners with its direct partners should possess a lower level of structural holes compared to other focal firms that do not. By sharing a common partner with its direct partner, a focal firm fills one of the structural holes in its alliance network. In an extreme case, if all of the

direct alliances know one another, one would have "the closure network," referring to a network in which all members are connected in such a manner that no member escapes the notice of others (Burt, 2000). In operational terms, this particular model requires a completely dense network.

Figure 5.2 illustrates the two scenarios of structural holes. Cases A and B represent a focal firm's (i.e., Merck) network including a direct partner (i.e., Genentech) and an indirect partner (Amgen). Because Merck does not directly collaborate with Amgen, there is a structural hole in Case A. Unlike Merck in Case A, Merck in Case B directly collaborates with both Genentech and Amgen. Therefore, Merck in Case B has no hole in its relationship structure. In Case B, because Merck shares its indirect partner (Amgen) with its direct partner (Genentech), the network of Merck can be recognized as a closure network.

On one hand, if the focal firms share indirect partners with direct partners, the focal firms' networks have low levels of structural holes. On the other hand, if the focal firms do not have common partners with direct partners, the focal firms' networks have high levels of structural holes. Thus, in measuring the levels of structural holes in the focal firm's network of direct and indirect partners, the study could count both the common partners of the focal firms and direct partners. Higher counts reflect lower levels of structural holes in the focal firm. Rather than counting the number of partners, the study gathered two important measures from the UCINET to capture the concepts of the structural holes (Borgatti et al., 2002).

First, the "Density" measure is "the number of ties divided by the number of pairs." Although the number of ties is an actual relationship, the number of pairs also indicates the number of possible directed ties in each ego network. Therefore, the "Density" measures the percentage of all possible ties that are actually present in each ego network (Hanneman et al., 2005). From the definition and characteristics of the structural hole, the high density measure

should suggest the low level of structural holes for the focal firm's network, whereas the low density measure should suggest otherwise.

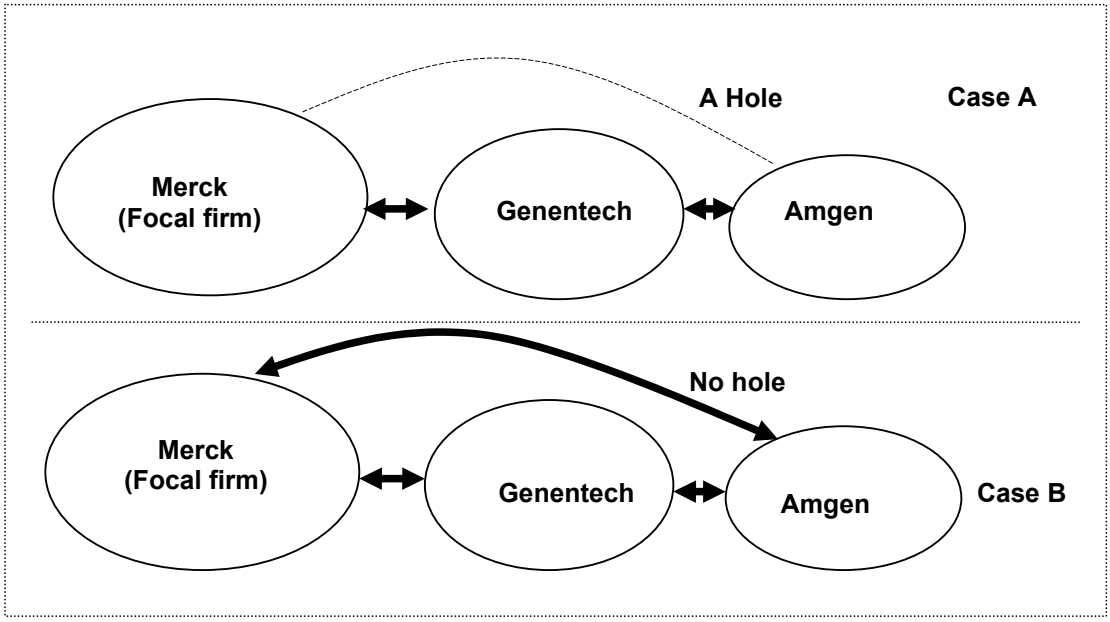


Figure 5.2 Two Scenarios of Structural Hole

For the second characteristic of the structural holes, the "Brokerage" measure is the number of pairs in the ego networks that are indirectly connected to one another, or a "broker" ego, according to Hanneman et al., (2005): "One item of interest is how much potential for brokerage there is for each actor (how many times pairs of neighbors in an ego's network are not directly connected)." Therefore, a high number of brokerage represents a high level of structural holes in the focal firm's network.

5.2.5 Strength of Direct Ties

To assess the strength of direct ties to the focal firm, the study calculated the average tenures of focal firms' relationship with their alliances. Some focal firms may frequently add new partners, whereas others may maintain their number of partners to be constant. If this is the case, the latter focal firms will achieve higher measures in the average tenure of focal firms' relationships with their alliances than do the former focal firms, over time.

Based on the perspective of Penrose's "The Theory of the Growth of the Firm" (1959), a focal firm that expands in size frequently and rapidly may face managerial problems. Penrose suggested that growth does not take place automatically, but must be planned strategically and implemented effectively by internal managers who have firm-specific experiences. Because such managers must be developed within the firm and cannot be hired from the outside, firm capacities of internal managers set a limit to expansion projects that a firm may undertake in any period of time (Penrose, 1959). Therefore, the focal firm's overall relationships with direct partners may be harmful if the firm cannot deal with the limitation of an increased network complexity.

Relatively, if a focal firm rarely adds new partners, that particular focal firm should be able to strategically and effectively maintain its internally managerial resources to strengthen the relationships of existing alliances. In comparision with a focal firm that frequently adds partners; the focal firm that rarely adds new partners should have a stronger alliance network.

5.2.6 The Prominence of the Focal Firm's Partners

Stuart (2000) suggested that high-status partners could act as endorsements for a focal firm by building additional public confidence in terms of the focal firm's products and services. Several proxies can be used in this study to measure the prominence of the focal firm's partners. For instance, annual revenues, the number of employees, and the number of drugs available in the market may be used as potential indicators of the status of partners. Unfortunately, these measures are unobtainable due to the lack of sufficient data in most alliances in BioScan.

To acquire the data regarding the prominence of the partners, however, the study consulted the LexisNexis® search engine to obtain news frequencies regarding the focal firms' partners. LexisNexis® is an online database providing a wide array of electronic and traditional media. The number of available articles generated by LexisNexis® in the

"business news" and the "industry news" sections conveys a measure of the reputation of each partner. Because the reputation of each partner is built over time, the study accumulated a number of news articles that mentioned the focal firm for a ten year period prior to the year of interest. Therefore, the prominence proxy used involves a time-varying variable. Within the ten-year span, a partner that did not appear frequently in the news, especially at LexisNexis®, should not be as prominent and reputable as others that appeared many times on the news. By counting the news articles for all partners in the period of ten years before their collaborations with a particular focal firm, I could measure the overall prominence of focal firm's partners.

The prominence measure used reflects only the public attention, without identification of the positive and negative events. Consequently, the measurement of the prominence solely reflects the amount of attention a company received. The measurement does not capture potential differences in effect between any positive or negative connotation.

5.2.7 Exploration and Exploitation Networks

In classifying a focal firm's partners as either exploration- or exploitation-oriented networks, the study followed the methodology of Rothaermel et al. (2004) which focused on primary activities of the focal firm's partners. Accordingly, the study regarded the partners by focusing on their activities in basic research, drug discovery, and development, as exploration alliances. The study regarded the partners that addressed activities toward commercialization (clinical trials, FDA regulatory process, and marketing and sales) as exploitation alliances. However, because of the limitation in the dataset, I only captured the number of issued patents and the number of drug applications approved by the FDA. To determine the propensity of the focal firm's partners to invent and to commercialize, the study accumulated the total number of issued patents and the total number of successful drug applications in the past ten years, prior to the collaboration with the focal firm. Because the

drug discovery and development process generally can extend from 5 to 15 years (Rothaermel et al., 2004), the use of a ten-year period to capture the exploration and exploitation activities of the focal firms' alliances sufficiently captures the exploration / exploitation propensities.

The partners that successfully achieved a high number of patents in the past ten years prior to collaboration with a focal firm represent the focal firm's exploration partners. On the contrary, the partners that successfully achieved a high number of drug applications approved by the FDA in the past ten years prior to collaboration with the focal firm represent the focal firm's exploitation partners. To maintain the valuable information of variables with continuous measures, the study did not transform the two variables into dichotomous or dummy variables. Therefore, established firms such as Abbott Laboratories and Pfizer that have achieved high numbers of both patents and drug applications each year could constitute the organizations that specialize in both invention and commercialization activities.

5.2.8 Upstream and Downstream Horizontal and Vertical Networks

After classifying the exploration- and exploitation-oriented networks in the focal firms' networks, the study identified the focal firms' positions in the drug development process (i.e., exploration or exploitation focal firms), using the same scheme that determines the networks of their alliances. Specifically, the study regarded focal firms that achieved as higher number of patents in the past ten years as the upstream focal firms. The focal firms that achieved a higher number of successful drug applications in the past ten years are considered the downstream focal firms. Note that like exploration and exploitation network variables, these two additional variables are not categorical variables, yet they are continuous variables by representing the degrees of focal firms' postures toward invention and commercialization.

In comparing the focal firms' degree of activity with those of their partners, the study could identify a position of a focal firm in its biopharmaceutical drug development network.

Figure 5.3 illustrates four positions of focal firms and their alliances. It also shows that the first two relationships are horizontal networks, and the other two types are vertical networks. First, if a focal firm has a high number of patents and also operates in the exploration network, the focal firm is regarded as the exploration firm collaborating in the upstream horizontal network. Second, if a focal firm has a high number of successful drug applications and collaborates with a high number of exploitation alliances, the focal firm's network is a downstream horizontal network. Third, if a focal firm is regarded as the exploration focal firm and it collaborates with a high number of exploration alliances, the focal firm's network is an upstream vertical network. Last, if the focal firm is regarded as the exploitation firm and it collaborates with a high number of exploration alliances, the focal firm's network is a downstream vertical network.

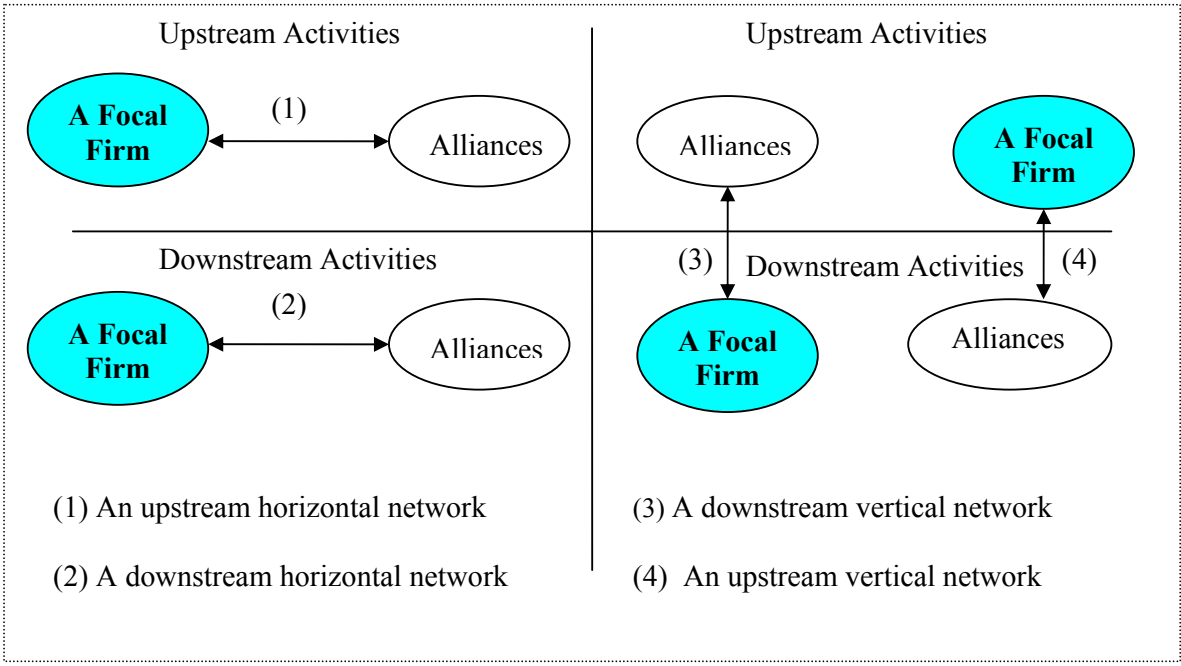


Figure 5.3 Horizontal and Vertical Collaborations

5.3 Control Variables

In order to understand the impact of the multiple dimensions of the interfirm network on the dependent variables, the study controlled for several internal and external factors that

might influence the dependent variables. First, the study controlled for both invention and commercialization performances of the focal firms prior to their observed collaborations by accumulating the number of patents approved by USPTO, as well as the number of drug applications approved by the FDA. The period of accumulation for each focal firm was ten years. Using the same logic as mentioned earlier, a ten-year span prior to the collaborations should provide reasonable time to capture the orientation and performance of the focal firms in the biopharmaceutical industry. Note that these controlled variables are the same as the focal firms' positions at the drug development process (i.e., exploration or exploitation postures), suggested in the previous section.

It is necessary to control for prior innovation and commercialization performance, yet applying for the number of prior invention and commercialization performances creates endogeneity problems. The endogeneity problem arises when the control variables included in the model correlate with other independent variables, and all variables influence the dependent variable. The two variables—the number of prior patents and the number of prior drugs at the FDA—are included to control for the heterogeneity associated with invention and commercialization performance of the focal firms. However, the two controls (10-year accumulation) are also correlated to direct ties ($r = .32$ and $.34$; $p < .05$), indirect ties ($r = .48$ and $.51$; $p < .05$), and brokerage measures of the structural holes ($r = .37$ and $.46$; $p < .05$). This endogeneity problem suggests that by controlling for prior invention and commercialization performances of a focal firm, a multicollinearity between the control variables and other independent variables occurs and affects the stability of regression coefficients (Schwab, 1999). For hierachical regression analysis, endogeneity implies a tendency to underestimate the effect of a variable added at a later time.

In addition to the previous performance of the focal firms, the study controlled for the equity financing events in the focal firms (Ahuja et al., 2001; Hitt et al., 1996). Data from

BioScan presents the history of a focal firm's equity events, including acquisitions and private placements. The study counted both the number of acquisition events of a focal firm and the number of private placements, a set of biotechnological companies that invested significant amounts of capital in a focal firm as shareholders, combining the two numbers to generate the number of "equity financing events" for the focal firm. This control variable was not led, because an acquisition may provide a focal firm with instantaneous access to acquired firms' current patenting and commercialization activities. Leading this control variable by one year suggested no significant results, indicating the robustness of the findings with regard to this assumption.

Private placement was a rare occurrence. There were only 22 focal firms that raised capital in this manner. When the private placements are separated from the equity financing event variable and entered as a separate control, this change does not affect results and does not improve model fit for all three dependent variables—patenting rates, marketed drug applications, and revenues (Chi^2 = .01, .08, and .35; Prob > Chi^2 = 0.9036, 0.5520, and 0.7758, respectively). Thus, the study used the combined variable "equity financing events" as a control in all models.

Next, the study obtained the data from the "Subject Terms" section provided by BioScan to control for an individual level of diversification. The section lists the subject interests and areas of concentration relative to the company. According to BioScan's user manual,

> "Subject assignments are based on information taken from the following fields: Agreements, Research and Development, Product in Development, and Products on the Market. As new disciplines of biotechnology research and development are introduced in the industry, the appropriate new subject titles will be added to this field in BioScan" (See Appendix for full details).

Ahuja (2000a) suggested that several arguments have been made for positive and negative impacts of diversification on invention performance. Therefore, following his argument, this study included the variable "diversification" to control for influence on dependent variables.

Further, COMPUSTAT provides data regarding R&D expenditures, years of public status, closing stock prices, employees, and net incomes. According to several previous studies, these factors were the important factors contributing to the invention and commercialization performances of the focal firms (Ahuja, 2000a; Ahuja et al., 2001; Rothaermel et al., 2004). Therefore, these control variables are obtained at the time t-1 or one year prior to the year of observation (t = 1) in order to take effect on the dependent variables. The one-year leading process of these controlled variables substantially reduced the number of observations from 3,501 to 1,879. This number of observations after the leading process, however, is still sufficient for the study.

While no study could be found that related R&D expenditures to the commercialization performances, several studies confirmed that R&D expenditures are at least a significant determinant of invention outputs (Greve, 2003; Hitt et al., 1996). Thus, this study collected the focal firms' R&D expenditures from COMPUSTAT to control for the focal firms' abilities to invent and to commercialize. Because about 5% the values for R&D expenditures were missing, I imputed the missing values based on available values in both the years before and after. Next, I controlled for the public status or the prestige of the focal firms using two control variables—annual closing stock prices and years as public companies. A focal firm with a high public status or a high prestige usually performs well in any stock market, as investors are willing to pay a high premium for its stock price. In fact, the prior research reviewed in the previous section suggested a significant relationship between shareholders' value creation (i.e., increased stock prices) and innovation and commercialization stages (Kelm et al., 1995).

With regard to the other dimension of the focal firm's status and prestige, I used the tenure of a focal firm as a public organization. As a publicly traded firm grows, its reputation and prestige should improve over time. Several studies mentioned numerous factors contributing to failures of public companies, especially during their initial public offerings (IPOs) or the early period of public companies (Certo, Covin, & Dalton, 2001; Fisher & Pollock, 2004; Welbourne & Andrews, 1996).

Although newly public firms receive a number of benefits from investors during the IPOs, they encountered a transformation that brings a number of costs and risks. Therefore, a newly public company will have a lower reputation and status, compared with other established or high-tenure public companies, placing the public company in an unfavorable position in the eyes of many investors, for any success in invention and commercialization activities. Thus, the study controlled the tenure years in which a focal firm operates as a public company.

For the next control variable, the study included the focal firm's net income to control for profitability. If a focal firm is profitable, it is more likely that the focal firm will engage in substantial R&D and advertising activities. Thus, the focal firm will perform well in terms of invention and commercialization activities, regardless of its alliances (Ahuja, 2000a). In addition to profitability, a prior study suggested a common method to control for firm-size effects in analyses of innovative productivity. It is also conventional to control for firm-size effects in analyses of invention performance (Cohen et al., 1989). While it is unclear in which directions size could influence commercialization activities, prior studies suggested significant relationships between firm size and invention outcomes (Damanpour, 1996; Shan et al., 1994). Obtaining data from COMPUSTAT, the study used the number of employees as a measurement of size to control for an effect on the dependent variables.

Focal firms are observed in different years. In a certain year the innovation process of all firms in the industry may have been affected by external factors, like speed of patent processing. To control for such year fixed effects, this study included dummy variables for every year from 1986 to 2002. These time dummies improve the model fit of two dependent variables: patenting rates and marketed drug applications (Chi^2 (10) = 167.18 and 18.93; P value > Chi^2 = 0.000 and 0.0412, respectively.) These time dummies, however, do not improve the model fit of the revenues (Chi^2 (10) = 10.79; P value > Chi^2 = 0.3744).

This study also added control variables for the four specific businesses within the pharmaceutical industry as specified by NAICS. These four specific businesses—medicinal and botanicals, pharmaceutical preparations, in vitro diagnostic substances, and biological products (except diagnostic)—should influence the propensity to invent and commercialize. "Biological products (except diagnostic)" constituted the omitted category. (Please see Appendix A for the summary of all measurements and data sources of the dependent, independent, and control variables in this study.) The following table summarizes all variables and their measurements.

(Please see the next page).

Table 5.1 All Variables and Their Measurements

Variables	Measurements
1. Patents	Observation YR (Time = T1)
2. Marketed Drug Apps	All drugs available in the market in the Observation YR, T1
3. Sales	Observation YR, T1
4. Upstream Horizontal	Variable 18 * Variable 8
5. Downstream Horizontal	Variable 19 * Variable 9
6. Upstream Vertical	Variable 18 * Variable 9
7. Downstream Vertical	Variable 19 * Variable 8
8. Partner's Patents	10-YR accumulation of partners' patents and led 1-YR, T0
9. Partners' Drugs	10-YR accumulation of partners' drugs and led 1-YR, T0
10. Partners' Prominence	10-YR accumulation of partners' news articles and led 1-YR, T0
11. Ties' Average Tenure	Average tenured of all partners and led 1-YR, T0
12. Brokerages	All direct and indirect ties and led 1-YR, T0
13. Densities	All direct and indirect ties and led 1-YR, T0
14. Direct*Indirect	7-YR accumulation and led 1-YR, T0
15. Direct Ties	7-YR accumulation and led 1-YR, T0
16. Indirect Ties	7-YR accumulation and led 1-YR, T0
17. Patents of Focal	10-YR accumulation of a focal firm's patents and led 1-YR, T0
18. Drug Apps of Focal	10-YR accumulation of a focal firm's drugs and led 1-YR, T0
19. Equity Financing Events	No lead (I will regard it as the control variable), T1
20. Closed Stock Prices	Led 1-YR, T0
21. Years as Public Status	Led 1-YR, T0
22. Diversification	Led 1-YR, T0
23. Net Income**	Led 1-YR, T0
24. Employees*	Led 1-YR, T0
25. R&D Expenses*	Led 1-YR, T0

1. YR = Year and T = Time;
2. This study did not lag the dependent variables, but lead the independent variables;
2. All variables are time varying, except for Diversification and Years as Public Status.

CHAPTER 6: ANALYTICAL TECHNIQUES AND RESULTS

6.1 Model Specifications and Estimations

Hypotheses of invention and commercialization performance were tested in a panel dataset containing annual observations of 262 biopharmaceutical firms during 1986 and 2003. When examining such panel dataset or clustered data, scholars generally encounter unobservable heterogeneity that leads to inefficiency or bias in estimated effects of measured variables. Fixed-effects or random-effects models present alternative approaches to account for unobserved heterogeneity (Teachman, Duncan, Yeung, & Levy, 2001). While there are no definitive criteria for choosing between random- and fixed-effects models (Greene, 1993; Johnston & DiNardo, 1997), the choice of fixed-effects versus random-effects models is not without consequences.

6.1.1 Fixed-Effects versus Random-Effects Models

Firm fixed-effects controls account for stable differences between firms. The firm fixed-effects model transforms both dependent and independent variables for a given year into deviations from the organization's mean across the entire years. This effectively removes all between-firm variances and error terms from the data. Consequently, the regression analysis for independent variables depends only on the within-firm variation.

In contrast to fixed-effects models, random-effects models treat the organizational-specific effects as random disturbances (Teachman et al., 2001). If unknown variables should randomly affect all observations, the random-effects models then allow researchers to evaluate effects of the independent variables based on both within- and between-organization variances (Greene, 1993). Under this circumstance, a simple generalized least square (GLS) estimator provides appropriate estimates of the coefficients and their standard errors. In this study, the random-effects GLS regression is used to test for one of the dependent variables—

the revenues of the focal firm. However, the more restrictive fixed-effects model will be used to evaluate the robustness of the results.

6.1.2 The Panel Negative Binomial Regression

The two other dependent variables—the number of patents and the number of drug applications—are non-negative count measures. The characteristics of the non-negative count dependent variables violate assumptions of linear regression models, including homoskedasticity (i.e., the variance of error terms appears constant over a range of predictor variables) and normally distributed errors (i.e., purely theoretical continuous probability that has the bell-shaped, or normal curve) (Hair, Anderson, Tatham, & Black, 1998).

Poisson's regression or negative binomial regression deal appropriately with dependent variables that are count and non-negative integers (Ahuja, 2000a; Ahuja et al., 2001; Hausman, Hall, & Griliches, 1984; Henderson & Cockburn, 1996; Stuart, 2000). However, Poisson's model requires that the mean and variance of a dependent variable are equal. When a dependent variable has variance that is greater than its mean (so-called over-dispersion), negative binomial regression models are appropriate (Arregle, Amburgey, & Dacin, 1997). The panel negative binomial model (Benner & Tushman, 2002) could be represented by the following equation:

$$E(P_{it}/X_{it-1}) = \exp(X_{it-1}\beta + \alpha\varepsilon_i + \mu_i)$$

where P_{it} is the observed count for firm i at time t; X_{it-1} is a vector of characteristics of firm i at time t-1; α is an estimated correction for over-dispersion (i.e., for mean not equal to variance) for all firm i; and μ_i is a time-invariant firm i effect, which can be treated as either fixed or random. Because the Poisson model is nested within the negative binomial model, when the estimated parameter alpha (α) is zero, the conditional mean is equal to the conditional variance and the negative binomial model reduces to the Poisson model (Cameron & Trivedi, 1998; Long, 1997).

6.1.3 The Zero Inflated Negative Binomial Regression for Panel Data

Based on its robust properties, the panel negative binomial model is a tentative specification and estimation model to test for the two dependent variables. However, prior scholars mentioned that unobserved heterogeneity that causes over-dispersion can also cause "excess zeros" (Cameron et al., 1998; Long, 1997). Based on these considerations, a negative binomial model, a zero-inflated Poisson, or a zero-inflated negative binomial model—are viable candidates for the intended hypothesis testing in the study. The preliminary evaluations of non-negative count dependent variables—the number of patents and the number of marketed drug applications—indicate not only over-dispersion, but also "excess zeros."

Table 6.1a shows that the unconditional variances of the two dependent count variables are much larger than their corresponding means, suggesting over-dispersion. These results indicate that the Poisson model is not appropriate for the intended analyses. To confirm the preliminary evaluations from Table 6.1a, several regression analyses are used to check the over-dispersion in the two models. Under the panel Poisson regression model, the extreme significances of the goodness-of-fit Chi^2 in both models indicate that the Poisson distribution is inappropriate for the two dependent variables—the number of patents and the number of successfully marketed drug applications—(Goodness-of-fit Chi^2 = 13026.17 and 6044.834; $p < 0.000$, respectively). Second, after running the negative binomial regressions on the two variables (marketed drug applications and patents), a likelihood-ratio tests supported this visual assessment (Chi^2 = 1117.74 and 3666.81; alpha = 2.2690 and 2.2610; $p = 0.000$, respectively). These tests confirm the over-dispersion for the two dependent variables.

Table 6.1a Evidence of Over-dispersion in Dependent Variables

Variables	Mean	Std. Dev.
# of Patents	9.9564	35.8610
# of Drug Apps	5.8473	24.0067

*All observation (N = 1,879)

Table 6.1b shows that the two dependent variables contain high percentages of zeros. According to Min and Agresti (2005), the characteristics of over-dispersed and zero-inflated data are common in many social science applications, especially when many subjects have zero observations, yet many also have much larger observations so that the overall mean need not be near zero. In the event of a zero-inflated situation, a study in political science compared King's "hurdle" event count model and Greene's "zero-inflated" model (Zorn, 1996). The hurdle model is a two-part model for count data—one part is a binary model for whether the response outcome is zero or positive, while the other part uses a truncated model that modifies an ordinary distribution by conditioning on positive outcomes (Min & Agresti, 2005).

Table 6.1b Evidence of Zero-inflation

Variables	Obs = 0	Percent
# of Patents	899	47.84
# of Drug Apps**	1,446	76.96

* All observations (N = 1,879); ** Potential variables with the Zero-inflation symptom

The zero-inflated model recognizes that two types of zeros can occur: one comes from the zero state and the other from the ordinary count model, such as the Poisson or negative binomial, with one that is degenerated at zero (Lambert, 1992). From the two perspectives, the latter model confers a more effective specification than that of the former one, because it separates the population of subjects that will have only a zero response from other subjects that may have a zero response, such as the number of successful marketed drug applications from the Drug@FDA database.

Recently, drawing on the benefits of the zero inflated specification, Min and Agresti (2005) proposed the "random-effects models for repeated measures of zero-inflated count data" to account for the between-and-within heterogeneities that could impact the dependent variables.

For the number of successful marketed drug applications in the current year, some focal firms may have many zero-value observations because of chance, whereas others may have

zero-value observations due to the fact that the focal firms generated drug products that are not compatible with the requirements of Drug@FDA database. Please note that while the Drug@FDA database contains the majority of prescriptions and over-the-counter human drugs currently approved for sale in the United States since 1911, it does not record all biologic therapeutic products. (Please see the Appendix for further details on what drug products are not in Drug@FDA). Additionally, there are many biopharmaceutical firms that do not aim to generate the number of drug applications, because they are involved in upstream activities such as R&D, clinical trials, and/or licensing technologies. These upstream firms do not intend to apply for the drug applications at the FDA. Thus, in the case of the number of marketed drug applications, these zero-value observations are potentially inflated and warrant control.

Regarding the zero-value observations of focal firms' patents in the biopharmaceutical industry, the tendency to engage in interorganizational collaborations causes focal firms generally to submit applications for patents as soon as the firms generate potential intellectual outputs. This process does not preclude many focal firms that may engage in commercialization activities. Therefore, it is unlikely that the focal firms will neglect the patenting process. Thus, zero value should potentially reflect the inability to generate invention, not the unavailability of the data. From the above arguments, the number of marketed drug applications is susceptible to zero-inflation, which needs to be taken into account for hypothesis testing.

Taking into account the propensity of focal firms to invent and to commercialize, control for zero-inflations of both invention and commercialization dependent variables. Therefore, focal firms with propensity to generate invention are less likely to consider applying for drugs applications at the FDA. In regard to the specification and estimation models, the study deployed 1) the negative binomial model for the number of patenting rates controlling for the

firm's fixed-effects, 2) the zero-inflated negative binomial model controlling for the firm's organizational fixed-effects, and 3) the random-effects GLS regression model with a fixed-effects model for robustness check. Additionally, the analysis of the same set of predictors was used on each dependent measure: patenting rates, marketed drug application rates, and revenues of the focal firms.

6.2 Results and Basic Information

The final number of focal firms in the result section is 262. The study period spans seventeen years (from 1986 to 2003). Several independent and control variables (i.e., net incomes, employees, R&D expenses) were led for one year, using a seven-year period prior to the year of observation to measure direct and indirect ties. To prevent left censoring, the study ran models for observations after 1992 (please see Table 5.1 for more details).

The study did not include the collaborations prior to 1986 because: 1) according to a prior study, the biotechnological collaborations were rare until the early 1980s (Hoang et al., 2005) and thus the number of collaborations should not be significant to analysis, and 2) the seventeen-year observation period (from 1986 to 2003) is theoretically adequate to capture the drug development process, which normally takes about 5 to 15 years.

Table 6.2 provides the complete list of 262 focal firms and their observation periods in the dataset between 1986 and 2003. In the dataset, only ten firms have one-year observation periods while seven firms have their eighteen-year observation periods. The majority of firms (65%) have between 3 and 9 years in the observation periods. Due to the following reasons, many focal firms did not appear across the observation period (1986-2003). First, the focal firms may have have been acquired by competitors. Second, firms may have changed their publicly traded status to private status. Last, the focal firms may have gone out of business, changed names, and/or ceased operations in biotechnology. For instance, Warner-Lambert was acquired by Pfizer in 2000 for $90 billion in stock; this acquisition

created the largest US drug maker, the second largest in the world. This should explain why the data for Warner-Lambert is unavailable in 2000. The previous study results suggested that there were a significant number of acquisition and merger activities among

Table 6.2: List of All Focal Firms and their Observation Period

No	Names	From	Until	No	Names	From	Until
1	3-Dimensional Pharm.	1998	2001	50	Celgene	1993	2003
2	Aastrom Biosciences	1996	2003	51	Cell Genesys	1998	2002
3	Abbott Laboratories	1998	2003	52	Cell Pathways	1997	2002
4	ACADIA Pharmaceuticals	2002	2003	53	Cell Therapeutics	1995	2003
5	Acambis plc.	1999	2003	54	Cellegy Pharmaceuticals	2000	2003
6	Adherex Technologies	1999	2003	55	CEL-SCI	1986	1997
7	Advanced Magnetics	1991	1993	56	Centocor	1991	1998
8	Affymax	1991	1993	57	Cephalon	1997	2003
9	Agouron Pharmaceuticals	1996	1998	58	Cerus	1996	2003
10	Alexion Pharmaceuticals	1995	2003	59	Chiron	1994	2003
11	Alfacell	1991	2003	60	Coley Pharmaceutical	2003	2003
12	Alkermes	1990	2003	61	CollaGenex Pharm.	1995	2003
13	Alliance Pharmaceutical	1991	2003	62	Columbia Laboratories	1996	2003
14	Alteon Inc.	1991	2000	63	Connetics	1998	2003
15	ALZA Corporation	1999	2000	64	Corautus Genetics	2000	2003
16	AMDL	1999	2003	65	Corgenix	2000	2003
17	Amgen	1992	2003	66	Corixa	1995	2003
18	Angiotech Pharmaceuticals	1998	2003	67	Cortex Pharmaceuticals	2001	2003
19	Anika Therapeutics	1992	2000	68	Crucell N.V.	1999	2003
20	AntexBiologics	2000	2001	69	Cubist Pharmaceuticals	1998	2003
21	Antigenics	1998	2003	70	CuraGen Corporation	2000	2003
22	Aphton	2000	2003	71	Curis	1998	2003
23	Argonaut Technologies	1998	2003	72	Cyanotech	1991	2003
24	Ariad Pharmaceuticals	1996	2003	73	Cygnus	1989	2003
25	ArQule	2001	2003	74	Cypress Bioscience	1986	2003
26	Astralis	2000	2003	75	CYTOGEN	1986	2003
27	AstraZeneca Group	2000	2003	76	Dendreon	1998	2003
28	AtheroGenics	1998	2003	77	DepoMed	1996	1997
29	Atrix Laboratories	1993	2003	78	Derma Sciences	1996	2002
30	AutoImmune	1991	2003	79	diaDexus, LLC	1998	1999
31	AVANIR Pharmaceuticals	1989	2003	80	Diagnostic Products	1996	1998
32	Avant Immunotherapeutics	1989	2003	81	Diatide	1996	1998
33	Aventis S.A.	1997	2003	82	Digene	1995	2003
34	AVI Biopharma	2003	2003	83	Discovery Laboratories	1995	2003
35	Axcan Pharma	1999	2003	84	DOR BioPharma	1989	1989
36	BACHEM AG	1999	2003	85	Draxis Health	2000	2003
37	BioMarin Pharmaceutical	2003	2003	86	Dynavax Technologies	2001	2003
38	Biomira	2001	2003	87	Elan Corporation,	1986	2003
39	BioSante Pharmaceuticals	2000	2003	88	Eli Lilly and Co.	1989	2003
40	Biosite Diagnostics	1995	2003	89	Emisphere Technologies	1994	2003
41	Biosource International	1991	2003	90	Encysive Pharmaceuticals	2001	2003
42	BioSpecifics Technologies	1992	2003	91	Endovasc	2001	2003
43	BioTime	1995	2002	92	EntreMed	1995	2003
44	Biovail Corporation	1993	1996	93	Enzon	1991	1994
45	BioWhittaker	1990	1996	94	EPIX Medical	1995	2003
46	Bristol-Myers Squibb	1996	2003	95	Epoch Biosciences	1996	2002
47	Calypte Biomedical	1995	2003	96	Essential Therapeutics	1995	2002
48	Cambrex	2003	2003	97	eXegenics	1996	2002
49	Cardiome Pharma	1999	2003	98	Flamel Technologies SA	2001	2002

Table 6.2 (Continued)

No	Names	From	Until
99	Gamma Biologicals	1995	1997
100	GelTex Pharmaceuticals	1994	1999
101	Genaera Corporation	1997	2003
102	Gene Logic	1995	2003
103	Genelabs Technologies	2000	2003
104	Genencor International	1998	2003
105	Genentech	1999	2003
106	Generex Biotechnology	1999	2003
107	GENTA Incorporated	2000	2003
108	GenVec	2003	2003
109	Genzyme Molecular Onco.	1997	2002
110	Geron	1995	2003
111	Gilead Sciences	1990	2002
112	GlaxoSmithKline plc	1995	2001
113	Gliatech	1996	2001
114	GlycoGenesys	1996	2003
115	Guilford Pharmaceuticals	1998	2000
116	Harvard Bioscience	1998	2000
117	Helix BioPharma	1998	2003
118	Hemagen Diagnostics	1995	2003
119	Hemosol	1998	2003
120	Heska Corporation	1995	2003
121	Human Genome Sciences	1996	2003
122	Hybridon	1994	2003
123	Icagen	2002	2003
124	ICOS	1994	1996
125	ID Biomedical	1992	2003
126	IDEXX Laboratories	1997	2003
127	ILEX Oncology	1996	2002
128	IMI	1999	2003
129	IMMTECH International	1997	2003
130	ImmuCell	1986	2003
131	Immunicon	2002	2003
132	ImmunoGen	1989	2003
133	Immunomedics	1990	2003
134	Inhibitex	2002	2003
135	InKine Pharmaceutical Co.	1994	2003
136	InSite Vision	2000	2003
137	Inspire Pharmaceuticals	1998	2002
138	Interferon Sciences	1998	1999
139	IntraBiotics Pharmaceuticals	2000	2003
140	Introgen Therapeutics	1999	2003
141	ISIS Pharmaceuticals	2003	2003
142	Isolagen	2000	2003
143	Johnson & Johnson	2000	2003
144	Kosan Biosciences	1998	2003
145	La Jolla Pharmaceutical Co.	2000	2003
146	Large Scale Biology	2000	2003
147	Life Sciences	1992	1992
148	Ligand Pharmaceuticals	1992	1996
149	Lorus Therapeutics	1997	2003
150	Lynx Therapeutics	1995	2003
151	MacroChem	1995	2003
152	Manhattan Pharmaceutcals	1994	2003
153	Matritech	1996	2003
154	Maxim Pharmaceuticals	1995	2003
155	Medarex	1990	2003
156	Medicure	2000	2003
157	Memory Pharmaceuticals	2002	2003
158	Merck & Co.	1986	2002
159	Metabasis Therapeutics	2002	2003
160	MGI PHARMA	1996	2003
161	Millennium Pharm.	1995	2003
162	Myogen	2001	2003
163	Myriad Genetics	1995	2003
164	Nabi Biopharmaceuticals	1994	2003
165	Nektar Therapeutics	1993	2003
166	Neogen	1996	2003
167	NeoPharm	1994	2003
168	NeoRx	1994	2003
169	Neurobiological Tech.	1996	2003
170	Neurocrine Biosciences	1995	2003
171	Neurogen	1998	2003
172	NitroMed	2001	2003
173	Novartis AG	1996	2003
174	Novavax	1995	2003
175	Noven Pharmaceuticals	1987	2003
176	Novo Nordisk A/S	1994	2003
177	NPS Pharmaceuticals	1993	2003
178	Nutrition 21	1996	2003
179	ONYX Pharmaceuticals	2000	2001
180	OraPharma	1998	2001
181	Organogenesis	1994	2001
182	Orphan Medical	1996	2003
183	Ortec International	1994	2003
184	OSI Pharmaceuticals	1995	2002
185	OSTEX International	1993	2002
186	OXiGENE	1992	2003
187	OXIS International	2000	2003
188	Pain Therapeutics	1999	2003
189	Palatin Technologies,	1992	2002
190	Pfizer	1986	2002
191	Pharmacopeia	2002	2003
192	Pharmacyclics	1995	2003
193	Pharmos	1986	2002
194	Polydex Pharmaceuticals	2000	2003
195	PRAECIS Pharmaceuticals	1998	2003
196	ProCyte	2000	2002
197	Progen Industries Limited	1997	2003
198	Progenics Pharmaceuticals	1995	2003
199	Protein Design Labs	1993	2003
200	Provalis	1992	2003
201	QLT	1992	2003
202	Questcor Pharmaceuticals	1992	2003
203	QUIDEL	1986	2001
204	RegeneRx Biopharm.	1986	2003
205	Repligen Corporation	2000	2003
206	Rigel Pharmaceuticals	1998	1999

Table 6.2 (Continued)

No	Names	From	Until
207	Samaritan Pharmaceuticals	2002	2002
208	SangStat Medical	1995	1996
209	Sanofi, S.A.	2000	2003
210	Savient Pharmaceuticals	1986	2003
211	Schering-Plough Corporation	1992	2003
212	SciClone Pharmaceuticals	2001	2003
213	Seattle Genetics, Inc	1999	2003
214	SeraCare Life Sciences	2000	2003
215	Serologicals Corporation	2000	2003
216	Serono International S.A.	1998	2000
217	Shaman Pharmaceuticals	1998	2000
218	Shire Pharmaceuticals	1996	2002
219	SICOR	2002	2002
220	Sigma-Aldrich	1998	2003
221	SkyePharma	1996	2003
222	SONUS Pharmaceuticals	1994	1997
223	Spectral Diagnostics	1996	2002
224	Spectrum Pharmaceuticals	1995	2003
225	Synaptic Pharmaceutical	1994	2001
226	Synbiotics	2000	2003
227	Tanox	1998	2003
228	Targeted Genetics	2000	2003
229	Tercica	2002	2003
230	Teva Pharm.	1986	2003
231	Theragenics	1992	1997
232	TolerRx	2001	2002
233	Transgene	1997	2003
234	Transkaryotic Therapies	1997	2003
235	Trimeris	1995	2003
236	Trinity Biotech U.S.A.	1999	2003
237	Tularik	1998	2003
238	Unigene Laboratories	1986	1997
239	Unimed Pharmaceuticals	1986	1998
240	Valeant Pharm. Intl'	1997	2003
241	Vasogen	1999	2003
242	VaxGen	1998	2002
243	Vernalis	1991	2003
244	ViaCell	2002	2003
245	Vical	2000	2003
246	Vicuron Pharmaceuticals	1998	2003
247	Vion Pharmaceuticals	1995	2003
248	Viragen	1996	2003
249	ViroPharma	1995	2003
250	VIVUS	1996	2000
251	Vyrex	1998	2000
252	Vysis	1995	1999
253	Warner-Lambert	1986	1999
254	Wyeth	1994	2002
255	Xechem International	1996	2000
256	Xenometrix	1995	2000
257	Xenova Group	1993	2003
258	XOMA	1988	2003
259	Xtrana	1987	1996
260	Zaxis International	1992	2001
261	Zila	1993	2003
262	Zonagen	1997	2001

firms in the biopharmaceutical industry (Hoang et al., 2005).

After the acquisitions and mergers, an acquired firm typically became one of several business units of an acquiring firm (i.e., Warner-Lambert, Upjohn, and Pharmacia became divisions under Pfizer in 2000). These acquired units carried interfirm agreements and interpersonal relationships with other firms for several years. In analysis, therefore, the study regarded the number of disappeared firms as still-active entities, contributing to such interfirm variables as direct ties, indirect ties, structural holes, and strength of ties (in the next seven year periods at most).

Table 6.3 presents several important indicators of 262 biopharmaceutical firms over the study period and on an annual basis. The value of most variables increased over time and peaked between 1996 and 1998. Later, most indicators obviously dropped; if not, the indicators increased at decreasing rates.

Table 6.3 Important Analytical Data of the Focal Firms

Year	#Obs	Total Patents	Total Approved Drugs	Total Approved Drug Apps	Total Sales ($MM)	Total Equity Events
1986	15	378	5	10	11,878.16	3
1987	17	396	2	27	13,617.1	1
1988	18	387	0	6	15,500.9	1
1989	24	477	4	23	20,965.57	8
1990	27	545	3	9	24,438.75	4
1991	37	564	6	11	26,980.16	10
1992	52	686	5	35	34,653.15	9
1993	60	680	6	22	36,955.24	15
1994	73	958	6	18	54,587.64	24
1995	106	1539	15	46	76,512.19	58
1996	136	992	40	79	129,484.5	72
1997	144	1,549	21	54	150,843.1	54
1998	171	1,773	27	68	164,646.6	69
1999	180	1,975	20	44	193,326.8	36
2000	207	2,055	35	57	277,344.1	49
2001	208	2,020	34	53	296,703.4	23
2002	205	1,295	19	57	289,772.7	21
2003	199	439	21	45	228,595.1	26
Total	**1,879**	**18,708**	**269**	**664**	**2,046,805.16**	**483**

The drops of the total patents in 2002 and 2003 might display the effect of the lengthy patenting process at the USPTO that normally takes around two or three years after the application dates. To ensure that the drops of the total patents in 2003 did not affect results, the study compared the findings from the models with and without the data in 2003. The significant results and the directions of all variables in these models are very comparable. Further, the declines in other indicators, such as the total approved drug applications, total approved drugs, total sales, and total number of collaborations of focal firms and their alliances indicated downward trends of the biopharmaceutical industry. The observed declines are consistent with arguments that the biopharmaceutical industry is reaching its carrying-capacity and approaching the mature stage (Wittcoff et al., 2004).

Table 6.4 provides basic descriptive statistics for the network measures overtime. The table suggests that the mean number of direct ties grew steadily over the period of the study, reaching its peak in 2001, and declining afterward. Like the means of direct ties, the means of indirect, density, and brokerage initially increased and later decreased.

Table 6.4 Basic Descriptive Statistics on the Linkages Network

Year	Mean Direct	S. D. Direct	Min Direct	Max Direct	Mean Indirect	Mean Density	Mean Brokerage
1986	0.20	0.41	0	1	0.00	0.00%	0.00
1987	0.41	0.51	0	1	0.00	0.00%	0.00
1988	0.78	1.06	0	3	0.00	0.00%	0.44
1989	0.96	1.57	0	6	0.00	0.00%	1.17
1990	1.52	2.49	0	8	0.00	0.00%	3.37
1991	2.19	3.95	0	18	0.05	0.02%	8.86
1992	2.48	4.34	0	19	0.04	0.01%	11.04
1993	2.78	4.65	0	20	0.03	0.01%	13.08
1994	3.44	5.84	0	22	0.08	0.02%	20.99
1995	4.23	6.57	0	30	0.15	0.07%	28.12
1996	5.40	7.92	0	41	0.38	0.55%	42.85
1997	7.78	11.43	0	70	1.83	0.87%	90.29
1998	8.72	13.47	0	88	3.20	2.40%	122.26
1999	8.81	13.58	0	88	3.68	2.49%	124.18
2000	8.62	13.03	0	88	3.86	2.62%	115.42
2001	8.85	13.42	0	89	4.04	2.69%	122.32
2002	8.54	12.58	0	66	4.12	2.91%	108.85
2003	8.47	12.14	0	68	3.88	2.87%	103.03

As a focal firm engaged with a higher number of collaborations, its partners also established their own networks, leading to an increased number of indirect partners, density, and brokerage. The overall density of the network indicates the proportion of potential network ties that are actually realized, whereas the overall brokerage of the network represents the two nodes of the focal firm's network that do not link. The differences between years also indicate the need to control for year fixed effects. Table 6.5 provides descriptive statistics and correlations for all variables, except year dummies (see the Appendix for the correlations of the year dummies).

The sample represents the prominent publicly traded firms in the industry. There is considerable variance on all the key dependent variables, such as patents, marketed drug applications, and total sales across organizations and across years. With regard to their

correlations, the three dependent variables are positively correlated. Patents and marketed drug applications are only moderately correlated ($r = .37$; $p < .000$). Sales, however, correlates with both ($r = .53$ and $.64$). As expected, the previous patents and previous drug applications of focal firms measured in the ten-year period prior to collaborations are correlated with the three dependent variables. Especially, the number of patents in the observation year is highly correlated with the number of drugs approved by the FDA ten years prior to the collaborations ($r = .89$). Additionally, the number of marketed drugs applications in the observation year is highly correlated with the number of patents acquired ten years prior to the collaborations ($r = .97$). Further, Direct and indirect ties are positively correlated ($r = .46$; $p < .000$). The last sets of highly correlated variables are net incomes, the number of employees, and R&D expenses ($r = .79$, $.81$, and $.85$).

Figures 6.1, 6.2, and 6.3 depict the visual relationships among the dependent variables. Specifically, Figure 6.1 shows the relationships between low patenting rates and low revenues. Focal firms that generate more patents also obtain greater revenues. Figure 6.2 also suggests the positve correlation between marketed drug applications and annual revenues. The higher number of marketed drug applications should indicate that the firms have more sources to commercialize their products to customers. Notice that there were also a few focal firms that generate the high number of marketed drug applications, but they had very little revenue.

Last, Figure 6.3 depicts the relationships between the number of marketed drug applications and patenting rates. Most of the plots locate along the vertical and horizontal axes (L-shape) indicating a tendency for the focal firms to perform well in terms of either the marketed drug application activities or the patenting activities. For instance, there are few firms that simultaneously acquired a high level of patents and a high level of marketed drugs

Table 6.5: Descriptive Statistic and Correlation Matrix

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1. Number of Patents	9.96	35.86											
2. Number of Marketable Drug Apps	5.85	24.01	.37										
3. Sales**	1,089.31	4,412.66	.64	.53									
4. Upstream Horizontal*	15.84	229.60	.26	.06	.09								
5. Downstream Horizontal	6.53	74.68	.07	.26	.19	.05							
6. Upstream Vertical	95.64	868.55	.19	.09	.13	.40	.41						
7. Downstream Vertical	632.64	9,142.69	.07	.22	.21	.21	.40	.11					
8. Partner's Patents	106.63	478.21	.08	.06	.09	.39	.18	.27	.46				
9. Partners' Drugs	1.89	9.24	.01	.01	.01	.04	.29	.37	.07	.36			
10. Partners' Prominence	191.62	516.25	.11	.09	.11	.14	.30	.30	.26	.63	.47		
11. Ties' Average Tenure	3.45	2.85	.03	.01	.09	-.05	-.01	-.03	.00	-.04	-.01	-.05	
12. Brokerages	85.45	322.82	.38	.46	.65	.03	.19	.14	.14	.06	.06	.18	.10
13. Densities	1.78	8.70	.00	-.02	-.01	-.01	.03	.01	-.01	.01	.08	.04	.08
14. Direct*Indirect	98.03	466.16	.24	.36	.45	.00	.09	.03	.07	.02	.01	.08	.09
15. Direct Ties	4.94	8.54	.27	.34	.44	.02	.16	.13	.12	.08	.09	.19	.14
16. Indirect Ties	3.12	6.58	.10	.13	.20	-.00	.05	.02	.04	.05	.02	.07	.12
17. Patents of Focal	3.03	13.29	.28	.97	.41	.05	.24	.08	.19	.05	.01	.08	-.02
18. Drug Apps of Focal	76.91	299.95	.89	.36	.70	.25	.03	.16	.05	.05	-.02	.06	.01
19. Equity Financing Events	0.26	0.62	.02	.01	-.00	.02	.08	.07	.02	.09	.13	.17	-.05
20. Closed Stock Prices	15.46	20.73	.09	.00	.02	.05	.00	.03	-.02	.02	.05	.02	.04
21. Years as Public Status	9.15	6.50	.34	.31	.43	.07	.11	.11	.07	.00	.00	.05	.12
22. Diversification	9.20	8.28	.53	.28	.51	.12	.13	.19	.12	.11	.08	.17	-.01
23. Net Income**	131.28	730.29	.02	-.02	.00	.03	-.01	.01	-.01	.01	.01	-.03	.12
24. Employees*	4.29	15.25	.08	.00	.05	.06	-.01	.04	-.01	.02	.03	-.02	.12
25. R&D Expenses*	1,54.95	597.96	.04	-.01	.03	.02	-.01	.01	-.01	.00	.02	-.02	.18

TABLE 6.5 (Continued)

Variable	12	13	14	15	16	17	18	19	20	21	22	23	24
13. Densities	-.01												
14. Direct*Indirect	.70	.04											
15. Direct Ties	.83	.01	.79										
16. Indirect Ties	.29	.19	.69	.46									
17. Patents of Focal	.37	-.02	.29	.28	.10								
18. Drug Apps of Focal	.46	-.00	.28	.30	.11	.26							
19. Equity Financing Events	.03	-.03	-.02	.03	-.00	.02	-.01						
20. Closed Stock Prices	.03	.03	-.00	.06	.00	-.01	.09	.03					
21. Years as Public Status	.42	.03	.31	.43	.22	.26	.42	.04	.03				
22. Diversification	.45	.01	.37	.47	.21	.21	.53	.05	.11	.41			
23. Net Income**	-.01	-.01	-.04	-.01	-.05	-.02	.02	.02	.40	-.01	.01		
24. Employees*	.00	-.01	-.04	-.01	.00	-.01	.09	.03	.53	.05	.07	.79	
25. R&D Expenses*	.01	-.01	-.03	.01	-.00	-.01	.04	.03	.43	.04	.02	.81	.85

Notes: All correlations with absolute values above .045 are statistically significant at $p < 0.05$; N = 1879; Correlations of all NAICS and years from STATA are available at the Appendix.
* In thousands **In Millions

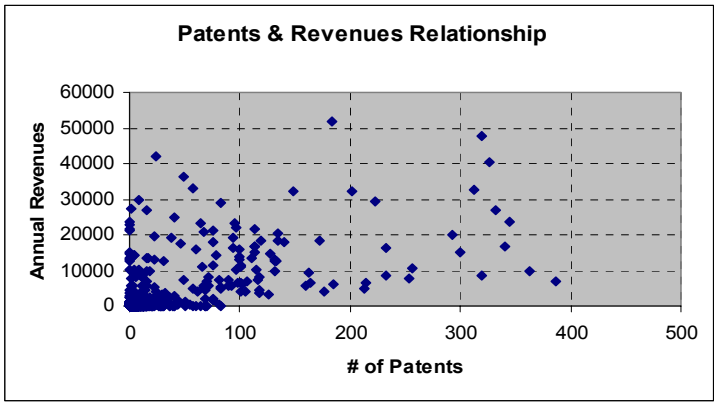


Figure 6.1 Relationships of Patents and Annual Revenues

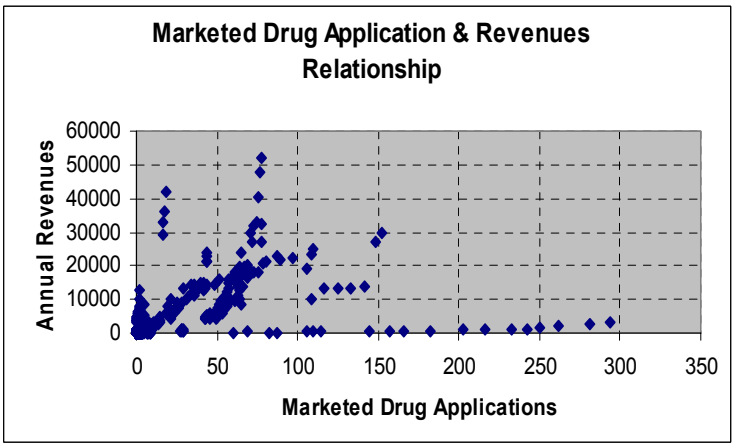


Figure 6.2 Relationships of Marketed Drug Applications and Annual Revenues

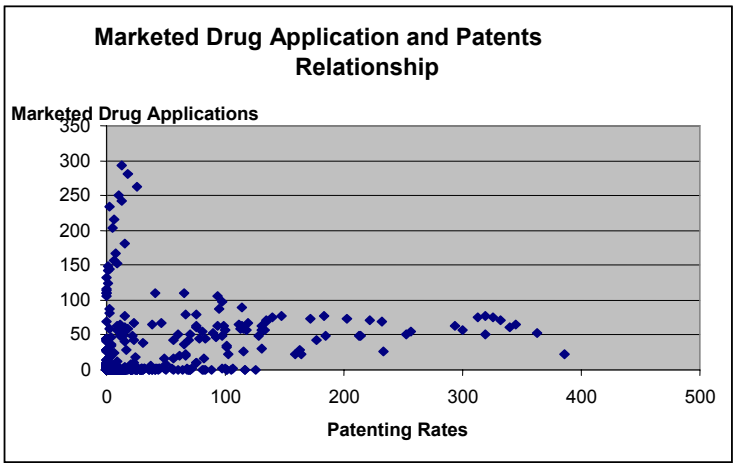


Figure 6.3 Relationships of Marketed Drug Applications and Patents

(e.g., in 2001, only Novartis AG achieved 106 marketed drug applications and 94 new patents).

Tables 6.6a, b, and c, report the results of the regression analyses using the panel negative binomial, the panel zero-inflated negative binomial, and the random-effects GLS models. Model 1 presents the base model with the control variables. Several of the control variable results are significant for all three tables. First, a focal firm's posture in terms of exploitation (a focal firm's propensity to generate a large number of drug applications) is positive and significant for all models. The focal firm with a high number of previous drug applications performs well in patenting rates, the number of marketed drug applications, and revenues. The number of equity financing events generates significantly positive outcomes for a focal firm's patenting rate and revenue.

Unlike a focal firm's posture in exploitation activities, a focal firm's posture in exploration activities (a propensity to generate patents) contributes to future patents and revenues. There is no significant effect of the the focal firm's posture in exploration activities on the subsequent number of marketed drug applications. Interestingly, the closing stock price of the previous year is the negative factor for the future revenue. The level of diversification—the extent that a focal firm engaged in several biopharmaceutical technologies—suggests the high number of patents, marketed drug applications, and revenue. Further, a long tenure as a publicly traded company decreases the focal firm's patenting rate. These results support a prior study using institutional perspectives to explain that established firms normally fail the disruptive technologies (Christensen et al., 1996), whereas startups were more likely to generate invention (Baum et al., 2000). For the last significant control variable, net income of a focal firm in the previous year only suggests the negative association with its revenue. Model 2 adds the three variables—direct ties, indirect ties, and their interaction—to the specification.

Table 6.6a: The Panel Negative Binomial Regression Estimates of Patenting

Predictors	Model #1	Model #2	Model #3	Model #4	Model #5	Model #6	Model #7
Constant	-.6488 **	-.6842 ***	-.7269 ***	-.2191	-.1711	-.2096	-.2104
Upstream Horizontal						1.05e-08	
						(9.43e-08)	
Downstream Horizontal						-.0002	
						.0002	
Upstream Vertical						-3.39e-06	
						(1.7e-05)	
Downstream Vertical						-7.38e-06 *	-8.40e-06 **
						(3.27e-06)	(3.23e-06)
Partner's Patents					-.0001 *	-1.76e-05	-1.91e-06
					(4.34e-05)	(7.07e-05)	(4.78e-05)
Partners' Drugs					-.0058 *	-.0054	-.0067 *
					(.0030)	(.0035)	(.0030)
Partners' Prominence				-5.17e-05	3.31e-05	2.98e-05	2.74e-05
				(4.50e-05)	(5.1e-05)	(5.04e-05)	(4.93e-05)
Ties' Average Tenure				-.0692 **	-.0687 **	-.0656 **	-.0660 **
				(.0246)	(.0244)	(.0242)	(.0242)
Brokerages			-.0006 **	-.0005 **	-.0005 ***	-.0005 ***	-.0005 ***
			(.0002)	(.0002)	(.0002)	(.0001)	(.0001)
Densities			.0073 *	.0074 *	.0078 *	.0078 *	.0079 *
			(.0037)	(.0037)	(.0037)	(.0037)	(.0037)
Direct*Indirect		-.0005 *	-.0006 **	-.0006 **	-.0005 *	-.0006 **	-.0006 **
		(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Direct Ties		.0130 **	.0267 **	.0236 ***	.0203 ***	.0211 ***	.0206 ***
		(.0049)	(.0060)	(.0059)	(.0058)	(.0055)	(.0055)
Indirect Ties		-.0026	-.0010	.0009	.0003	.0023	.0020
		(.0070)	(.0070)	(.0072)	(.0072)	(.0071)	(.0071)

Selected control variables for all models are reported next page.

Table 6.6a (Continued)

Control Variables	Model #1	Model #2	Model #3	Model #4	Model #5	Model #6	Model #7
Year Dummies[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS Dummies[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug Apps of Focal	.0046	.0041	.0047	.0057	.0068 *	.0095 *	.0087 *
	(.0038)	(.0038)	(.0038)	(.0040)	(.0040)	(.0043)	(.0042)
Patents of Focal	.0005 ***	.0005 ***	.0010 ***	.0011 ***	.0011 ***	.0010 ***	.0010 ***
	(.0001)	(.0001)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Equity Financing Events	.0584 †	.0560 †	.0633 †	.0701 *	.0862 **	.0821 **	.0805 **
	(.0329)	(.0326)	(.0325)	(.0322)	(.0328)	(.0324)	(.0323)
Closed Stock Prices	.0019	.0022	.0019	.0020	.0017	.0014	.0013
	(.0014)	(.0014)	(.0014)	(.0013)	(.0013)	(.0013)	(.0013)
Years as Public Status	-.0206	-.0187	-.0181	-.0222 *	-.0310 **	-.0366 **	-.0352 **
	(.0117)	(.0117)	(.0114)	(.0117)	(.0124)	(.0127)	(.0125)
Diversification	.0286 **	.0244 **	.0203 *	.0252 **	.0334 ***	.0430 ***	.0421 ***
	(.0087)	(.0092)	(.0089)	(.0093)	(.0103)	.0108	(.0108)
Net Income**	-3.75e-05	-1.58e-05	-3.01e-05	-2.8e-05	-3.99e-05	-3.62e-05	-3.93e-05
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Employees*	.0083	.0063	.0042	.0059	.0071	.0061	.0062
	(.0062)	(.0061)	(.0058)	(.0059)	(.0058)	(.0058)	(.0058)
R&D Expenses*	.0001	.0001	.0001	.0001	.0001	.0001	.0001
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Log likelihood	-3108.34	-3104.52	-3097.04	-3092.50	-3087.37	-3082.04	-3082.52
Δ Chi^2	N/A	8.42 *	15.79 ***	12.97 **	9.40 **	8.64 †	N/A
Degree of Freedom	22	25	27	29	31	35	32
Wald Chi^2	344.15	366.24	403.69	421.16	452.59	483.12	477.33
N	1689	1689	1689	1689	1689	1689	1689

† = p < .10; * = p < .05; ** = p < .01 *** = p < .001; significance tests are two-tailed for control variables and one-tailed for hypothesized effects.

1. Because of large numbers of additional predictors NAICS Dummies and Year Dummies are not reported in this Table (please see Appendix for complete outputs from STATA)
2. Because of seven-year period of accumulations in several variables (i.e., direct and indirect ties), the analysis is for all observations occurred after 1992.
3. Model#7 drops non-significant interaction variables. This is the model that I use to test all hypotheses.

Table 6.6b: The Panel Zero-inflated Negative Binomial Regression Estimates of Marketed Drug Applications

Predictors	Model #1	Model #2	Model #3	Model #4	Model #5	Model #6	Model #7
Constant	-.3032	-.5714	-.5966	-.2882	-.2918	-.2252	-.3694
Upstream Horizontal						2.08e-07	
						(2.02e-07)	
Downstream Horizontal						.0005	
						(.0003)	
Upstream Vertical						-3.47e-05 *	-2.16e-05
						(1.77e-05)	(1.8e-05)
Downstream Vertical						7.63e-06 *	7.14e-06 *
						(4.19e-06)	(3.29e-06)
Partner's Patents					-.2.43e-05	-.0003 *	-.0003 **
					(.0001)	(.0001)	(.0001)
Partners' Drugs					-.0065	-.0059 *	-.0025
					(.0051)	(.0035)	(.0045)
Partners' Prominence				.0003 **	.0003 **	.0003 **	.0003 **
				(.0001)	(.0001)	(.0001)	(.0001)
Ties' Average Tenure				-.0329	-.0335	-.0360	-.0320
				(.0476)	(.0477)	(.0482)	(.0476)
Brokerages			.0004 †	.0004	.0004	.0004	.0004
			(.0003)	(.0003)	(.0003)	(.0003)	(.0003)
Densities			-.0120 ***	-.0121 ***	-.0114 ***	-.0116 ***	-.0124 ***
			(.0036)	(.0033)	(.0036)	(.0035)	(.0037)
Direct*Indirect		.0004	.0001	.0006	.0006	.0008	
		(.0008)	(.0008)	(.0008)	(.0008)	(.0009)	
Direct Ties		-.0102	-.0246 *	-.0294 *	-.0295 *	-.0310 *	-.0235 *
		(.0155)	(.0141)	(.0141)	(.0143)	(.0144)	(.0107)
Indirect Ties		.0132	.0299 †	.0203	.0192	.0172	.0319 **
		(.0155)	(.0155)	(.0149)	(.0151)	(.0154)	(.0120)

Selected control variables for all models are reported next page.

Table 6.6b (Continued)

Control Variables	Model#1	Model#2	Model#3	Model#4	Model#5	Model#6	Model#7
Year Dummies[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS Dummies[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug Apps of Focal	.0403 ***	.0414 **	.0388 ***	.0380 ***	.0380 ***	.0367 ***	0.373 ***
	(.0101)	(.0124)	(.0099)	(.0083)	(.0082)	(.0069)	(.0073)
Patents of Focal	.0001	.0001	-5.38e-05	-1.01e-05	-2.42e-05	-2.09e-05	3.07e-06
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Equity Financing Events	-.1084	-.1072	-.1281 †	-.1257 *	-.1178 *	-.1031	-.1133
	(.0782)	(.0669)	(.0698)	(.0683)	(.0675)	(.0720)	(.0778)
Closed Stock Prices	-.0064 *	-.0053 †	-.0033 *	-.0037	-.0037 †	-.0033	-.0033
	(.0031)	(.0029)	(.0026)	(.0025)	(.0024)	(.0024)	(.0025)
Years as Public Status	.0140	.0151	.0143	.0106	.0103	.0087	.0092
	(.0163)	(.0178)	(.0184)	(.0187)	(.0186)	(.0205)	(.0184)
Diversification	.0535 ***	.0562 ***	.0570 ***	.0564 ***	.0572 ***	.0587 ***	.0566 ***
	(.0105)	(.0122)	(.0118)	(.0121)	(.0120)	(.0127)	(.0112)
Net Income**	.0002 †	.0001	.0001	7.32e-10	8.12e-05	6.17e-05	.0001
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Employees*	-.0175	-.0202	-.0195	-.0162	-.0162	-.0145	-.0137
	(.0147)	(.0151)	(.0157)	(.0161)	(.0157)	(.0160)	(.0160)
R&D Expenses*	.0004	.0005 †	.0005 †	.0006 †	.0006 †	.0006 †	.0005
	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)
Log Pseudo-likelihood	-1179.82	-1386.49	-1374.58	-1365.16	-1363.75	-1358.66	-1362.16
Δ Chi2		2.9	12.53 **	10.64 **	2.19	12.31 *	N/A
Degree of Freedom	22	25	27	29	31	35	32
Wald Chi[2]	1729.25	2964.23	2006.76	2359.67	2560.79	6034.79	3150.26
N	1689	1689	1689	1689	1689	1689	1689

† = p < .10; * = p < .05; ** = p < .01 *** = p < .001; significance tests are two-tailed for control variables and one-tailed for hypothesized effects.

1. Because of large numbers of additional predictors NAICS Dummies and Year Dummies are not reported in this Table (please see Appendix for complete outputs from STATA)
2. Because of seven years accumulative lags in several variables (i.e., direct and indirect ties), the analysis is for all observations occurred after 1992.
3. Model#7 drops non-significant interaction variables. I use all results in this model to test for all hypotheses.
4. All models are controlled for the zero-inflated observations of the dependent variable using propensities to invent and commercialize of the focal firms.

Table 6.6c: The Panel Regression Estimates of Total Annual Sales

Predictors	Model #1	Model #2	Model #3	Model #4	Model #5	Model #6	Model (Fixed) #7
Constant	130.3243	78.7958	-128.2834	-590.8986	-588.0686	-577.0613	-6130.564
Upstream Horizontal						-.0014 ***	-.0014 ***
						(.0003)	(.0003)
Downstream Horizontal						-1.7076 ***	-1.7603 ***
						(.5035)	(.4942)
Upstream Vertical						.1353 **	.1313 **
						(.0474)	(.0467)
Downstream Vertical						.0243 ***	.0234 ***
						(.0047)	(.0048)
Partner's Patents					.4248 ***	.3370 ***	.3437 ***
					(.0848)	(.0993)	(.0973)
Partners' Drugs					3.2991 *	4.0455	3.4233
					(3.7102)	(3.9225)	(3.8449)
Partners' Prominence				-.1088	-.3674 ***	-.3571 ***	-.3111 ***
				(.0710)	(.0880)	(.0883)	(.0869)
Ties' Average Tenure				68.024 *	68.8925 *	68.6065 *	57.9035 †
				(32.6314)	(32.4226)	(31.8606)	(36.1958)
Brokerages			4.4837 ***	4.5355 ***	4.7438 ***	5.3149 ***	4.3373 ***
			(.3319)	(.3338)	(.3338)	(.3409)	(.3631)
Densities			-4.2936	-4.2167	-3.9617	-3.2596	-4.5902
			(5.3483)	(5.3459)	(5.3212)	(5.2471)	(5.2698)
Direct*Indirect		-.1442	-2.2048 ***	-2.3951 ***	-2.3856 ***	-2.2605 ***	-2.1784 **
		(.6671)	(.6560)	(.6619)	(.6595)	(.6822)	(.7027)
Direct Ties		34.3910 **	-65.9707 **	-67.5208 ***	-70.1489 ***	-77.6504 ***	-62.8015 ***
		(12.8566)	(14.3213)	(14.3397)	(14.2853)	(14.2201)	(14.8294)
Indirect Ties		-20.8585 *	17.6121	18.5499 *	19.8435 *	17.6211	13.4454
		(11.2032)	(11.1216)	(11.1144)	(11.0722)	(11.0687)	(11.3249)

Selected control variables for all models are reported next page.

Table 6.6c (Continued)

Control Variables	Model #1	Model #2	Model #3	Model #4	Model #5	Model #6	Model (Fixed) #7
Year Dummies[1]	Yes	Yes	Yes	Yes	Yes	Yes	Year
NAICS Dummies[1]	Yes	Yes	Yes	Yes	Yes	Yes	Dropped
Drug Apps of Focal	147.4105 ***	138.423 ***	103.3026 ***	102.9821 ***	104.4588 ***	103.9359 ***	220.8077 ***
	(14.0915)	(13.9716)	(13.2332)	(13.2073)	(13.1669)	(12.8576)	(25.0458)
Patents of Focal	13.8958 ***	13.3903 ***	10.5171 ***	10.3995 ***	10.2827 ***	9.9110 ***	12.6972 ***
	(.5157)	(.5348)	(.5418)	(.5428)	(.5405)	(.5341)	(.7163)
Equity Financing Events	112.9404 †	121.0456 *	91.7278	92.5070 *	98.2841 *	116.3305 *	135.1334 **
	(57.6315)	(57.8095)	(55.3488)	(55.3928)	(55.0527)	(54.4288)	(53.4871)
Closed Stock Prices	-9.4200 **	-9.4057 **	-8.4651 **	-8.4658 **	-8.5565 **	-6.9179 **	-5.3540 *
	(2.8461)	(2.8494)	(2.7222)	(2.7209)	(2.6991)	(2.6723)	(2.7211)
Years as Public Status	-44.3976	-45.0160	-22.9100	-19.1206	-18.9036	-18.2673	389.1471
	(29.1408)	(28.4935)	(26.2879)	(26.2682)	(26.2183)	(25.4480)	(995.1599)
Diversification	29.6431	28.3299	54.9107 *	56.1624 *	54.5925 *	51.7061 *	Dropped
	(27.1981)	(26.6196)	(24.5939)	(24.5873)	(24.5401)	(23.8489)	
Net Income**	-.2797 *	-.2843 **	-.2167 *	-.2091 *	-.1994 *	-.1921 *	-.1926 †
	(.1135)	(.1135)	(.1084)	(.1084)	(.1075)	(.1059)	(.1095)
Employees*	19.0826	19.2193	16.1514	14.0315	12.8751	14.3923	20.0806
	(12.2325)	(12.1844)	(11.5264)	(11.5525)	(11.4827)	(11.2849)	(13.4840)
R&D Expenses*	.1623	.1565	.1341	.1557	.1513	.1278	.0953
	(.1460)	(.1461)	(.1394)	(.1395)	(.1384)	(.1365)	(.1429)
Overall R-sq	.5878	.5952	.6527	.6539	.6573	0.6667	0.5747
Δ Chi-sq		14.19 **	183.42 ***	6.46 *	26.82 ***	58.77 ***	
Degree of Freedom	22	24	27	29	31	35	31
Wald Chi[2]	1256.88	1284.92	1618.57	1629.94	1978.37	1799.73	
N	1689	1689	1689	1689	1689	1689	1689

† = p < .10; * = p < .05; ** = p < .01 *** = p < .001; significance tests are two-tailed for control variables and one-tailed for hypothesized effects.

1. Because of large numbers of additional predictors NAICS Dummies and Year Dummies are not reported in this Table (please see Appendix for complete outputs from STATA)
2. Because of seven years accumulative lags in several variables (i.e., direct and indirect ties), the analysis is for all observations occurred after 1992.
3. Since all interaction variables are significant, I use Model#6 to test all hypotheses.
4. Model# 7 is a fixed-effects model.

Model 3 adds the two measures (brokerages and density) of structural holes variables. Model 4 includes two other network measures: Ties' average tenure and partners' prominence to test for the impact of tie-strength and reputation of partners. The next two variables—number of partners' patents (exploration partners) and number of partners' successful drug applications (exploitation partners)—are added in Model 5. Model 6 adds four variables: upstream horizontal ties, downstream horizontal ties, upstream vertical ties, and downstream vertical ties. While these four variables complete the specification for Model 6, Model 7 drops non-significant network measures for hypothesis testing.

Table 6.6c shows results of panel regression analysis for total sales. Since the interaction predictors are significant in Model 6, this particular model tests the hypotheses. Model 7 in Table 6.6c reports the findings of the fixed-effects model, to check for the robustness of the findings from the random-effects GLS regression model.

The first set of hypotheses predicted that the number of direct ties and indirect ties should have positive impacts on firm invention and commercialization outputs. A prediction was also presented that the impact of interaction between direct ties and indirect ties would be negatively associated with invention, but positively associated with commercialization. The coefficient of direct ties in the patents model is significant and supported the hypothesis. The coefficients of direct ties for the marketed drug applications and sales are also significant, but suggest negative associations. These results do not support the hypotheses in the study. The coefficient of indirect ties is only significant in the marketed drug applications model in Table 6.6b. However, because the coefficient suggests a negative relationship, the hypothesis is not supported. Next, the interaction variable of direct and indirect ties is significant in Model 7, Table 6.6a (patenting

rates), but not significant for marketed drug applications in Model 6, Table 6.6b and for revenue in Model 6, Table 6.6c.

Hierachical analyses indicate that adding interaction terms significantly improves model fit. The study tested the change of log likelihood and the change of overall R-squared after inclusive of the interaction terms in the two models. The results show that by including the interaction term for direct and indirect ties in the patents model (Table 6.6a) and the sales model (Table 6.6c), the log likihood changed significantly in Model 7, Table 6.6a (Δ Log-Likelihood = 4.74; p = 0.0294); however, the change in R-squared is not significant in the revenue Model 6, Table 6.6c (Δ overall R-squared = .011; Δ chi2 (1) = 0.05; p > 0.8289).

Since the model to predict the number of market drug applications has no significant interaction effect (thus, the rejection of H1f (c)), the effects of direct ties and indirect ties are significant (B = -0.235 and .0319; p < .05 and .01, respectively). However, as the direction of the coefficient for direct ties is opposite of the earlier prediction, the study rejects H1d (c) and accepts H1e (c). To interpret the effects of the main predictors (i.e., direct and indirect ties) in a model containing a significant interaction effect (direct ties*indirect ties), conditional analyses are needed (Aiken & West, 1991). The conditional analyses take into account that the significant interaction term (i.e., XZ) indicates that the regression of the dependent variable (Y) on the first predictor (X) depends upon the specific value of the second predictor (Z), at which the slope of Y on X is measured. Because the interaction is symmetrical, the presence of the interaction means that the effect of the second predictor (Z) is also conditional on the first predictor (X): there is a different regression coefficient of Y on Z at each value of X.

Aiken & West (1991) suggested calculating simple slopes for the variable of interest conditional on reasonable value of the moderator. They suggested that reasonable moderator

values are the mean, the mean minus one standard deviation, and the mean plus one standard deviation. Because the number of direct and indirect ties cannot be negative (i.e., they are count and non-negative integers), these analyses offer the value "zero" of direct and indirect ties to illustrate the significant contributions of the two predictors at the lowest possible value. To determine whether the simple slope is significantly different from zero requires the calculation of the standard errors. T-tests for the significance of the simple slopes were computed (Aiken et al., 1991). These conditional analyses led to the following results:

[∂ Patenting Rates/∂ Direct Ties | Indirect Ties = 0.00] = .0206*** (.0055)
[∂ Patenting Rates/∂ Direct Ties | Indirect Ties = 3.12] = .0187*** (.0052)
[∂ Patenting Rates/∂ Direct Ties | Indirect Ties = 9.70] = .0148** (.0049)

[∂ Patenting Rates/∂ Indirect | Direct = 0.00] = .0020 (.0071)
[∂ Patenting Rates/∂ indirect | Direct = 4.94] = -.0010 (.0052)
[∂ Patenting Rates/∂ indirect | Direct = 13.48] = -.0062 (.0049).

The conditional analyses reveal that direct ties have a significantly positive effect on the number of patents across reasonable values, supporting H1a. However, indirect ties have no significant effect on patenting rates at any level of direct ties. From the conditional analysis, the coefficient of direct ties is positive and significant on the patenting rates of the focal firms, supporting H1a (i); ($B = .0206$; $p < 0.001$). With regard to the interaction effect of direct and indirect ties, I found that the negative coefficient of the interaction variable is significant ($B = -.0006$; $p < .01$). The finding supports H1c (i), predicting the negative moderator in the model.

In the case of sales model (Table 6.6c), the significant interaction term requires a conditional analyses:

[∂ Sales/∂ Direct Ties | Indirect Ties = 0.00] = -77.65*** (14.22)
[∂ Sales/∂ Direct Ties | Indirect Ties = 3.12] = -84.71*** (13.39)
[∂ Sales/∂ Direct Ties | Indirect Ties = 9.70] = -99.59*** (12.69)

[∂ Sales/∂ Indirect | Direct = 0.00] = 17.62† (11.07)
[∂ Sales/∂ Indirect | Direct = 4.94] = 6.45 (9.35)
[∂ Sales/∂ Indirect | Direct = 13.48] = -12.84 (8.95).

The coefficients of direct ties are negative and significant across all three reasonable levels of indirect ties. This suggests the negative contributions of direct ties to sales. Thus, the study rejects H1d (c). With regard to the interaction effect on commercialization performance, the final model from Table 6.6c suggests that the interaction of direct and indirect ties reduces sales (B = -2.2605; $p < .01$). Therefore, the outcome rejects H1f (c), because the hypothesis predicted the opposite direction.

To further probe the impact of direct and indirect ties on the three dependent variables, some quantitative indication of the interaction effect could illustrate the impact of the variables on both invention and commercialization. Suppose that a firm is at the mean levels of direct ties (5) and indirect ties (3). For this firm, direct ties increase the patenting rate by a multiplier of 1.099 (=exp [.0206*5 - .0006*5*3]). The other firm has the same number of indirect ties, but with a higher number of direct ties (a mean + a standard deviation). For this firm, direct ties increase the patenting rate by a multiplier of 1.301 (= exp [.0206*14 - .0006*14*3]). From the results, while a focal firm could generate 11 (= 1.099*9.96) patents on an average, adding the number of direct partners by one standard deviation (9) greatly improves the number of patents by 2 [= (1.301*9.96)-(1.099*9.96)].

With regard to the second set of hypotheses, the impact of the number of structural holes among direct and indirect ties of a focal firm will have a negative effect on invention performance and positive effect on commercialization performance. In my study, density and

brokerage are the two dimensions that theoretically capture the characteristics of a focal firm's level of structural holes. The density measure is the number of ties divided by the number of pairs, whereas the brokerage measure is the number of pairs in the ego network that are not directly connected to each other. As both measures capture structural holes, the measures should be highly negative correlated. The correlation coefficient of these two indicators turned out to be an insignificant level ($r = -.01$; $p = .6483$), however.

Figure 6.1 depicts two scenarios using the two measures—density and brokerage—to capture the characteristics of structural holes. Whereas the two networks are different, the density measures are the same at 50%. In either Situation A or B, if the actual relationship is half of the possible relationships, the density is always at 50%. The brokerage numbers in Situation A and B, however, are obviously different as they indicate the unconnected direct partners in the two different networks. Depending on the size of the networks, the low measures of density might not necessarily represent the high level of brokerage.

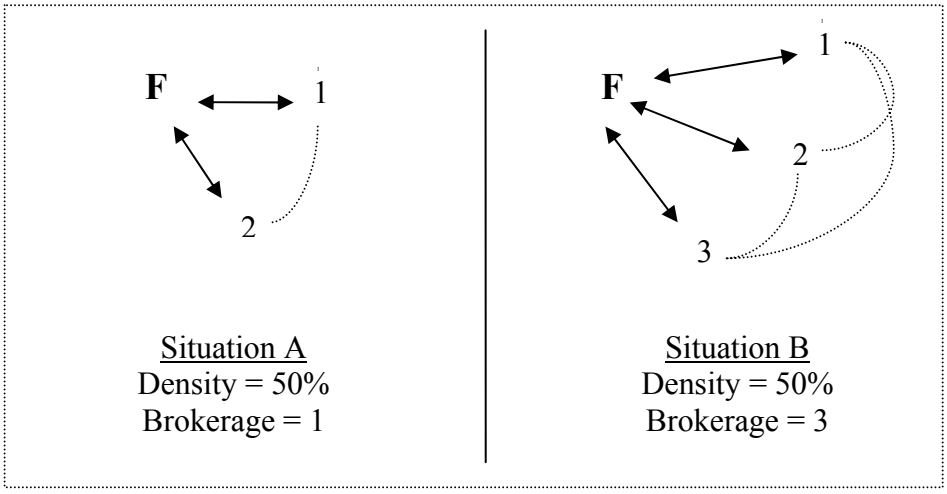


Figure 6.4 Two Scenarios of Density and Brokerage Measures

The regression coefficients of density and brokerage for the number of patents in Table 6.6a are significant ($B = .0079$ and $-.0005$; $p < .05$ and $.001$). Theoretically, a high density reflects a

low level of structural holes, whereas a high brokerage suggests a high level of structural holes. Therefore, the significant findings in this model support H2 (i). On average (when a focal firm has a density and a brokerage measure at mean levels), the incident rates of density and of brokerage to generate the number of patents are the multipliers of 1.014 = exp (.0079*1.78) and 0.958 = exp (-.0005*85). However, additional increases in density and brokerage by one standard deviations (8.7 and 323) change the multipliers to 1.086 = exp (.0079*10.48) and to 0.8509 = exp (-.0005*323), respectively.

Next, the coefficient of density for the number of marketed drug applications in Table 6.6b is negative and significant (B = -.0124; $p < .001$). The incident rate in this case is .9782 = exp (-.0124*1.78). Additionally, in Table 6.6c, the coefficient of brokerage is positive and significant (B = 4.3373; $p < .001$). On average, one unit increased in a brokerage measure generates revenue by $4.3373 MM. From the results, the significant findings for the density in the marketed drug applications model and the brokerage in the sales model supported H2 (c).

From the patents model (Table 6.6a) and the sales model (Table 6.6c), the coefficients of the tie strength, as measured by the average length of ties, are significant (B = -.0660; $p < .01$ and 68.6065; $p < .05$). Interestingly, whereas H3 (i) predicts that the strength of ties should increase the number of patents generated and H3 (c) predicts that the strength of ties should decrease the commercialization output, both findings indicate opposite effects. From both models, the coefficients of the tie strength suggest a negative association with the focal firm's patenting rate and a positive association with the focal firm's revenue. The coefficient of tie strength for the marketed drug application is negative, but non-significant. These results suggest a lack of support for the hypothesized effects of strength of ties on invention and commercialization.

Next, the alliances' prominence—as measured by the frequencies of direct partners' news articles in the past ten years—is predicted to deteriorate the focal firm's invention while facilitating its commercialization performance, yet the coefficient of the partners' prominence has no significant effect on the number of patents. However, the coefficients are positive for the number of marketed drug applications (B = .0003; $p < .01$ and negative for the revenues of the focal firms (B = -.3571; $p < .001$). Therefore, these first findings provide a support for H4 (c) with regard to the marketed drug applications, but not with regard to sales. To calculate for the incident rate ratio of partners' prominence, the multiplier on the marketed drug applications is 1.059 = exp (.0003*192) when a focal firm has its partners' prominence at the mean level (192). An additional increase by one standard deviation in its partners' prominence helps improve the incident rate ratio by 1.237 = exp (.0003*(192+516)).

With regard to the focal firm's network orientations, exploration and exploitation networks—as measured by the two corresponding proxies of the number of partners' patents and the number of partners' successful drug applications in the past ten years prior to the collaboration—there is no significant effect on invention outcomes in Model 6 (Table 6.6a). However, in Model 7, the model that includes only one significant interaction variable—a downstream vertical network—the number of partners' drugs has a negative coefficient (B = -.0067), which is significant at $p < .05$. Since the exploitation network, as measured by the number of partners' drugs, is not a main predictor for any interaction variable in the model, the study uses the available coefficient to accept H 5b (i); predicting that a greater preponderance of exploitation-oriented relationships will reduce the patenting performance of the focal firm. To test the incident rate of the variable, the exploitation network, as captured by the number of partners' drugs on an average (2), will deteriorate the number of patents of a focal firm by the multiplier of 0.987 = exp (-.0067*2). An

additional increase by one standard deviation in the exploitation network reduces the multiplier to 0.929 = exp (-.0067*(2+9)).

To evaluate the significance of the exploration-oriented partners as measured by the number of patents acquired by a focal firm's partners, the study conducted the conditional analysis. Because the downstream vertical network which is the interaction term (the propensity of the focal firm to obtain the drug applications at the FDA * Exploration-oriented partners) is included in the model, the conditional analysis is needed to evaluate the contribution of an exploration-oriented partner at different reasonable levels of the focal firm's drug applications.

[∂ Patenting Rates/∂ Explor Partners | Focal Drug = 0.00] = .0000 (.0050)
[∂ Patenting Rates/∂ Explor Partners | Focal Drug = 3.03] = .0000 (.0027)
[∂ Patenting Rates/∂ Explor Partners | Focal Drug = 16.32] = -.0001 (.0063)

From the conditional analyses, exploration partners have no significant effect on patenting across reasonable levels of a focal firm's propensity to issue drugs at the FDA. Therefore, downstream vertical networks, indicating collaboration between an exploitation focal firm and its exploration partners, have no significant effect on the number of patents. Thus, H5a (i) is rejected. Next, the coefficient of exploration partners is negative and significant for the number of marketed drug applications (B = -.0003; $p < .01$). In this particular model, the downstream vertical network is significant and included in the regression equation; therefore, the conditional analysis is required to evaluate the contributions of exploration partners to the dependent variable across reasonable levels of a focal firm's propensity to obtain the drug applications at the FDA.

[∂ Mkt Drug Apps /∂ Explor Partners | Focal Drug = 0.00] = -.0003** (.0001)
[∂ Mkt Drug Apps /∂ Explor Partners | Focal Drug = 3.03] = -.0002** (.0001)
[∂ Mkt Drug Apps /∂ Explor Partners | Focal Drug = 16.32] = -.0002* (.0001)

From the conditional analyses, the effects of exploration partners on the number of marketed drug applications are all negative and significant at the three reasonable levels of the moderator variable. The exploration partners deteriorate the number of marketed drug applications of a focal firm. Thus, H5c (c) is supported. To report the incident rate ratio of the average number of exploration partners on the number of marketed drug applications, the study calculates the following multiplier, exp (-.0003*107 - 7.14e-06*107*77) = 0.913. Adding additional exploration partners by one standard deviation reduces the multipler to = exp (-.0003*(107+478) - 7.14e-06*(107+478)*77) = 0.6083. On average, adding exploration partners at the mean level vastly deteriorates a focal firm's number of marketed drug applications from 5 = (6*0.913) applications to about 4 = (6*0.608) applications, or 20% fewer. With regard to the exploitation partners, the marketed drug applications model (Table 6.6b) indicates non-significant results. Thus, H5d (c) is rejected.

In Table 6.6c, the interpretation of impacts of the exploration and exploitation partners on sales becomes more complicated as the four interaction variables—upstream horizontal, downstream horizontal, upstream vertical, and downstream vertical networks—are all significant and thus used for hypothesis testing (Model 7). To understand the contributions of exploration and exploitation partners to sales, the two-way interaction conditional analyses are needed. For instance, the interpretation of the main predictor—exploration partners—requires the point estimations of the other two main predictors—the focal firms' propensity to invention and its propensity to commercialization. This is because the three predictors together generate the upstream horizontal and downstream vertical networks (the two significant interaction variables in the regression equation). Therefore, to understand the contributions of the exploration

partners on sales, the reasonable values from the associated two main predictors are substituted (Aiken & West, 1991).

[∂ Sales /∂ Explor Partners | Focal Drugs = 0.00, Focal Patents = 0.00] = 0.3370*** (0.0993)
[∂ Sales /∂ Explor Partners | Focal Drugs = 0.00, Focal Patents = 76.91] = 0.2299*** (0.0941)
[∂ Sales /∂ Explor Partners | Focal Drugs = 0.00, Focal Patents = 376.86] = -0.1876 (0.1217)

[∂ Sales /∂ Explor Partners | Focal Drugs = 3.03, Focal Patents = 0.00] = 0.4108*** (0.0094)
[∂ Sales /∂ Explor Partners | Focal Drugs = 3.03, Focal Patents = 76.91] = 0.3038*** (0.0887)
[∂ Sales /∂ Explor Partners | Focal Drugs = 3.03, Focal Patents = 376.86] = -0.1137 (0.1190)

[∂ Sales /∂ Explor Partners | Focal Drugs = 16.32, Focal Patents = 0.00] = 0.7344*** (0.0943)
[∂ Sales /∂ Explor Partners | Focal Drugs = 16.32, Focal Patents = 76.91] = 0.6273*** (0.0913)
[∂ Sales /∂ Explor Partners | Focal Drugs = 16.32, Focal Patents = 376.86] = 0.2100† (0.1271)

Interestingly, the exploration partners contribute significantly and positively to sales if the focal firm's patenting rates are low and moderate (at zero and at its mean). When the number of the focal firm's patents is high (at mean plus one standard deviation), the exploration partners contribute immaterially to sales. Therefore, the two interaction conditional analyses support the hypothesized effects of exploration partners on sales, H5c (c), at firms with previous patents below 107 (a mean level). Next, the study offers a nine point estimation to test for the significant contributions of the exploitation partners to sales.

[∂ Sales /∂ Exploit Partners | Focal Drugs = 0.00, Focal Patents = 0.00] = 4.0455 (3.9225)
[∂ Sales /∂ Exploit Partners | Focal Drugs = 0.00, Focal Patents = 76.91] = 14.4599*** (4.6530)
[∂ Sales /∂ Exploit Partners | Focal Drugs = 0.00, Focal Patents = 376.86] = 5.0261*** (17.3312)

[∂ Sales /∂ Exploit Partners | Focal Drugs = 3.03, Focal Patents = 0.00] = -1.134 (4.0076)
[∂ Sales /∂ Exploit Partners | Focal Drugs = 3.03, Focal Patents = 76.91] = 9.27* (4.70)
[∂ Sales /∂ Exploit Partners | Focal Drugs = 3.03, Focal Patents = 376.86] = 49.84*** (17.31)

[∂ Sales /∂ Exploit Partners | Focal Drugs = 16.32, Focal Patents = 0.00] = -23.8286*** (8.6029)
[∂ Sales /∂ Exploit Partners | Focal Drugs = 16.32, Focal Patents = 76.91] = -13.42† (8.88)
[∂ Sales /∂ Exploit Partners | Focal Drugs = 16.32, Focal Patents = 376.86] = 27.15† (18.76)

The two-way interaction conditional analysis indicates that of the five significant regression

coefficients, four are positive. These findings offer support for H5d (C), except for firms with low levels of previous patents and high levels of previous drug applications. Without the aforementioned exception, exploitation partners have a positive effect on sales.

The last set of hypotheses deals with four interaction variables—upstream horizontal network, downstream horizontal network, upstream vertical network, and downstream vertical network. The upstream horizontal network measure was generated by multiplying the propensity of a focal firm's patenting rates with the exploration network measure from a previous set of hypotheses. The downstream horizontal network measure is also a product of the propensity of a focal firm's drug applications and the exploitation network measure from a previous set of hypotheses. Further, the upstream and downstream vertical networks are a product of the propensity of a focal firm's patenting rates and its exploitation network measure and a product of the propensity of a focal firm's prior drug applications and its exploration network measure, respectively.

In the upstream and downstream horizontal networks effects on patents (Model 6, Table 6.6a), there is no statistical support for H6a (i) and b (i) ($B = 1.05e\text{-}08$; $p > 0.911$ and $B = .0002$; $p > 0.347$). Likewise, the upstream and downstream horizontal networks contribute non-significant results to the number of drug applications (Model 6, Table 6.6b) ($B = 2.08e\text{-}07$; $p > 0.303$ and $B = .0005$; $p > 0.138$). Therefore, the study does not include these network variables in the final model of patents (Table 6.6a) and in the marketed drug applications model (Table 6.6b).

With regard to the revenue model (Table 6.6c), the study tested for the improvement of model fit and found that the inclusions of upstream and downstream horizontal network variables on the revenue model do not improve the overall R-squared at all. These findings raise concerns of multicollinearity in the variables and cautiously flag the interpretation of the results. With regard

to the coefficients, however, the effects of upstream and downstream horizontal networks on revenue are negative and significant (B = -.0014 and -1.7076; $p < .001$, respectively) (Model 6, Table 6.6c). The former finding supports H6c (c), whereas the latter finding rejects H6d (c).

As for the tests to understand the impact of upstream and downstream vertical networks on patents, only the downstream vertical network yields a negative and significant coefficient in Model 7, Table 6.6a (B = -8.40e-06; $p < .01$). This result supports H6g (i), predicting a negative relationship of the downstream vertical network on invention performance. Due to the non-significant finding for the effect of upstream vertical networks on patents (Model 6, Table 6.6a), H6e (i) was rejected. The study tested for the improvement of model fit after adding a downstream vertical network. The results suggest that the interaction variable improves the model fit (Δ Log-Likelihood = 9.70; $p = 0.0018$).

With regard to the model of marketed drug applications (Table 6.6b), only the downstream vertical network positively influences the number of marketed drug applications in Model 7, Table 6.6b (B = 7.14e-06; $p < .05$). This finding supports H6h (c). Adding the downstream vertical network variable also improves the model fit (Δ Log-Likelihood = 2; $p < 0.05$). For the focal firm's revenue, the coefficients of the upstream and downstream vertical networks in Table 6.6c are both positive and significant in Model 7, Table 6.6c (B = .1353 and .0243; $p <.01$ and .001). To test for the improvement of model fit after the inclusions of each interaction variable for the revenue model, hierachical analyses are used. After omitting each variable from Model 7 (Table 6.6c), the overall R-squared does not reduce. These findings raise concerns of multicollinearity in the variables and cautiously flag the interpretation of the results. However, the significant coefficients indicate that H6f (c) and H6h (c) are supported.

The following example illustrates the supplementary moderating effect of downstream vertical networks on the number of marketed drug applications. Adding one standard deviation of the partners' patents, a focal firm's multiplier of the number of marketed drug applications—as generated by its own patents—increases significantly. Suppose a focal firm has three biotechnological drugs (at the mean level), generated in the past ten years. The firm deals with the exploration alliances that possess 107 patents altogether (the mean level). For this firm, the multiplier of marketed drug applications is 1.001 [= exp (-.0003*(3) + 7.14-e06*(3)*(107))]. For the other firm, which shares everything in common with the previous firm, the number of partners' patents is greater by one standard deviation. The multiplier of marketed drug applications is increased to 1.012 [=exp (-.0003*(3) + 7.14-e06 *(3)*(107+478))].

As for the last hypothesis, which predicted that most predictors should have a positive or negative effect on the dependent variables, the findings are mixed. Table 6.7 summarizes effects of the different independent variables for invention and commercialization, with 24 of 39 effects shown as statistically significant. Of the 24 significant effects, 6 were not in the hypothesized direction. Therefore, based on the limited significant findings, only six predictors are potential candidates for identification as to whether the last hypothesis is supported or not.

However, this study will not include the two significant interaction variables—direct*indirect ties and downstream vertical networks in determining the trade-off position between invention and commercialization. Although the coefficients of interaction variables could suggest positive or negative directions, the variables do not influence the dependent variables directly. Specifically, the interaction variables work through the main predictors, displaying substitutional or supplementary effects on the dependent variables. Therefore, the final five main predictors are used for testing Hypothesis 7. First, in regard t o the impact of the number of direct partners

on patents, marketed drug applications and revenues, the directions of the coefficients of direct partners are opposite and significant between invention and commercialization activities. Therefore, the number of direct ties is the first predictor that supports H7.

Table 6.7 Predicted Directions and Findings for Hypothesis 7

Predictors (Independent Variables)	Predicted Invention	Predicted Commercialization	Patenting Rates	Marketed Drug Apps	Revenues	Tests for H 7
Direct Ties	+	+	+	(-)	(-)	**Yes**
Indirect Ties	+	+	N/S	+	N/S	N/S
Direct*Indirect Ties	-	+	-	N/S	(-)	Excluded
Structural Holes (Density)	+	-	+	-	-	**Yes**
Structural Holes (Brokerage)	-	+	-	N/S	+	**Yes**
Strength of Ties	+	-	(-)	N/S	(+)	**Yes**
Prominence of Ties	-	+	N/S	+	(-)	N/S
Exploration Ties	+	-	N/S	-	N/S	N/S
Exploitation Ties	-	+	-	N/S	N/S	N/S
Upstream Horizontal	+	-	N/S	N/S	-	N/S
Downstream Horizontal	-	+	N/S	N/S	-	N/S
Upstream Vertical	-	+	N/S	N/S	+	N/S
Downstream Vertical	-	+	-	+	+	Excluded

1. The bold predictors provide results that support H7.
2. The signs in the parentheses indicate significant findings that are not consistent with the hypotheses.
3. N/S is a Non-significant finding; only results that significant at $p < .05$ are included.

Second, it is clear that the two measures of structural holes—density and brokerage—suggest a trade-off position between invention and commercialization outcome. Therefore, these measures are the second and third predictors that support H7. Third, although the significant findings in terms of strength of ties are inconsistent with the hypotheses, the findings suggest opposite directions between invention and commercialization outcomes. Thus, these findings indicate that strength of ties is the fourth predictor supporting the argument of H7. Therefore, all four significant main predictors in the study suggest that interfirm networks could provide a trade-off position between invention and commercialization outcomes.

CHAPTER 7: DISCUSSION AND CONCLUSION

Although prior studies argued that the interfirm network contributes toward innovation (Ahuja, 2000a; Baum et al., 2000), these studies did not recognize or take into account the critical fact that the innovation process is a lengthy and complex process, comprising, at least, invention and commercialization activities. Greve (2003) claimed that innovation research will be enriched if more studies take into account the difference between developing (inventing) and launching (commercializing) innovation. He argued that firms could generate inventions, the vast majority of which are little worth; however, some inventions are extremely important and valuable. Therefore, if scholars pay attention to only one activity at a time, knowledge regarding the innovation process as a whole will never be complete or moving forward.

Schumpter (1939) posited that the making of the invention and the carrying out of the corresponding commercialization comprise two entirely different processes, economically and sociologically. This study confirms that invention and commercialization react differently upon the same set of interfirm variables. In an examination of these interfirm variables, the study frames why some firms generate a substantial numbers of patents that are worth little to the firms, and why other firms generate only a few patents, yet these patents are successfully commercial.

Consistent with prior studies, the study indicates that a focal firm's direct ties and a low level of structural holes contribute to its invention performance (Ahuja, 2000a). Additionally, the prominence of a focal firm's partners improves the number of new products, together with product marketability status (Stuart, 2000). In addition to these consistent results, the study examines several other relationships between interfirm variables and product innovation outcomes. Table 7.1 illustrates the potential contributions of this study in the areas that have not

yet been empirically examined (the shade areas in the first three columns). The shade areas in the last three columns indicate the currently empirical findings that potentially contribute to the product innovation literature.

Table 7.1 Empirical Contributions from This Study

Predictors Interfirm Network Variables	Patents	Marketed Drug Apps	Revenues	Patents	Marketed Drug Apps	Revenues
Direct Ties	+	+	+	+	(-)	(-)
Indirect Ties	+	+	+	N/S	+	N/S
Direct*Indirect Ties	-	+	+	-	N/S	(-)
Structural Holes (Density)	+	-	-	+	-	-
Structural Holes (Brokerage)	-	+	+	-	N/S	+
Strength of Ties	+	-	-	(-)	N/S	(+)
Prominence of Ties	-	+	+	N/S	+	(-)
Exploration Ties	+	-	-	N/S	-	N/S
Exploitation Ties	-	+	+	-	N/S	N/S
Upstream Horizontal	+	-	-	N/S	N/S	-
Downstream Horizontal	-	+	+	N/S	N/S	-
Upstream Vertical	-	+	+	N/S	N/S	+
Downstream Vertical	-	+	+	-	+	+
	Potential Contributions & Hypotheses			Empirical Contributions from this Study		

N/S is Non-Significant.
( ) is Opposite Direction of the Hypothesis.
Density represents a low level of structural holes; brokerage represents a high level of structural holes.

Although 4 out of 16 findings in the study are opposite directions, compared to the hypothesized directions, these findings provide important clues for future research to examine the effects of direct, indirect ties, and strength of ties upon the product innovation performance. With regard to 12 significant findings that are consistent with my hypotheses, I found that exploitation partners and downstream vertical networks are associated with reduced invention performance. Indirect partners and structural holes are associated with commercialization performance. In addition, horizontal networks are associated with detrimental commercialization, whereas vertical networks are associated with beneficial commercialization.

The study extends the concept of commercialization by probing the two commercialization performances—the number of marketed drug applications and revenues. Interestingly, I found that the number of marketed drug applications may not be the only indicator to measure

commercialization performance. Several firms such as ISIS Pharmaceuticals and Amgen during 1986 and 2003 could generate substantial revenues, but these firms rarely possessed the FDA's marketed drug applications. The fact that these firms engaged in upstream positions of the drug development process, licensed their technologies to the downstream partners, and significantly enhanced their revenues, indicates that commercialization is a complex and lengthy activity. Accordingly, at least two measurements are proven to capture commercialization performance.

The integrated framework of invention and commercialization actitvities extends the understanding of these several dimensions of the interfirm network beyond invention or commercialization outcomes. Importantly, scholars or practitioners may not recognize that these dimensions could either facilitate or harm invention and commercialization activities. Using the integrated framework to understand the impact of interfirm networks on product innovation process provides fuller perspectives for both strategic management scholars and practitioners by enhancing the performance of the organization.

7.1 Revisited Significant Predictors

7.1.1 Direct and Indirect Ties

This study offers results that confirm the importance of direct and indirect ties toward invention outcomes (Ahuja, 2000a). However, while Ahuja (2000a) found that both direct and indirect ties contribute to invention outcomes, my study found no significant contribution of indirect ties to invention outcomes. As mentioned earlier, this study's count of the number of indirect ties reflects only the limited number of firms listed in the BioScan directory. Accordingly, the study showed less than the actual number of indirect ties of focal firms. Therefore the limited information may undervalue the effects of indirect ties on invention outcomes.

Despite the indirect ties being a non-significant factor, the interaction effect of direct and indirect ties indicates the involvement of indirect ties as a critical moderator. Ahuja wrote:

> In many networks, indirect ties simultaneously play two different roles vis-à-vis the focal actor. On the one hand, they are resources that extend the actor's reach in the network and improve his or her access to information. On the other hand, in many networks, such indirect ties are also competitors of the focal actor in terms of using such information (2000: 449).

The higher number of indirect ties implies a higher number of potential competitors who share the limited resources of focal firms' direct partners. Once the limited resources necessary to generate invention activities are shared and split among the focal firms and their indirect ties, the focal firms' capability to generate invention is reduced. Accordingly, the negative interaction effect of direct and indirect ties on patenting rates is consistent with Ahuja (2000a).

Interestingly, direct ties contribute negatively to both revenue and the number of marketed drug applications. Further, the interaction effect between the direct and indirect ties suggests a substitutional influence upon the revenue. The negative effects of direct ties and the interaction variable on commercialization performance are unexpected. Previously, the study assumed that a focal firm regards both direct and indirect ties as opinion leaders that could effectively and quickly build the critical mass for its commercialization (Rogers, 1995). However, the findings show that there is little reason that direct ties would assist the focal firm's commercialization activities without reducing the focal firm's revenue and opportunities to generate the marketed drug applications.

The positive effects of indirect ties upon the focal firm's marketed drug applications support the study's hypothesis. Because a firm's indirect ties can serve as a channel for knowledge spill-

over, Ahuja (2000a) argued that indirect ties contribute positively and significantly to the focal firm's abilities to introduce and to maintain the marketable status of new products in the market.

7.1.2 Structural Holes (Density and Brokerage)

According to several prior studies, the impact of structural holes upon organizational outcomes is proven and wide-ranging. Burt (1997) specified information and control advantages as two important benefits of structural holes, whereas Ahuja (2000a) found that high magnitudes of disconnections among partners (a high level of structural holes) would decrease the number of patents in firms operating in the chemical industry. Using the institutional perspectives, Hargadon and Sutton (1997) argued that a high level of structural holes allows the product development firm—called IDEO—to be successful in terms of meeting and satisfying its diverse customers' demands.

The results of my study confirm the findings of Hargadon and Sutton (1997) and Ahuja (2000a), regarding the empirical relationships between the two measures of structural holes (e.g., the ego network's density and brokerage) and invention and commercialization. It appears that high density and low brokerage positions offer the benefits by increasing trust, by developing and improving collaboration routines, and by reducing opportunism. In the context of invention outcomes, these benefits outweigh the disadvantages of lacking any new information provided by low density and high brokerage positions in a firm's network. The arguments are supported by Walker, Kogut and Shan's (1997) suggestion that the formation of network structure in the biotechnology industry empirically aims for the long-term benefits of interfirm collaboration over the short-term benefits of brokering opportunities. Apparently, the focal firm's brokerage opportunities and low density network reduce the special relationships and trust that are used to generate increased patents within alliances.

With regard to the impact of the density measure and the brokerage measure on commercialization outcomes, the study finds that a high density in the focal firm's network decreases the number of marketed drug applications. As Ahuja (2000a) averred, the impact of different network attributes and positions may only be understood relative to a particular context. For the number of marketed drug applications, a high density-alliance network reduces a focal firm's capability to obtain the FDA's approvals and to maintain the marketable status of its drug applications on the market. The redundant information among partners does not permit the focal firm to discover unique marketing opportunities and attain success in commercialization activities within a dense network.

According to the findings, a focal firm should rely on a low density network position to generate marketed drug applications. By collaborating with isolated partners (and thus building a low density network), the focal firm receives non-redundant information about its business opportunities to enhance its capabilities to meet demands of customers and in so doing, maintain the marketable status of its products. This argument is consistent with Hargadon and Sutton's (1997) suggestions that low density levels among partners help a focal firm to effectively offer the products and to understand the unique demands of the consumers in a greater number of market segments (Hargadon et al., 1997).

Further, a high brokerage level, coupled with a low density in a focal firm's network, proved to be useful to the focal firm's revenue. This finding is consistent with a recent study, suggesting that brokers between disconnected partners normally benefit from their positions, yet the brokerage benefits primarily rely on the number of resourceful partners in the network (Bae & Gargiulo, 2004). At the stage when generating revenue is a primary objective, the bridge positions are significantly beneficial to a focal firm. Due to the costs associated with securing

cooperative ties with resourceful partners (i.e., isolated partners with potential technologies) in the biopharmaceutical industry, focal firms, acting to maximize revenues, rely on as many bridges as firms can possibly establish between the small number of resourceful partners and the large number of other downstream partners.

7.1.3 Strength of Ties

Theoretically, a strong tie is better than a weak tie in conveying technical knowledge between organizational units (Hansen, 1999). Among biopharmaceutical firms, Silverman and Buam (2002) found that successful biotech university scientists, whose research efforts have a tremendous impact on biotechnology firms' success, rarely interacted or associated with more than one firm at a time. Shan et al., (1994) also found that 85% of the biopharmaceutical alliances from the early 1970s were maintained through 1989. Apparently, firms in the biopharmaceutical industry established strong relationships with their partners. Using the average length of interfirm network, the study hypothesized that a focal firm's strong-tie network should contribute to its invention performance and that a focal firm's weak-tie network should correspond to its commercialization performance.

Unfortunately, the empirical findings of the study suggest that the average relationship length between a focal firm and its direct partners not only contributes negatively to the invention outcome, but it also significantly improves commercialization as measured by increased revenue. These unexpected findings suggest that the measurements of tie-strength may be limited or flawed. Accordingly, this study will speculate upon measurements of these variables and their impacts upon invention and commercialization.

Using a key insight from organizational learning literature, the study regards focal firms that engage in multiple projects with many new partners in a short time frame as exploration firms;

additionally, the focal firms that maintain and continuously exploit relationships with existing partners are recognized as exploitation firms. Exploitation, or the ongoing use of a firm's knowledge base (existing network), helps an organization to refine current routines in marketing, logistics, and sales. Exploration, in contrast, enables a focal firm to renew and generate knowledge base (potential network), but in this case, the process is costly (March, 1991; Vermeulen & Barkema, 2001).

By maintaining and exploiting its existing partners, a focal firm simultaneously consumes and burns knowledge resources in order to win in marketing competition. This process generates revenues, yet it reduces the chance to accumulate and establish a new knowledge base—the number of patents. In contrast, by searching and collaborating with new partners, a focal firm is exploring and attempting to establish new knowledge and relevant technologies. Thus, this firm learns substantially from its alliances in terms of technologies and increases its patenting rates. However, because learning is always costly, the particular firm sacrifices the opportunity to generate future revenue.

7.1.4 The Prominence of Partners

While the effect of prominent partners upon a focal firm's patenting capability is insignificant, the prominence of partners delivers significant effects in influencing the focal firm's number of marketed drug applications and revenues. In this study, the prominence of the focal firm's partners was derived by the counts of direct partners' news articles that appeared in LexisNexis in a ten-year period prior to the observation. Such well-known and reputable firms as Merck, Pfizer, Johnson and Johnson, and Abbott Laboratories appeared in more than 1,000 news articles, whereas relatively new and less well-known firms such as Affymax and Aphton, in the early years, may have appeared in only 5 to 10 news articles (or none). Therefore, partners

that appeared frequently in news articles are prominent, while others that rarely appeared in news articles are less prominent.

Collaborating with high-status and reputable alliances gives the focal firm legitimate endorsement (Stuart, 2000), building additional confidence in drug application processes. Additionally, experiences gained from collaborating with prominent partners improve capabilities in FDA drug approval processes. Accordingly, the prominent network positively contributes to a number of marketed drug applications granted by the FDA.

With regard to revenue, a focal firm with a network of prominent partners performs relatively poorly. This finding is unexpected and inconsistent with Stuart's (2000) finding that high-status partners help lower-status partners to attract more customers and to improve revenue growth. It is suspected that because focal firms in the study are publicly traded companies, the benefits and outcomes gained from working with the high-status partners are dissimilar. Additionally, while the study used the partners' number of news articles, Stuart (2000) used several measurements (i.e., sales of partners, age of partners, and innovativeness of partners) to assess the status of partners. Obviously, the dimension of partners' prominence captured in this study differs from Stuart's (2000) alliance status. Accordingly, the partners' prominence in the study conveys different meanings and thus different empirical results.

7.1.5 Exploration and Exploitation Partners

This study used two measurements that directly captured the impact of the focal firms' exploration and exploitation partners on invention and commercialization performances. The exploration and exploitation partners are necessary to focal firms, because most focal firms simultaneously engage in differing stages of several projects involving exploration and exploitation activities.

Rothaermel and Deed (2004) found that exploration partners contribute to invention activities, while exploitation partners contribute to commercialization activities. However, the authors found no relationship between exploitation partners and invention activities or a relationship between exploration partners and commercialization activities. This study extends Rothaermel and Deed's (2004) framework to examine the roles of exploitation and exploration partners in the product development process. As expected, the study detects a negative influence on patenting rates of a focal firm's exploitation network. Additionally, a focal firm with a prominent exploration network is negatively associated with the number of marketed drug applications.

If a focal firm collaborates with exploration partners that seek to generate the patents, the focal firm gains no benefit for its exploitation activities. Instead, the focal firm may pull resources to deal with its partners' exploration activities. Should the focal firm rearrange internal resources to deal with the new knowledge, its capability to generate more marketed drug applications is weakened. Similarly, if a focal firm collaborates with exploitation partners, it gains nothing from the collaboration to facilitate exploration activities. Instead, the focal firm refocuses its attention to exploitation activities. Therefore, the exploitation partners negatively influence a focal firm's invention performance. Since the contributions of exploration and exploitation partners depend largely on the position of a focal firm in the drug development process, this study discusses their contributions in detail in the next sections (the horizontal and vertical networks).

7.1.6 Upstream and Downstream Horizontal Networks

Results indicate that upstream and downstream horizontal networks contribute immaterially to a focal firm's patents and to marketed drug applications. However, the upstream and

downstream horizontal networks significantly decrease the revenue of the focal firm. Basically, the horizontal networks have two main effects. For the upstream horizontal network, the main effect relates to a focal firm and its partners' propensities to generate patents. For the downstream horizontal network, the main effect pivots upon a focal firm and its partners' propensities to generate drugs with FDA approved. The negative interaction variables for the two networks represent moderating effects.

Kotabe and Swan (1995) suggested that downstream horizontal alliances commonly focus on long-term product development. Due to U.S. anti-trust law, downstream horizontal alliances that seek concentrated commercial activities are prohibited. Therefore, the establishment of a downstream horizontal network in the U.S. is likely to involve R&D or exploration activities (Kotabe et al., 1995). However, exactly because the downstream horizontal alliances involve working closely with direct competitors, these collaborations represent the least successful form (Silverman et al., 2002). Accordingly, a downstream horizontal network reduces the revenue of a focal firm.

With regard to an upstream horizontal network, the contribution of a focal firm's patents toward its focal firm's revenue is moderated by an additional exploration partner. In regard to the two-way interaction conditional analysis, results confirm that exploration partners contribute positively to the focal firms' revenues only when the focal firm's propensity to generate patents is at the lowest or moderate levels (i.e., at zero or mean). By collaborating with exploration partners, the focal firm with an already high propensity to generate patents receives redundant knowledge and overlapped capabilities. Should the upstream focal firm require patents possessed by exploration partners to supplement its internal capability to invent, the upstream

horizontal network suggests complementary effects between the external capability and the internal capability on a focal firm's revenue.

7.1.7 Upstream and Downstream Vertical Networks

As expected, empirical findings indicate that having an upstream vertical network will have a favorable effect on the focal firm's revenue. In generating revenues, the upstream focal firm exploits its patents through downstream alliances, suggesting commercialization benefits. This result corresponds to Silverman and Baum's (2002) finding that upstream focal firms tend to survive the competition because the firms receive a significant infusion of capital resources from downstream alliances. Providing that an upstream focal firm can generate its technologies (invention), the upstream vertical network is in a favorable position to generate revenue.

Next, the downstream vertical network represents alliances that decrease the number of a focal firm's patents, yet will simultaneously facilitate the number of marketed drug applications and help to increase revenue. In this particular network, a focal firm represents an exploitation entity, collaborating with exploration alliances. Findings indicate that partners' patents do not help a downstream focal firm to improve its capabilities in generating patents. Liebeskind and his associates (1996) suggested that the downstream focal firm lacks a university-like environment to encourage its patenting rates. As a result, despite intensive collaborations with exploration partners, the firm finds it difficult to become successful in generating novel technologies.

Further, with regard to the commercialization outcomes, a downstream focal firm acquires disruptive technologies from its upstream alliances (i.e., their patents), transforming the technologies into marketed drug applications and revenues. Interestingly, the upstream and downstream vertical networks may increase the focal firms' revenues by means of

complementary effects between upstream and downstream firms in the vertical collaborations. Yet, in terms of patenting rates and the number of marketed drug applications, the complementary effects of the vertical networks remain statistically questionable.

7.2 Internal and External Validity

In this section, the study discusses internal and external validy. Internal validity addresses the "true" causes of the outcomes observed in the study. Strong internal validity means that not only does the study presents reliable measures of independent and dependent variables, but also a strong justification causally links the independent variables to the dependent variables (Shadish, Cook, & Campbell, 2002). At the same time, this study utilizes internal validity to rule out extraneous variables for the dependent variables. Thus, internal validity refers to the clear and relevant assignment of causes to effects. External validity addresses the ability to generalize the study to other organizations and other situations. To have strong external validity, a sample of subjects or respondents, drawn by using "chance methods" presents a clearly defined population. In this study, the subjects represent publicly traded biopharmaceutical firms in the U.S. in the period between 1986 and 2003. When a strong external validity is present, one may generalize the empirical findings to other settings and situations with confidence.

To support the evidence of internal validity (i.e., A causes B), the researcher must show the following three aspects in their studies: 1) “A” precedes “B”, 2) “A” is co-related with “B”, and 3) there is no plausible alternative explanation of “B”. The characteristics of my dataset—a cross-sectional time-series analysis or longitudinal analysis with panel data—strengthen the first aspect of the internal validity. The statistical results of the three models also suggest that several independents measured at prior periods are significantly correlated with the dependent variables. These results provide the second aspect of the internal validity. In my study, the only threat of

internal validity falls primarily in the third aspect: the plausible alternative explanation. In other words, there might be other independent variables that determine the invention and commercialization outcomes of the focal firms during the observation period. Shadish et al., (2002) termed these variables, or threats, as "history."

In laboratory research, history may be controlled by separating the respondents from outside events, but in the field research, it is difficult to separate outside events from the observations. In this dissertation, the 262 focal firms are publicly traded companies from the biopharmaceutical industry. Consequently, encountering the same external environment during the same period reduces the threats of history. To further minimize the threats to internal validity, the study controls for the effects of year and industry differences. Additionally, numerous organizational characteristics including a) size, b) age, c) year as publicly traded status, e) diversification level, R&D expenditure, f) profitability, and d) propensity to invent and to commercialize, are controlled to make sure that the contribution of most independent variables is isolated. Given the attempts to control for the threats to internal validity, the study will address one potential threat—the potential reversed causality—in the limitation section.

External validity concerns inferences about the extent to which a causal relationship holds over variations in persons, settings, treatments, and outcomes. Several researchers argue that most external validity questions involve persons, settings, treatments, and outcomes not studied in the experiment (Shadish et al., 2002). In this study, the drug development process in the biopharmaceutical industry is a unique testing ground for the study of innovation process. The exclusive characteristics of the drug development process increase the threats to external validity. Because the setting is unique, it is questionable that the findings in this particular setting are applicable to different settings or industries.

To some extent, however, the results may be externalized. In general, the setting of this study comprises those focal firms that determine to explore and exploit interfirm networks to generate invention and commercialization performance. These settings hold true in most industries, especially in the high-tech industries such as the chemical and electronics industries, in which invention and commercialization are critical. The USPTO database provides numerous assignees from almost every industry. These assignees choose to acquire a number of patents, to protect intellectual properties, and to seek for legal protection during exploitation activities. While some firms may decide to keep their inventions within the organizations, treating the inventions as secret sources of competitive advantages most firms turn their inventions in product development processes into successful commercialization, thus generating revenues.

With regard to treatments, multiple dimensions of the interfirm network are prevalent not only in the biopharmaceutical industry, but also in other industries. Accordingly, the multiple dimensions of the interfirm network—direct ties, indirect ties, structural holes, and horizontal and vertical networks—hold true among interfirm collaborations across industries. For instance, in the software industry, established companies such as Microsoft and Google collaborate with many nascent partners for R&D activities. From the perspectives of these nascent partners, collaborating with downstream partners allows an exploitation of disruptive technologies. Therefore, the multiple dimensions of the interfirm network in the biopharmaceutical industry may be compared to others in different industries.

With regard to outcomes, the dynamics of the interfirm network result primarily in invention and/or commercialization for all industries, with outcomes not limited to the biopharmaceutical industry. The measurements of invention and commercialization performance across industries, however, may differ due to the characteristics of the market-cycle. For the fast-cycle industries,

firms may ignore a lengthy process of patenting because the primary concern is rapidly developing technology. These firms collaborate to speed the innovation process (i.e., from the beginning of invention to the end of commercialization). In this particular market-cycle, patenting rates may not reflect invention performance. However, the number of marketed products and revenues of the focal firms in this market-cycle should reflect the commercialization performance.

In slow-cycle industries (i.e., industries that rely heavily on the legal protection of their inventions), the invention performance of the collaborations may be measured by the number of patents generated each year. The biopharmaceutical industry may be deemed a slow-cycle market, due to a heavy reliance on the legal protection process. Therefore, firms operating in the slow-cycle industries are comparable to the biopharmaceutical firms in both invention and commercialization outcomes. Given understanding and some adjustments due to industry differences, comprehension of how multiple dimensions of interfirm network influence product innovation may prove useful and applicable across different settings, treatments, and outcomes.

7.3 Managerial Implications

The theoretical frameworks—organizational learning and institutional perspectives—suggest that six dimensions of the interfirm network play important roles in the product innovation process. While firms generally rely on strategic alliances to generate invention and commercialization, some are not as successful as others. Interestingly, some alliances may not only delay, but concurrently also harm the patenting capability, the marketed drug activities, and the revenues of the firms. The findings of this study draw managers' attention to several paradoxical findings in the multiple dimensions of an interfirm network on product innovation outcomes.

The combined invention and commercialization perspective in this study offers a realistic framework for managers and managerial actions. As Rothaermel and Deed (2004) averred that realistically, most firms engage in both exploration and exploitation activities simultaneously, because the firms manage several projects that seek to generate invention and commercialization. To achieve exploration activities, firms associate with potential dimensions of the interfirm network to generate invention performance. Unfortunately, these particular dimensions may not be the best engine to entrust commercialization activities. The scenario holds true for those firms associating with dimensions of interfirm network for the purpose of promoting commercialization, yet the dimensions may not be the optimal choice for their inventions. With this integrated framework, management may recognize a trade-off situation in the interfirm network toward generating either invention or commercialization. Therefore, an integrated framework facilitates management to maximize the value of product innovation through leverage of the interfirm network.

Therefore, the purpose of this section is to provide some critical information of the strategic alliances. Prior research and the current study underscored that the benefits of interfirm collaborations depend largely on the objectives of the focal firm (Ahuja, 2000a). Therefore, it becomes critical for a firm to clarify its objective before selecting its partners, engaging in appropriate collaborations, and building the effective interfirm network. According to the perspective of scholars in organizational learning, firms that are involved in both exploration and exploitation activities must importantly strike a balance between exploration and exploitation (March, 1991; Vermeulen et al., 2001). Further, a firm must be precise about how, when and what it means to achieve from interfirm network. In so doing, the firm should understand not

only its capabilities in the drug development process, but also the responding capabilities of partners in the collaborative network.

In most industries, a firm will examine the patents and/or the number of innovative products generated over a specific period to understand its propensity toward invention. Additionally, the firm may count the number of successful products in the market and/or the amount of revenue generated over a specific period to understand its propensity toward commercialization. Deploying similar analyses to understand partners' propensities is the next important step. By incorporating the information of the focal firms and that of their partners, managements understand the focal firms' postures and the types of the collaborative networks (i.e., horizontal or vertical networks).

When a firm wants to achieve exploration performance, it may want to select the interfirm network that promotes its knowledge base and invention activities. The firm may increase its direct partners and decrease its indirect partners (i.e., by collaborating with isolated direct partners) to generate invention. Similarly, because low levels of structural holes (e.g., a high density network and low brokerage positions) contribute to invention outcomes, a dense network of direct partners would be desired to generate invention. Finally, the downstream firm may choose never to rely on its upstream partners in generating its inventions (e.g., patents). It is shown in this study that the upstream vertical network is ineffective in this regard.

When a firm makes a decision to establish its presence with new products, it may follow the findings from the marketed drug applications model. The number of marketed drug applications generally reflects a portfolio of successful inventions available for commercialization. To achieve the successful portfolio of inventions, the focal firm may want to collaborate within a low density network—a high level of structural holes. A sparse network provides non-redundant

information and diverse knowledge, allowing the firm to bridge disparate technologies and to satisfy more customer segments (Hargadon et al., 1997). Next, the focal firm may want to collaborate with prominent partners to obtain and maintain legitimacy and acceptance of its innovative products. Finally, working with upstream partners, the downstream focal firm could bring additional innovative products to the market.

A company that aims to increase its revenue in general, may need to be cautious with the recommendation given above in achieving a portfolio of successful inventions. To generate revenue, the firm can commercialize both proprietary technologies and its portfolio of innovative products in market. The findings suggest that the firm with a low density network and/or a high brokerage network generates more revenue. Further, the firm should establish its vertical networks. It is proven that the complementary effects obtained from the vertical networks are a key implication for the focal firm to maximize revenues.

7.4 Research Implications

This study assessed the multiple impacts of interfirm networks on the patents, marketed drug applications, and revenues of each focal firm. However, the study did not completely capture the entire outcomes of product innovation. Rothaermel and Deed (2004) found the series of casual relationships among the following constructs: exploration alliances, product in development, exploitation alliances, and product on market. My study added to their findings by examining the set of interfirm predictors that could simultaneously affect invention and commercialization activities. Future research may want to integrate the significant relationships between independent and dependent variables from previous studies to better capture the working concepts of the product innovation process.

Specifically, the number of marketed drug applications may be used to capture another aspect of a focal firm's commercialization performance; this measurement, however, represents only one of several performances in the commercialization activities. Future research may want to examine other commercialization activities, such as the licensing fees, service fees for clinical trials, and several other incomes from marketing and sales. These activities do not link directly to the number of successful drug applications available on market, but they certainly determine the amount of revenues in commercialization.

Like revenue, the number of patents represents only one of several invention outcomes. In the biopharmaceutical industry, the firms generally acquire patents as soon as possible. At a later date, the focal firms normally share proprietary technologies from these patents with downstream partners in the drug development process. In other industries, companies may want to keep new technologies or inventions internal as trade secrets. If this is the case, researchers must propose a new scheme of measurements that effectively reflects the focal firms' invention performance and propensity to invent.

7.5 Limitations

This study encountered some methodological limitations. The unique characteristics of the three dependent variables required three analytical models to accommodate the statistical specifications and estimations of the results. Prior studies used a traditional analytical model—the panel Poisson regression—to specify and estimate the count, non-negative integer, dependent variables (Ahuja, 2000a; Ahuja et al., 2001; Baum et al., 2000). Because the characteristics of the dataset challenged Poisson's assumptions, this study used differing statistical methods to correct the violations and that were more suitable with the variables. To replace the panel

Poisson regression model, the study instead used the panel negative binomial regression model and the zero-inflated negative binomial regression model to obtain results.

While it is common in social science research to find that the data is over-dispersed (Min et al., 2005), scholars should examine carefully the sources of this over-dispersion. One important reason for over-dispersion is the fact that measurements contain excessive zero values in the observations (Long, 1997). In my study, both patents and marketed drug applications have high levels of zero value in their observations. However, because the study justified the high level of zero value in the patents, I did not use the zero-inflated models to control for the excessive zero.

In the case of marketed drug applications, the zero value of the applications may be inflated, because the Drug@FDA database does not provide all information about drugs. Additionally, several firms might obtain their drug applications approved and listed elsewhere (e.g., FDA's Center for Biologics Evaluation and Research), instead of the Drug@FDA database, and further, some firms might sell drug products internationally bypassing drug applications with the FDA. As a result, the excessive zero-value observations would not reflect the meaning of the variable occurred. Additionally, there was no detection of dissolution with strategic alliances during a seven-year accumulative period of direct and indirect ties, providing another reason for increasing excessive zero-value observations in the study.

The zero-inflated negative binomial regression accounted for excessive zeros in the marketed drug applications model. To account for excessive zeros, the two control variables—a focal firm's propensity to invent and a focal firm's propensity to commercialize—were used to identify the excessive zero observations. While the two control variables could control for potential factors that generate zero-inflated symptoms, the variables could not control for other sources of excessive zeros. For instance, the two variables could not control for the zero-value

observations that occurred due to unidentifiable dissolutions. Future research may discover a better methodology for zero-inflated observations in the marketed drug applications.

The next limitation is the robustness of the models. The study could only use the fixed-effects model to estimate the focal firms' revenue. A comparison between the results of the random-effects and fixed-effects models in the focal firm's revenue model suggests quite comparable results. Unfortunately, in the panel negative binomial regression model—patenting capability—the study could not achieve the convergence of the results in the fixed-effects model. After controlling for the number of iterations at 100, the results of the conditional fixed-effects negative binomial regression revealed that most coefficients, except for upstream horizontal network, downstream vertical network, exploitation network, and the alliances' prominence, were significant. These rudimentary results are inconsistent with those results from the random-effects model. Because the results in the random-effects model are obtained completely with convergence and the results of the fixed-effects model are obviously incomplete and lack reliability, this study will not compare the results from the random-effects models with the rudimentary results of the fixed-effects model.

Like the panel negative binomial model, the zero-inflated negative binomial regression model does not have the fixed effect command to test for the fixed-effects results. Although generated dummy codes for all focal firms in the dataset are tested for the fixed-effects of the zero-inflated model, this study could not achieve the convergence of the results. Due to the limitation in the fixed-effects results, future research may attempt to find out other statistical approaches to achieve the complete robustness tests of the findings.

The last limitation includes the potential reversed causality. Although the study used the longitudinal and panel data analytical technique to account for causality between independent

and dependent variables, the potential reversed causality remains questionable. Specifically, both control variables—the propensities to invent and to commercialize—are generated by the number of patents and the number of FDA approved drugs that acquired in the ten-year period prior to the observation. While the two control variables control for some unobservable heterogeneity that influences the number of future patents and drugs, the prior performances of patents and drugs might influence the effects of other independent variables to influence the dependent variables.

For instance, Company "X" produced a high number of patents in the past decade (from 1986 to 1995). The number of prior patents attracted other partners to collaborate with X in invention activities. The attractiveness caused by the number of its prior patents also increased the number of direct and indirect ties, as well as the main independent variables of invention and commercialization performances. Since the prior patents simultaneously influenced independent and dependent variables (in 1995), the sources of the patenting rate and the number of marketed drug applications of X in 1996 remain unclear.

Although the study attempted to control for organizational specific effects such as a focal firm's profitability, R&D expense, and years as a publicly traded organization, these variables may correlate with other independent variables (i.e., dimensions of the interfirm network) and produce noises for the study. Therefore, the network structures that the study measured are not the sole cause of invention and commercialization success. Further, the previous success may enable certain network structures, as well as determine the invention and commercialization performance.

7.6 Conclusion

Success in both invention and commercialization creates product innovation. Several dimensions of the interfirm network generate invention outcomes, yet these dimensions may also carry a negative impact to commercialization outcomes. Likewise, some dimensions of the interfirm network are appropriate for exploiation activities; however, the dimensions simultaneously hinder exploration activities. For instance, some focal firms are strengthened by having prominent partners to endorse commercialization in the market, but in a cautionary note, prominent partners are also associated with lower revenues. The integrated framework in this study proffers empirical findings useful to both scholars and practitioners. The framework subsequently motivates a focal firm toward accruing the right allies at the right time and for the right reasons.

In this study, six potential aspects of interfirm networks are tested. The multiple dimensions of the interfirm networks are significantly the critical sources of product innovation, specifically among the public firms in the biopharmaceutical industry. While this study provides insights into an understanding of product innovation, there are missing parts of the lengthy and complex process that remain unsolved. By means of varying contexts, other activities and measurements carry the potential to extend an effective capture of firm invention and commercialization. The question remains as to whether these activities will behave as consistently as the findings of this study. Nevertheless, more expansive investigation into further activities and measurements improve the likelihood of successful product innovation as a warrant and challenge for scholaristic endeavors in the future.

REFERENCES

Ahuja, G. 2000a. Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. ***Administrative Science Quarterly***, 45: 425-455.

Ahuja, G. 2000b. The Duality of Collaboration: Inducements and Opportunities in the Formation of Interfirm Linkages. ***Strategic Management Journal***, 21: 317-343.

Ahuja, G., & Katila, R. 2001. Technological Acquisitions and the Innovation Performance of Acquiring Firms: A Longitudinal Study. ***Strategic Management Journal***, 22: 197-220.

Aiken, L. S., & West, S. G. 1991. ***Multiple regression: Testing and interpreting interactions***. Newbury Park, CA: Sage.

Aldrich, H. 1999. ***Organizations Evolving***. Thousand Oaks, California 91320: SAGE Publications Inc.

Almeida, P., & Phene, A. 2004. Subsidiaries and Knowledge Creation: The Influence of the MNC and Host Country on Innovation. ***Strategic Management Journal***, 25: 847-864.

Anderson, P., & Tushman, M. L. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. ***Administrative Science Quarterly***, 35(4): 604-633.

Argote, L. 1993. Group and Individual Learning Curve: Individual, System, and Environmental Components. ***British Journal of Social Psychology***, 32(1): 31-51.

Arregle, J.-L., Amburgey, T., & Dacin, T. 1997. Event Count Analysis and Strategic Management. In J.-L. Arregle (Ed.), ***Statistical Models for Strategic Management***. Boston: Kluwer Academic Publishers.

Bae, J., & Gargiulo, M. 2004. Partner Substitutability, Alliance Network Structure, and Firm Profitability in the Telecomunication Industry. ***Academy of Management Journal***, 47(6): 843-859.

Barnum, S. R. 2005. ***Biotechnology: An introduction***. Belmont, CA 94002: Thomson Brooks/Cole.

Barrett, A. 2005. Pfizer's Funk, ***Business Week***: 72-82.

Baum, J. A. C., Calabrese, T., & Silverman, B. S. 2000. Don't Go It Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology. ***Strategic Management Journal***, 21: 267-294.

Baum, J. A. C., & Ingram, P. 1998. Survival-Enhancing Learning in the Manhattan Hotel Industry, 1898-1980. ***Management Science***, 44(7): 996-1016.

Baum, J. A. C., & Oliver, C. 1991. Institutional Linkages and Organizational Mortality. ***Administrative Science Quarterly***, 36: 187-218.

Baysinger, B., & Hoskisson, R. E. 1989. Diversification Strategy and R&D Intensity in Multiproduct Firms. ***The Academy of Management Journal***, 32(2): 310-332.

Beckman, C. M., Haunschild, P. R., & Phillips, D. J. 2004. Friends or Strangers? Firm-Specific Uncertainty, Market Uncertainty, and Network Partner Selection. ***Organization Science***, 15(3): 259-275.

Benner, M. J., & Tushman, M. L. 2002. Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries. ***Administrative Science Quarterly***, 47: 676-706.

Bergeron, B., & Chan, P. 2004. ***Biotech Industry: A Global, Economic, and Financing Overview***. Hoboken, NJ: John Wiley & Sons.

Borgatti, S. P., Everett, M. G., & Freeman, L. C. 2002. Ucinet for Windows: Software for Social Network Analysis: Analytic Technologies, 6.105 ed. Harvard, MA.

Burt, R. S. 1992. ***Structural Holes: The Social Structure of Competition***. Cambrigde, MA: Harvard University Press.

Burt, R. S. 1997. The Contingent Value of Social Capital. ***Administrative Science Quarterly***, 42: 339-365.

Burt, R. S. 2000. The Network Structure of Social Capital. ***Research in Organizational Behavior***, 22: 345-423.

Cameron, A. C., & Trivedi, P. K. 1998. ***Regression Analysis of Count Data***. Cambridge: Cambridge University Press.

Carbone, J. 2003. Ethics, Patents and the Sustainability of the Biotech Business Model. ***International Review of Law Computers & Technology***, 17(2): 203-218.

Certo, S. T., Covin, J. G., & Dalton, D. R. 2001. Wealth and the Effects of Founder Management among IPO-stage New Ventures. ***Strategic Management Journal***, 22: 641-658.

Christensen, C. M., & Bower, J. L. 1996. Customer Power, Strategic Investment, and The Failure of Leading Firms. ***Strategic Management Journal***, 17: 197-218.

Cohen, W. M., & Levin, R. C. 1989. ***Empirical Studies of Innovation and Market Structure***. New York: North-Holland.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. ***Administrative Science Quarterly***, 35: 128-152.

Coleman, J. S. 1988. Social Cpaital in the Creation of Human Capital. ***American Journal of Sociology***, 94(Supplement): S95-S120.

Cool, K. O., Dierickx, I., & Szulanski, G. 1997. Diffusion of Innovations within Organizations: Electronic Switching in the Bell System, 1971-1982. ***Organization Science***, 8(5): 543-559.

Cyert, R. M., & March, J. G. 1963. ***A Behavioral Theory of the Firm***. New Jersey: Blackwell Publishers Inc.

Damanpour, F. 1996. Organizational Complexity and Innovation: Developing and Testing Multiple Contingency Models. ***Management Science***, 42(5): 693-716.

Darby, M. R., Zucker, L., & Wang, A. 2004. Joint Ventures, Universities, and Success in the Advanced Technology Program. ***Contemporary Economic Policy***, 22(2): 145-161.

Davis, G. F. 1991. Agents without Principles? The Spread of the Poison Pill through the Intercorporate network. ***Administrative Science Quarterly***, 36: 583-613.

Deephouse, D. L. 1996. Does Isomorphism Legitimate? ***Academy of Management Journal***, 39(4): 1024-1039.

DiMaggio, P. J., & Powell, T. C. 1983. The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Field. ***American Sociological Review***, 48: 147-160.

Dougherty, D., & Hardy, C. 1996. Sustained Product Innovation in Large, Mature Organizations: Overcoming Innovation-to-Organization Problems. ***Academy of Management Journal***, 39(5): 1120-1153.

Doz, Y. 1996. The Evolution of Cooperation in Strategic Alliance: Initial Conditions or Learning Processes? ***Strategic Management Journal***, 17: 55-83.

Drazin, R., & Schoonhoven, C. B. 1996. Community, Population, and Organization Effects on Innovation: A Multilevel Perspective. ***Academy of Management Journal***, 39(5): 1065-1083.

Ducor, P. G. 1998. ***Patenting the Recombinant Products of Biotechnology and Other Molecules***. London, UK: Kluwer Law International Ltd.

Fisher, M. H., & Pollock, T. G. 2004. Effects of Social Capital and Power on Surviving Transformational Change: The Case of Initial Public Offering. ***Academy of Management Journal***, 47(4): 463-481.

Folta, T., & D., M. K. 2002. Real Options in Equity Partnerships. ***Strategic Management Journal***, 23: 77-88.

Goes, J. B., & Park, S. H. 1997. Interorganizational Links and Innovation: The Case of Hospital Services. ***Academy of Management Journal***, 40(3): 673-396.

Good, E. C. 2000. Patent Drive the Future of Gene-Based Pharmaceuticals, ***Corporate Legal Times***: 18. Washington D.C.

Granovetter, M. S. 1973. The Strength of Weak Ties. ***American Journal of Sociology***, 78(6): 1360-1380.

Granovetter, M. S. 1983. The Strength of Weak Ties: A Network Theory Revisited. ***Sociological Theory***, 1: 201-233.

Greene, W. H. 1993. ***Econometric Analysis***. New York: Macmillan.

Greve, H. 2003. A Behavioral Theory of R&D Expenditures and Innovations: Evidence from Shipbuilding. ***Academy of Management Journal***, 46(6): 685-702.

Gulati, R. 1995. Social Structure and Alliance Formation Patterns: A Longitudinal Analysis. ***Administrative Science Quarterly***, 40: 619-652.

Gulati, R., & Gargiulo, M. 1999. Where Do Interorganizational Networks Come From? ***American Journal of Sociology***, 104(5): 1439-1493.

Gulati, R., & Higgins, M. C. 2003. Which Ties Matter When? The Contingent Effect of Interorganizational Partnerships on IPO Success. ***Strategic Management Journal***, 24: 127-144.

Guth, W. D., & Ginsburg, A. 1990. Guest Editor's Introduction: Corporate Entrepreneurship. ***Strategic Management Journal***, 11: 5-16.

Hagedoorn, J. 1993. Understanding the Rationale of Strategic Technology Partnering: Interorganizational Modes of Cooperation and Sectoral Differences. ***Strategic Management Journal***, 20(1): 15-29.

Hair, J. F. J., Anderson, R. E., Tatham, R. L., & Black, W. C. 1998. ***Multivariate Data Analysis*** (5th ed.). Upper Saddle River, New Jersy.

Hamel, G. 1991. Competition for Competence and Interpartner Learning within International Strategic Alliances. ***Strategic Management Journal***, 12: 83-103.

Hannan, M. T., & Freeman, J. 1984. Structural Inertia and Organizational Change. ***American Sociological Review***, 49: 149-164.

Hanneman, R. A., & Riddle, M. 2005. Introduction to social network methods, Vol. 2005: University of California, Riverside.

Hansen, M. T. 1999. The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge Across Organization Subunits. ***Administrative Science Quarterly***, 44: 82-111.

Hargadon, A., & Douglas, Y. 2001. When Innovations Meet Institutions: Edison and the Design of Electric Light. ***Administrative Science Quarterly***, 46: 476-501.

Hargadon, A., & Sutton, R. I. 1997. Technology Brokering and Innovation in a Product Development Firm. ***Administrative Science Quarterly***, 42: 716-749.

Hausman, J., Hall, B., & Griliches, Z. 1984. Econometric Models for Count Data with an Application to the Patents-R&D relationship. ***Econometrica***, 52: 909-938.

Henderson, R., & Cockburn, I. 1996. Scale, Scope, and Spillovers: The Determinants of Research Productivity in Drug Discovery. ***RAND Journal of Economics***, 27(1): 32-59.

Hill, C. W., & Rothaermel, F. T. 2003. The Performance of Incumbent Firms in the Face of Radical Technological Innovation. ***Academy of Management Journal***, 28(2): 257-274.

Hitt, M. A., Hoskisson, R. E., Johnson, R. A., & Moesel, D. D. 1996. The Market for Corporate Control and Firm Innovation. ***Academy of Management Journal***, 39(5): 1084-1119.

Hoang, H., & Rothaermel, F. T. 2005. The Effect of General and Partner-Specific Alliance Experience on Joint R&D Project Performance. ***Academy of Management Journal***, 48(2): 332-345.

Hoskisson, R. E., Hitt, M. A., & Hill, C. W. L. 1993. Managerial Incentives and Investment in R&D in Large Multiproduct Firms. ***Organization Science***, 4(2): 325-341.

Johnston, J., & DiNardo, J. 1997. ***Econometric Methods***. New York: McGraw-Hill.

Kelm, K. M., Narayanan, V. K., & Pinches, G. E. 1995. Shareholder Value Creation During R&D Innovation and Commercialization Stages. ***Academy of Management Journal***, 38(3): 770-786.

Kenis, P., & Knoke, D. 2002. How Organizational Field Networks Shape Interorganizational Tie-Formation Rates. ***Academy of Management Review***, 27(2): 275-293.

Kermani, F., & Bonacossa, P. 2003. Patent Issues and Future Trends in Drug Development. ***Journal of Commercial Biotechnology***, 9(4): 332-338.

Kessler, E. H., Bierly, P. E., & Gopalakrishnan, S. 2000. Internal vs. External Learning in New Product Development: Effects on Speed, Costs and Competitive Advantage. ***R & D Management***, 30(3): 213.

Khight, J. H. 2001. ***Patent Strategy for Researchers and Research Managers*** (2nd ed.). Chichester, West Sussex: John Wiley & Sons.

Kim, L. 1998. Crisis Construction and Organizatinal Learning: Capability Building in Catching-Up At Hyudai. ***Organization Science***, 9(4): 506-521.

Knight, J. H. 2001. ***Patent Strategy for Researchers and Research Managers*** (2nd ed.). Chichester, West Sussex: John Wiley & Sons.

Kochhar, R., & David, P. 1996. Institutional Investors and Firm Innovation: A Test of Competing Hypotheses. ***Strategic Management Journal***, 17(1): 73-84.

Kotabe, M., & Swan, S. K. 1995. The Role of Strategic Alliances in High-Technology New Product Development. ***Strategic Management Journal***, 16(8): 621-636.

Koza, M., & Lewin, A. Y. 1998. The Co-evolution of Strategic Alliances. ***Organization Science***, 9: 255-264.

Koza, M. P., & Lewin, A. Y. 1999. The Coevolution of Network Alliances: A Longitudinal Analysis of an International Professional Service Network. ***Organization Science***, 10(5): 255-264.

Kraatz, M. S. 1998. Learning by Association? Interorganizational Networks and Adaptation to Environment Change. ***Academy of Management Journal***, 41(6): 621-643.

Lambert, D. 1992. Zero-inflated Poisson Regression, with an Application of Defects in Manufacturing. ***Technometrics***, 34: 1-14.

Leblebici, H., Salancik, G. R., Copay, A., & King, T. 1991. Institutional Change and the Transformation of Interorganizational Fields: An Organizational History of the U.S. Radio Broadcasting Industry. ***Administrative Science Quarterly***, 36: 333-363.

Lechtenberg, V. L. 1989. Intellectual Property Rights-Industry/University Agreement. In R. F. Barnes (Ed.), ***Intellectual Property Rights Associated with Plants***. Madison, Wisconsin: ASA Special Publication.

Lerner, J., Shane, H., & Tsai, A. 2003. Do Equity Financing Cycles Matter? Evidence from Biotechnology Alliances. ***Journal of Financial Economics***, 67: 411-446.

Levin, R. C., Klevorick, A. K., Nelson, R. R., & Winter, S. G. 1987. Appropriating the Returns from Research and Development. ***Brookings Papers on Economic Activity***, 3: 783-820.

Li, S. X., & Rowley, T. J. 2002. Inertia and Evaluation Mechanisms in Interorganizational Partner Selection: Syndicate Formation Among U.S. Investment Banks. ***Academy of Management Journal***, 45(6): 1104-1119.

Liebeskind, J. P., Oliver, A. L., Zucker, L., & Brewer, M. 1996. Social Networks, Learning, and Flexibility: Sourcing Scientific Knowledge in New Biotechnology Firms. ***Organization Science***, 7(4): 428-443.

Long, J. S. 1997. ***Regression Models for Categorical and Limited Dependent Variables***. Thousand Oaks, CA: Sage.

March, J. G. 1991. Exploration and Exploitation in Organizational learning. ***Organization Science***, 2(1): 71-87.

McDaniel, B. A. 2005. A Contemporary View of Joseph A. Schumpeter's Theory of the Entrepreneur. ***Journal of Economic Issues***, 39(2): 485-489.

McKenna, C. 2002. Pfizer buys Pharmacia for $60bn. ***British Medical Journal***, 325(7356): 123.

Min, Y., & Agresti, A. 2005. Random Effect Models for Repeated Measures of Zero-inlfated Count Data. ***Statistical Modeling***, 5: 1-19.

Miner, S. A., Amburgey, T. L., & Stearns, T. M. 1990. Interorganizational Linkages and Population Dynamics: Buffering and Transformational Shields. ***Administrative Science Quarterly***, 35: 689-713.

Nahapiet, J., & Ghoshal, S. 1998. Social Capital, Intellectual Capital, and the Organizational Advantage. ***Academy of Management Journal***, 23(2): 242-266.

Nelson, R. R., & Winter, S. G. 1982. ***An Evolutionary Theory of Economic Change***. Cambridge, Massachusetts: The Belknap Press of Harvard University Press.

Nicholls-Nixon, C., & Woo, C. 2003. Technology Sourcing and Output for Established Firms in A Regime of Encompassing Technology Change. ***Strategic Management Journal***, 24: 651-666.

Nohria, N., & Gulati, R. 1996. Is Slack Good or Bad for Innovation? ***Academy of Management Journal***, 39(5): 1245-1264.

Owen-Smith, J., & Powell, W. W. 2004. Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. ***Organization Science***, 15(1): 5-21.

Penrose, E. 1959. ***The Theory of the Growth of the Firm***. New York: Oxford University Press.

Pfeffer, J. 1993. Barriers to the advance of organizational science: Paradigm development as a dependable variable. ***Academy of Management Review***, 18(4): 599.

Podolny, J. M., & Baron, J. N. 1997. Resources and Relationships: Social Networks and Mobility in the Work Place. ***American Sociological Review***, 62: 673-693.

Podolny, J. M., & Page, K. L. 1998. Network Forms of Organization. ***Annu. Rev. Sociol.***, 24: 57-76.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. ***Administrative Science Quarterly***, 41: 116-145.

Qian, G., & Li, L. 2003. Profitability of Small-and Medium-Sized Enterprises in High-Tech Industries: The Case of the Biotechnology Industry. ***Strategic Management Journal***, 24: 881-887.

Reuer, J. J., Zollo, M., & Singh, H. 2002. Post-Formation Dynamics in Strategic Alliances. ***Strategic Management Journal***, 23: 135-151.

Rochin, D. 2006. ***Hunter or Hunted? Technology, Innovation, and Competitive Strategy*** (1 ed.). Mason, Ohio: Thomson Higher Education.

Rogers, E. M. 1995. ***Diffusion of Innovation*** (fourth ed.). New York: The Free Press.

Rothaermel, F. T. 2000. Technological Discontinuities and the Nature of Competition. ***Technology Analysis & Strategic Management***, 12(2): 149-160.

Rothaermel, F. T. 2001. Incumbent's Advantage through Exploiting Complementary Assets via Interfirm Cooperation. ***Strategic Management Journal***, 22: 687-699.

Rothaermel, F. T., & Deeds, D. L. 2004. Exploration and Exploitation Alliances in Biotechnology: A System of New Product Development. ***Strategic Management Journal***, 25: 201-221.

Schumpeter, J. 1934. ***The Theory of Economic Development***. Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1950. ***Capitalism, Socialism, and Democracy*** (3 ed.). New York: Harper.

Schwab, D. P. 1999. ***Research Methods for Organizational Studies***. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Scott, J. 1991. ***Social Network Analysis***. Thousand Oaks, California: SAGE Publications Inc.

Sellers, L. J. 2002. Pfizer Buys Another Marketing Partner, ***Pharmaceutical Executive***: 16.

Selznick, P. 1996. "Institutionalism 'old' and 'new'". ***Administrative Science Quarterly***, 41: 270-277.

Setzer, F. 1974. ***Technical Change over the Life of a Product: Changes in Skilled Inputs and Production Processes***. Unpublished Dissertation, Yale University, New Haven.

Shadish, W. R., Cook, T. D., & Campbell, D. T. 2002. ***Experimental and Quasi-Experimental Designs for Generalized Casual Inference***. Boston, MA: Houghton Fifflin Company.

Shan, W., Walker, G., & Kogut, B. 1994. Interfirm Cooperation and Startup Innovation in the Biotechnology Industry. ***Strategic Management Journal***, 15(5): 387-394.

Sherer, P. D., & Lee, K. 2002. Institutional Change in Large Law Firms: A Resource Dependency and Institutional Perspective. ***Academy of Management Journal***, 45(1): 102-119.

Silverman, B. S., & Baum, J. A. C. 2002. Alliance-Based Competitive Dynamics. ***Academy of Management Journal***, 45(4): 791-806.

Smith, K. G., Collins, C. J., & Clark, K. D. 2005. Existing Knowledge, Knowledge Creation Capacity, and the Rate of New Product Introduction in the High-Tech Firms. ***Academy of Management Journal***, 48(2): 346-357.

Sparrowe, R. T., Liden, R. C., & Kraimer, M. L. 2001. Social Networks and The Performance of Individuals and Groups. ***Academy of Management Journal***, 44(2): 316-325.

Spencer, J. W. 2003. Firms' Knowledge-Sharing Strategies in the Global Innovation System: Empirical Evidence from the Flat Panel Display Industry. ***Strategic Management Journal***, 24: 217-233.

Stehr, N. 2004. ***Biotechnology: Between Commerce and Civil Society***. New Brunswick, NJ: Transaction Publishers.

Stuart, T. 1998. Network Positions and Propensities to Collaborate: An Investigation of Strategic Alliance Formation in a High-tech Industry. ***Administrative Science Quarterly***, 43: 668-698.

Stuart, T. 2000. Interorganizational Alliances and The Performance of Firms: A Study of Growth and Innovation Rates in a High Technology Industry. ***Strategic Management Journal***, 21: 791-811.

Teachman, J., Duncan, G., Yeung, W. J., & Levy, D. 2001. Covariance Structure Models for Fixed and Random Effects. ***Sociological Methods & Research***, 30(2): 271-288.

Terry, M. 2004. Biotech Patents Have Power to Turn Research into Royalty. ***Drug Discovery & Development***, 7(4): 61-65.

Tidd, J., Bessant, J., & Pavitt, K. 1997. ***Managing Innovation: Integrating Technological, Market and Organizational Change***. New York: John Wiley & Sons, Inc.

Trajenberg, M. 1990. ***Economic Analysis of Product Innovation: The Case of CT Scanners***. Cambridge, MA: Harvard University Press.

Tsai, W. 2001. Knowledge Transfer in Intraorganization Networks: Effects of Network Position and Absorptive Capacity on Business Unit Innovation and Performance. ***Academy of Management Journal***, 44(5): 996-1004.

Tushman, M. L., & Anderson, P. 1986. Technological Discontinuities and Organizational Environments. ***Administrative Science Quarterly***, 31(3): 439-465.

Tushman, M. L., & Nelson, R. R. 1990. Introduction: Technology, Organizations, and Innovation. ***Administrative Science Quarterly***, 35: 1-8.

Uhl-Bien, M., Graen, G. B., & Scandura, T. A. 2000. Implication of Leader-Member Exchange (LMX) for Strategic Human Resource Management Systems: Relationships as Social Captital for Competitive Advantage. ***Research in Organizational Behavior***, 18: 137-185.

Uzzi, B. 1997. Networks and the Paradox of Embeddedness. ***Administrative Science Quarterly***, 42: 35-67.

Van De Ven, A. H., & Polley, D. 1992. Learning while Innovating. ***Organization Science***, 3(1): 92-116.

Vassolo, R. S., Anand, J., & Folta, T. 2004. Non-Additivity in Portfolios of Exploration Activities: A Real Options-Based Analysis of Equity Alliances in Biotechnology. ***Strategic Management Journal***, 25: 1045-1061.

Vermeulen, F., & Barkema, H. 2001. Learning Through Acquisitions. ***Academy of Management Journal***, 44(3): 457-476.

Walker, G., Kogut, B., & Shan, W. 1997. Social Capital, Structural Holes and the Formation of an Industry Network. ***Organization Science***, 8(2): 109-125.

Walsh, J. P., & Ungson, G., Rivera. 1991. Organizational Memory. ***Academy of Management Review***, 16(1): 57-91.

Wejnert, B. 2002. Integrating Models of Diffusion of Innovation: A Conceptual Framework. ***Annu. Rev. Sociol.***, 28: 297-326.

Welbourne, T. M., & Andrews, A. O. 1996. Predicting the Performance of Initial Public Offerings: Should Human Resource Management Be in the Equation? ***Academy of Management Journal***, 39: 891-919.

Wittcoff, H. A., Reuben, B. G., & Plotkin, J. S. 2004. ***Industrial Organic Chemicals***. Hoboken, NJ: John Wiley & Sons.

Wuyts, S., Dutta, S., & Stremersch, S. 2004. Portfolio of Interfirm Agreements in Technology-Intensive Markets: Consequences for Innovation and Profitability. ***Journal of Marketing***, 68: 88-100.

Zaheer, A., & Usai, A. in press. The Social Network Approach in Strategy Research: Theoretical Challenges and Methodological Issues. In D. Ketchen (Ed.), ***Research Methodology in Strategy and Management Volume I***. Elsevier.

Zahra, S. A., & Nielsen, A. P. 2002. Sources of Capabilities, Integration, and Technology Commercialization. ***Strategic Management Journal***, 23: 377-398.

Zollo, M., Reuer, J. J., & Singh, H. 2002. Interorganizational Routines and Performance in Strategic Alliances. ***Organization Science***, 13(6): 701-713.

Zorn, C. J. W. 1996. Evaluating Zero-inlfated and Hurdle Poisson Specifications. ***Midwest Political Science Association***(April 18-20): 1-16.

Zucker, L., Darby, M. R., & Armstrong, J. S. 2002. Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology. ***Management Science***, 48(1): 138-153.

Zucker, L., Darby, M. R., & Brewer, M. 1998. Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises. ***The American Economic Review***, 88(1): 290-306.

MEASUREMENTS AND DATA SOURCES

DV ==> for Focal Firms	Measurements	Data Sources
Invention Performance	1. # of Patent applications	USPTO
Commercialization Performance	1. # of Marketed drug applications approved by FDA	Drugs@FDA
	3. Revenues of the focal firms	COMPUSTAT
IVs	**Structures of Focal Firm's Network**	
Direct Ties	1. # of Nodes that one-step out neighbors of ego	BioScan, UCINET
Indirect Ties	1. # of Connections among all the nodes in the ego network	BioScan, UCINET
Structural Holes	1. Levels of Density=# of Ties divided by the number of pairs 2. # of Brokerage=Numbers of pairs not directly connected	BioScan, UCINET
Strength of Direct Ties	1. Avg # of lengths of focal firm's collaborations each year	BioScan
IVs	**Characteristics of Alliances**	
Prominence of Ties	1. Frequencies of appearances at news 10 Yrs prior	LexisNexis®
IVs	**Orientations of Alliances**	
Exploration Networks	1. # of Alliances' patents in the past 10 Yr prior	USPTO
Exploitation Networks	1. # of Alliances' drug applications in the past 10 yr prior	Drugs@FDA
Upstream Horizontal Networks	1. Prior Invention*Exploration Networks	USPTO and Drug@FDA
Downstream Horizontal Networks	1. Prior Commercialization*Exploitation Networks	USPTO and Drug@FDA
Upstream Vertical Networks	1. Prior Invention*Exploitation Networks	USPTO and Drug@FDA
Downstream Vertical Networks	1. Prior Commercialization*Exploration Networks	USPTO and Drug@FDA
CV ==> for Focal Firms	**Focal Firms' Individual Characteristics**	
Prior Invention	1. # of Issued Patent Applications 10 yrs Prior (Exploration)	USPTO
Prior Commercialization	1. # of Successful Drug applications 10 yr Prior (Exploitation)	Drugs@FDA
Equity Financing Events	1.# of Acquired firms by the focal firms	BioScan
	2. # of Private placements in the focal Firms	BioScan
Focal Firm's Status or Prestige	1. Years since IPO 2. Closed stock prices	COMPUSTAT
Diversification Level	1. Technological areas of Interest and action	BioScan
Profitability Level	1. Net Income	COMPUSTAT
Sizes	1. # of Employees	COMPUSTAT
Innovativeness Level	1. R&D Expenses	COMPUSTAT
Year Differences	1986-2002, 2003 omitted	COMPUSTAT
NAICS Differences	325411-325413, 325414 omitted	COMPUSTAT

APPENDIX B

CORRELATION OF ALL VARIABLES AND RESULTS

	pat_ap~1	succmk~n	sales_~2	Uphori~2	DNhori~n	UPvert~2	DNvert~n
pat_app_yr~1	1.0000						
succmktapp_n	0.3691 0.0000	1.0000					
sales_12_D2	0.6423 0.0000	0.5326 0.0000	1.0000				
Uphorizont~2	0.2597 0.0000	0.0633 0.0060	0.0865 0.0002	1.0000			
DNhorizont~n	0.0663 0.0041	0.2568 0.0000	0.1902 0.0000	0.0506 0.0281	1.0000		
UPvertical~2	0.1942 0.0000	0.0907 0.0001	0.1280 0.0000	0.4026 0.0000	0.4149 0.0000	1.0000	
DNvertical_n	0.0706 0.0022	0.2152 0.0000	0.2105 0.0000	0.2137 0.0000	0.3970 0.0000	0.1148 0.0000	1.0000
tot_prtpat	0.0822 0.0004	0.0603 0.0089	0.0851 0.0002	0.3894 0.0000	0.1760 0.0000	0.2685 0.0000	0.4628 0.0000
prtcomm	0.0066 0.7751	0.0070 0.7623	0.0053 0.8176	0.0433 0.0608	0.2854 0.0000	0.3705 0.0000	0.0685 0.0030
partnersta~s	0.1137 0.0000	0.0936 0.0000	0.1110 0.0000	0.1351 0.0000	0.3036 0.0000	0.2968 0.0000	0.2572 0.0000
lead1YRavg~l	-0.0263 0.2553	0.0051 0.8261	0.0934 0.0000	-0.0488 0.0345	-0.0061 0.7928	-0.0272 0.2382	-0.0032 0.8897
brok_fixmis	0.3787 0.0000	0.4553 0.0000	0.6498 0.0000	0.0301 0.1919	0.1915 0.0000	0.1415 0.0000	0.1352 0.0000
dens_fixmis	-0.0014 0.9517	-0.0232 0.3145	-0.0130 0.5730	-0.0079 0.7314	0.0280 0.2252	0.0113 0.6236	-0.0070 0.7627
InterDirec~7	0.2390 0.0000	0.3571 0.0000	0.4486 0.0000	0.0027 0.9073	0.0928 0.0001	0.0332 0.1506	0.0654 0.0046
direct_t_7	0.2716 0.0000	0.3408 0.0000	0.4395 0.0000	0.0203 0.3792	0.1573 0.0000	0.1252 0.0000	0.1234 0.0000
ind_t_7	0.0983 0.0000	0.1340 0.0000	0.1999 0.0000	-0.0035 0.8801	0.0484 0.0359	0.0160 0.4884	0.0423 0.0670
_10yrapp	0.2785 0.0000	0.9700 0.0000	0.4147 0.0000	0.0492 0.0330	0.2419 0.0000	0.0780 0.0007	0.1863 0.0000
_10yrpatapp	0.8913 0.0000	0.3560 0.0000	0.6974 0.0000	0.2507 0.0000	0.0307 0.1831	0.1575 0.0000	0.0545 0.0181
EquityEvents	0.0247 0.2853	0.0064 0.7810	-0.0013 0.9561	0.0227 0.3255	0.0833 0.0003	0.0691 0.0027	0.0224 0.3308
lead1YRs~24_	0.0852 0.0002	-0.0021 0.9276	0.0202 0.3820	0.0505 0.0285	-0.0015 0.9487	0.0301 0.1924	-0.0202 0.3808

yrcompst_C	0.3425	0.3091	0.4349	0.0743	0.1095	0.1066	0.0692
	0.0000	0.0000	0.0000	0.0013	0.0000	0.0000	0.0027
diversific~C	0.5284	0.2848	0.5134	0.1220	0.1271	0.1871	0.1163
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
lead1YRnet~C	0.0150	-0.0220	-0.0037	0.0299	-0.0100	0.0058	-0.0118
	0.5168	0.3414	0.8716	0.1949	0.6664	0.8019	0.6090
lead1YRe~29_	0.0841	-0.0027	0.0465	0.0647	-0.0115	0.0404	-0.0136
	0.0003	0.9083	0.0439	0.0050	0.6191	0.0800	0.5560
lead1YRr~46_	0.0387	-0.0070	0.0349	0.0208	-0.0108	0.0104	-0.0116
	0.0932	0.7611	0.1302	0.3684	0.6402	0.6538	0.6163
ydum01	0.0381	0.0153	-0.0060	0.0798	-0.0075	-0.0099	0.0158
	0.0984	0.5082	0.7933	0.0005	0.7445	0.6686	0.4947
ydum02	0.0355	0.0179	-0.0062	-0.0065	-0.0084	-0.0105	-0.0066
	0.1235	0.4371	0.7868	0.7798	0.7174	0.6485	0.7745
ydum03	0.0317	0.0175	-0.0051	-0.0065	0.0024	0.0349	-0.0068
	0.1700	0.4491	0.8256	0.7794	0.9180	0.1303	0.7699
ydum04	0.0315	0.0167	-0.0056	0.1384	-0.0026	0.0347	0.0407
	0.1727	0.4689	0.8096	0.0000	0.9087	0.1325	0.0780
ydum05	0.0344	0.0142	-0.0050	0.0655	-0.0092	0.0408	-0.0080
	0.1355	0.5389	0.8272	0.0045	0.6908	0.0774	0.7276
ydum06	0.0209	0.0043	-0.0116	0.0038	-0.0124	-0.0156	-0.0073
	0.3652	0.8538	0.6162	0.8696	0.5913	0.4989	0.7518
ydum07	0.0152	0.0031	-0.0162	-0.0114	-0.0016	-0.0125	-0.0111
	0.5095	0.8931	0.4835	0.6224	0.9452	0.5889	0.6302
ydum08	0.0070	0.0007	-0.0195	-0.0096	-0.0150	-0.0119	-0.0112
	0.7625	0.9775	0.3985	0.6779	0.5149	0.6068	0.6286
ydum09	0.0178	-0.0027	-0.0156	-0.0008	-0.0118	-0.0014	-0.0065
	0.4417	0.9056	0.5001	0.9724	0.6095	0.9523	0.7790
ydum10	0.0311	-0.0076	-0.0204	0.0355	-0.0027	0.0208	0.0062
	0.1776	0.7428	0.3775	0.1243	0.9083	0.3667	0.7890
ydum12	-0.0207	-0.0038	-0.0087	-0.0100	0.0513	0.0041	0.1016
	0.3688	0.8698	0.7066	0.6654	0.0261	0.8607	0.0000
ydum13	0.0064	0.0010	-0.0027	-0.0002	0.1155	0.0953	0.0263
	0.7805	0.9655	0.9059	0.9915	0.0000	0.0000	0.2538
ydum14	0.0036	-0.0042	-0.0091	-0.0058	-0.0054	-0.0032	-0.0052
	0.8748	0.8572	0.6944	0.8032	0.8162	0.8886	0.8208
ydum15	0.0092	-0.0009	-0.0011	-0.0188	-0.0164	-0.0064	-0.0197
	0.6895	0.9700	0.9611	0.4153	0.4780	0.7804	0.3925
ydum16	-0.0003	-0.0022	0.0200	-0.0121	-0.0101	-0.0110	-0.0146
	0.9902	0.9257	0.3867	0.5990	0.6618	0.6352	0.5268
ydum17	-0.0024	-0.0003	0.0270	-0.0212	-0.0295	-0.0325	-0.0229
	0.9169	0.9897	0.2427	0.3589	0.2010	0.1588	0.3206
ydum18	-0.0355	-0.0015	0.0257	-0.0220	-0.0188	-0.0242	-0.0201
	0.1237	0.9492	0.2652	0.3405	0.4164	0.2940	0.3845

naics325411	-0.0319	-0.0289	-0.0287	-0.0082	-0.0104	-0.0130	-0.0082
	0.1672	0.2112	0.2133	0.7236	0.6536	0.5719	0.7225
naics325412	0.1919	0.2445	0.2387	0.0578	0.0841	0.0698	0.0691
	0.0000	0.0000	0.0000	0.0123	0.0003	0.0025	0.0027
naics325413	-0.0665	-0.1110	-0.1105	-0.0189	-0.0382	-0.0188	-0.0304
	0.0039	0.0000	0.0000	0.4124	0.0978	0.4163	0.1877

	tot_pr~t	prtcomm	partne~s	lea~rcol	brok_f~s	dens_f~s	InterD~7
tot_prtpat	1.0000						
prtcomm	0.3559	1.0000					
	0.0000						
partnersta~s	0.6258	0.4693	1.0000				
	0.0000	0.0000					
lead1YRavg~l	-0.0418	-0.0141	-0.0507	1.0000			
	0.0701	0.5411	0.0280				
brok_fixmis	0.0553	0.0625	0.1814	0.1042	1.0000		
	0.0165	0.0068	0.0000	0.0000			
dens_fixmis	0.0099	0.0765	0.0354	0.0752	-0.0105	1.0000	
	0.6666	0.0009	0.1251	0.0011	0.6483		
InterDirec~7	0.0234	0.0059	0.0753	0.1197	0.6977	0.0439	1.0000
	0.3107	0.7983	0.0011	0.0000	0.0000	0.0573	
direct_t_7	0.0838	0.0866	0.1886	0.0922	0.8291	0.0159	0.7856
	0.0003	0.0002	0.0000	0.0001	0.0000	0.4904	0.0000
ind_t_7	0.0510	0.0236	0.0687	0.1445	0.2866	0.1943	0.6926
	0.0270	0.3070	0.0029	0.0000	0.0000	0.0000	0.0000
_10yrapp	0.0487	0.0065	0.0764	-0.0236	0.3738	-0.0155	0.2880
	0.0348	0.7793	0.0009	0.3075	0.0000	0.5031	0.0000
_10yrpatapp	0.0533	-0.0180	0.0611	0.0063	0.4597	-0.0028	0.2772
	0.0209	0.4361	0.0081	0.7860	0.0000	0.9031	0.0000
EquityEvents	0.0944	0.1340	0.1696	-0.0505	0.0254	-0.0268	-0.0200
	0.0000	0.0000	0.0000	0.0287	0.2719	0.2453	0.3873
lead1YRs~24_	0.0184	0.0454	0.0169	0.0443	0.0320	0.0349	-0.0012
	0.4247	0.0492	0.4643	0.0549	0.1662	0.1309	0.9589
yrcompst_C	0.0037	-0.0007	0.0479	0.1178	0.4177	0.0331	0.3132
	0.8731	0.9775	0.0378	0.0000	0.0000	0.1512	0.0000
diversific~C	0.1072	0.0841	0.1694	-0.0122	0.4523	0.0079	0.3663
	0.0000	0.0003	0.0000	0.5958	0.0000	0.7317	0.0000
lead1YRnet~C	0.0096	0.0121	-0.0251	0.1244	-0.0138	-0.0134	-0.0417
	0.6785	0.5997	0.2762	0.0000	0.5509	0.5620	0.0710
lead1YRe~29_	0.0213	0.0293	-0.0241	0.1163	-0.0031	-0.0131	-0.0355
	0.3564	0.2036	0.2965	0.0000	0.8931	0.5703	0.1235
lead1YRr~46_	0.0035	0.0209	-0.0241	0.1798	0.0126	-0.0089	-0.0260
	0.8786	0.3660	0.2960	0.0000	0.5850	0.7000	0.2593

ydum01	0.0081	-0.0158	-0.0253	-0.1023	-0.0238	-0.0183	-0.0262
	0.7244	0.4944	0.2739	0.0000	0.3034	0.4270	0.2561
ydum02	-0.0212	-0.0196	-0.0354	-0.1047	-0.0253	-0.0195	-0.0279
	0.3580	0.3968	0.1246	0.0000	0.2730	0.3975	0.2264
ydum03	-0.0215	-0.0142	-0.0352	-0.1032	-0.0259	-0.0201	-0.0287
	0.3506	0.5380	0.1273	0.0000	0.2617	0.3838	0.2131
ydum04	0.0159	-0.0207	-0.0269	-0.1107	-0.0297	-0.0233	-0.0331
	0.4920	0.3694	0.2431	0.0000	0.1981	0.3138	0.1510
ydum05	0.0225	-0.0194	-0.0286	-0.1124	-0.0307	-0.0247	-0.0350
	0.3305	0.4009	0.2150	0.0000	0.1833	0.2849	0.1290
ydum06	-0.0201	-0.0290	-0.0440	-0.1253	-0.0336	-0.0287	-0.0389
	0.3845	0.2088	0.0567	0.0000	0.1450	0.2139	0.0922
ydum07	-0.0273	0.0048	-0.0435	-0.1288	-0.0389	-0.0343	-0.0452
	0.2364	0.8352	0.0593	0.0000	0.0918	0.1376	0.0501
ydum08	0.0074	-0.0316	-0.0351	-0.1330	-0.0407	-0.0369	-0.0475
	0.7480	0.1709	0.1286	0.0000	0.0776	0.1094	0.0395
ydum09	0.0179	-0.0045	-0.0175	-0.1242	-0.0402	-0.0405	-0.0515
	0.4391	0.8460	0.4483	0.0000	0.0818	0.0789	0.0255
ydum10	0.0031	0.0151	0.0355	-0.1292	-0.0434	-0.0480	-0.0622
	0.8928	0.5124	0.1238	0.0000	0.0598	0.0374	0.0070
ydum12	0.0961	0.0689	0.1097	-0.1241	-0.0369	-0.0394	-0.0639
	0.0000	0.0028	0.0000	0.0000	0.1100	0.0878	0.0056
ydum13	0.1149	0.1069	0.2518	-0.1069	0.0043	-0.0299	-0.0510
	0.0000	0.0000	0.0000	0.0000	0.8516	0.1948	0.0272
ydum14	0.0278	0.0256	0.1288	-0.0691	0.0361	0.0228	0.0265
	0.2277	0.2679	0.0000	0.0027	0.1179	0.3232	0.2505
ydum15	-0.0323	0.0375	-0.0406	0.0032	0.0391	0.0265	0.0840
	0.1610	0.1040	0.0783	0.8893	0.0905	0.2502	0.0003
ydum16	-0.0179	0.0088	-0.0460	0.0627	0.0327	0.0340	0.0662
	0.4385	0.7045	0.0463	0.0066	0.1569	0.1403	0.0041
ydum17	-0.0447	-0.0621	-0.0736	0.1541	0.0403	0.0369	0.0672
	0.0530	0.0071	0.0014	0.0000	0.0807	0.1101	0.0035
ydum18	-0.0684	-0.0650	-0.1008	0.2462	0.0254	0.0456	0.0394
	0.0030	0.0048	0.0000	0.0000	0.2717	0.0480	0.0874
naics325411	-0.0244	-0.0242	-0.0334	0.0455	-0.0311	-0.0242	-0.0346
	0.2901	0.2935	0.1482	0.0485	0.1783	0.2942	0.1336
naics325412	0.0117	0.0110	0.0155	-0.0619	0.1711	0.0643	0.1002
	0.6112	0.6350	0.5017	0.0073	0.0000	0.0053	0.0000
naics325413	-0.0071	-0.0251	-0.0037	0.0007	-0.0940	-0.0336	-0.0609
	0.7598	0.2764	0.8731	0.9757	0.0000	0.1452	0.0083

	direct~7	ind_t_7	_10yrapp	_10yrp~p	equity~R	lead~24_	yrcomp~C
direct_t_7	1.0000						
ind_t_7	0.4673	1.0000					
	0.0000						
_10yrapp	0.2785	0.1021	1.0000				
	0.0000	0.0000					
_10yrpatapp	0.2963	0.1077	0.2626	1.0000			
	0.0000	0.0000	0.0000				
EquityEvents	0.0258	-0.0008	0.0217	-0.0194	1.0000		
	0.2636	0.9713	0.3465	0.4019			
lead1YRs~24_	0.0578	0.0028	-0.0101	0.0944	0.0334	1.0000	
	0.0122	0.9021	0.6605	0.0000	0.1473		

yrcompst_C	0.4275	0.2195	0.2607	0.4173	0.0370	0.0300	1.0000
	0.0000	0.0000	0.0000	0.0000	0.1091	0.1937	
diversific~C	0.4692	0.2077	0.2076	0.5283	0.0535	0.1121	0.4101
	0.0000	0.0000	0.0000	0.0000	0.0203	0.0000	0.0000
lead1YRnet~C	-0.0144	-0.0524	-0.0207	0.0202	0.0248	0.4036	-0.0067
	0.5323	0.0231	0.3702	0.3813	0.2826	0.0000	0.7722
lead1YRe~29_	-0.0095	0.0013	-0.0145	0.0901	0.0278	0.5332	0.0503
	0.6803	0.9539	0.5293	0.0001	0.2283	0.0000	0.0293
lead1YRr~46_	0.0110	-0.0009	-0.0136	0.0387	0.0263	0.4338	0.0437
	0.6348	0.9690	0.5556	0.0932	0.2548	0.0000	0.0581
ydum01	-0.0519	-0.0425	0.0173	0.0393	-0.0083	0.0528	-0.0526
	0.0243	0.0653	0.4527	0.0889	0.7196	0.0222	0.0225
ydum02	-0.0540	-0.0453	0.0146	0.0352	-0.0307	0.0310	-0.0506
	0.0192	0.0496	0.5279	0.1271	0.1839	0.1791	0.0283
ydum03	-0.0544	-0.0466	0.0232	0.0334	-0.0321	0.0322	-0.0392
	0.0184	0.0433	0.3149	0.1477	0.1645	0.1628	0.0892
ydum04	-0.0598	-0.0532	0.0254	0.0374	0.0140	0.0407	-0.0412
	0.0096	0.0211	0.2711	0.1050	0.5428	0.0775	0.0739
ydum05	-0.0605	-0.0559	0.0253	0.0329	-0.0213	0.0222	-0.0406
	0.0087	0.0154	0.2734	0.1545	0.3564	0.3364	0.0785
ydum06	-0.0583	-0.0596	0.0118	0.0210	0.0030	0.0799	-0.0410
	0.0115	0.0097	0.6105	0.3628	0.8955	0.0005	0.0760
ydum07	-0.0684	-0.0706	0.0072	0.0080	-0.0229	0.0283	-0.0403
	0.0030	0.0022	0.7567	0.7299	0.3204	0.2197	0.0808
ydum08	-0.0647	-0.0709	0.0073	0.0045	-0.0021	0.0109	-0.0442
	0.0050	0.0021	0.7520	0.8470	0.9284	0.6358	0.0554
ydum09	-0.0680	-0.0773	0.0072	-0.0001	0.0233	-0.0372	-0.0326
	0.0032	0.0008	0.7561	0.9951	0.3119	0.1067	0.1583
ydum10	-0.0675	-0.0925	-0.0008	-0.0159	0.1148	0.0028	-0.0748
	0.0034	0.0001	0.9730	0.4916	0.0000	0.9021	0.0012
ydum12	-0.0472	-0.0803	-0.0041	-0.0179	0.1232	-0.0014	-0.0633
	0.0409	0.0005	0.8592	0.4390	0.0000	0.9522	0.0061
ydum13	-0.0097	-0.0579	0.0006	-0.0177	0.0550	-0.0011	-0.0284
	0.6734	0.0121	0.9779	0.4426	0.0171	0.9628	0.2177

```
      ydum14 |   0.0495   0.0409  -0.0076  -0.0138   0.0750  -0.0433  -0.0428
             |   0.0320   0.0766   0.7416   0.5508   0.0011   0.0607   0.0635
             |
      ydum15 |   0.0853   0.0907   0.0000  -0.0046  -0.0301   0.0302  -0.0102
             |   0.0002   0.0001   0.9997   0.8430   0.1927   0.1904   0.6573
             |
      ydum16 |   0.0761   0.0816  -0.0074  -0.0064  -0.0116   0.0507   0.0283
             |   0.0010   0.0004   0.7486   0.7807   0.6158   0.0278   0.2206
             |
      ydum17 |   0.0730   0.0832  -0.0067  -0.0020  -0.0837  -0.0082   0.0697
             |   0.0015   0.0003   0.7700   0.9313   0.0003   0.7221   0.0025
             |
      ydum18 |   0.0408   0.0672  -0.0082   0.0047  -0.0876  -0.0970   0.0988
             |   0.0768   0.0035   0.7227   0.8384   0.0001   0.0000   0.0000
             |
 naics325411 |  -0.0622  -0.0562  -0.0270  -0.0297  -0.0198  -0.0393   0.0190
             |   0.0070   0.0149   0.2413   0.1984   0.3912   0.0887   0.4103
             |
 naics325412 |   0.0815   0.0251   0.2257   0.2020   0.0234  -0.0057   0.1669
             |   0.0004   0.2763   0.0000   0.0000   0.3098   0.8064   0.0000
             |
 naics325413 |  -0.0641  -0.0172  -0.1025  -0.0788  -0.0569   0.0228  -0.0420
             |   0.0054   0.4570   0.0000   0.0006   0.0136   0.3227   0.0685
             |

             | divers~C lead1Y~C lead~29_ lead~46_   ydum01   ydum02   ydum03
-------------+------------------------------------------------------------------
diversific~C |   1.0000
             |
             |
lead1YRnet~C |   0.0123   1.0000
             |   0.5954
             |
lead1YRe~29_ |   0.0704   0.7938   1.0000
             |   0.0023   0.0000
             |
lead1YRr~46_ |   0.0235   0.8076   0.8500   1.0000
             |   0.3089   0.0000   0.0000
             |
      ydum01 |   0.0433   0.0001   0.0334  -0.0091   1.0000
             |   0.0603   0.9968   0.1479   0.6939
             |
      ydum02 |   0.0493   0.0007   0.0283  -0.0092  -0.0086   1.0000
             |   0.0326   0.9751   0.2203   0.6915   0.7104
             |
      ydum03 |   0.0471   0.0029   0.0254  -0.0087  -0.0088  -0.0094   1.0000
             |   0.0411   0.9010   0.2710   0.7066   0.7023   0.6839
             |
      ydum04 |   0.0505   0.0048   0.0423  -0.0069  -0.0102  -0.0109  -0.0112
             |   0.0286   0.8365   0.0666   0.7636   0.6585   0.6378   0.6280
             |
      ydum05 |   0.0500   0.0202   0.0620   0.0058  -0.0108  -0.0115  -0.0119
             |   0.0302   0.3808   0.0072   0.8031   0.6389   0.6172   0.6070
             |
      ydum06 |   0.0313   0.0147   0.0441  -0.0009  -0.0127  -0.0135  -0.0139
             |   0.1757   0.5240   0.0560   0.9695   0.5818   0.5574   0.5460
             |
      ydum07 |   0.0217   0.0036   0.0319  -0.0037  -0.0151  -0.0161  -0.0166
             |   0.3461   0.8747   0.1670   0.8715   0.5121   0.4850   0.4723
             |
      ydum08 |   0.0146   0.0002   0.0225  -0.0069  -0.0163  -0.0174  -0.0179
             |   0.5278   0.9947   0.3289   0.7664   0.4803   0.4522   0.4390
             |
      ydum09 |   0.0210  -0.0004   0.0145  -0.0110  -0.0180  -0.0192  -0.0198
             |   0.3621   0.9854   0.5299   0.6330   0.4346   0.4053   0.3917
             |
```

ydum10	0.0085	-0.0171	-0.0168	-0.0317	-0.0219	-0.0234	-0.0240
	0.7125	0.4587	0.4655	0.1695	0.3420	0.3114	0.2975
ydum12	0.0033	-0.0052	-0.0102	-0.0239	-0.0251	-0.0267	-0.0275
	0.8852	0.8222	0.6574	0.3013	0.2776	0.2475	0.2339
ydum13	0.0128	-0.0246	-0.0209	-0.0225	-0.0258	-0.0275	-0.0283
	0.5802	0.2869	0.3663	0.3292	0.2628	0.2330	0.2196
ydum14	-0.0019	-0.0165	-0.0323	-0.0275	-0.0284	-0.0302	-0.0311
	0.9330	0.4759	0.1614	0.2328	0.2188	0.1902	0.1776
ydum15	-0.0110	-0.0295	-0.0300	-0.0248	-0.0292	-0.0311	-0.0320
	0.6325	0.2011	0.1931	0.2818	0.2058	0.1778	0.1654
ydum16	-0.0292	-0.0078	-0.0201	0.0011	-0.0316	-0.0336	-0.0346
	0.2063	0.7344	0.3843	0.9622	0.1714	0.1452	0.1338
ydum17	-0.0328	0.0108	-0.0101	0.0169	-0.0316	-0.0337	-0.0347
	0.1547	0.6387	0.6616	0.4648	0.1703	0.1441	0.1327
ydum18	-0.0300	0.0253	0.0017	0.0474	-0.0314	-0.0334	-0.0344
	0.1931	0.2726	0.9397	0.0400	0.1738	0.1474	0.1359
naics325411	0.1105	-0.0231	-0.0327	-0.0285	0.0406	0.0368	0.0351
	0.0000	0.3163	0.1568	0.2169	0.0787	0.1108	0.1280
naics325412	0.0490	-0.0501	0.0135	-0.0373	0.0210	0.0201	0.0142
	0.0336	0.0300	0.5600	0.1059	0.3638	0.3844	0.5375
naics325413	-0.0213	0.0272	0.0003	0.0366	-0.0096	0.0006	-0.0019
	0.3570	0.2385	0.9880	0.1124	0.6766	0.9787	0.9341

	ydum04	ydum05	ydum06	ydum07	ydum08	ydum09	ydum10
ydum04	1.0000						
ydum05	-0.0137	1.0000					
	0.5519						
ydum06	-0.0161	-0.0171	1.0000				
	0.4849	0.4585					
ydum07	-0.0192	-0.0204	-0.0239	1.0000			
	0.4058	0.3775	0.3002				
ydum08	-0.0207	-0.0219	-0.0257	-0.0306	1.0000		
	0.3708	0.3421	0.2648	0.1843			
ydum09	-0.0229	-0.0243	-0.0285	-0.0339	-0.0365	1.0000	
	0.3218	0.2929	0.2170	0.1416	0.1136		
ydum10	-0.0278	-0.0295	-0.0347	-0.0413	-0.0444	-0.0492	1.0000
	0.2282	0.2008	0.1332	0.0738	0.0543	0.0331	
ydum12	-0.0318	-0.0337	-0.0396	-0.0471	-0.0507	-0.0562	-0.0683
	0.1686	0.1439	0.0862	0.0411	0.0279	0.0149	0.0031
ydum13	-0.0328	-0.0348	-0.0408	-0.0486	-0.0523	-0.0579	-0.0704
	0.1556	0.1317	0.0768	0.0351	0.0233	0.0120	0.0022
ydum14	-0.0360	-0.0382	-0.0448	-0.0534	-0.0575	-0.0636	-0.0774
	0.1189	0.0978	0.0519	0.0207	0.0127	0.0058	0.0008
ydum15	-0.0370	-0.0393	-0.0461	-0.0549	-0.0591	-0.0654	-0.0796
	0.1086	0.0885	0.0456	0.0173	0.0104	0.0045	0.0006
ydum16	-0.0400	-0.0425	-0.0499	-0.0594	-0.0639	-0.0707	-0.0860
	0.0828	0.0656	0.0307	0.0101	0.0056	0.0022	0.0002
ydum17	-0.0401	-0.0426	-0.0500	-0.0595	-0.0641	-0.0709	-0.0863
	0.0820	0.0649	0.0302	0.0099	0.0055	0.0021	0.0002
ydum18	-0.0398	-0.0423	-0.0496	-0.0590	-0.0636	-0.0704	-0.0856
	0.0845	0.0671	0.0316	0.0105	0.0059	0.0023	0.0002
naics325411	0.0271	0.0240	0.0488	0.0356	0.0303	0.0233	0.0105
	0.2404	0.2988	0.0344	0.1233	0.1891	0.3120	0.6483
naics325412	0.0418	0.0264	0.0009	-0.0008	0.0061	0.0150	-0.0195

	0.0704	0.2523	0.9681	0.9712	0.7918	0.5155	0.3984
naics325413	-0.0147	-0.0082	0.0057	0.0167	0.0045	-0.0124	0.0338
	0.5240	0.7211	0.8061	0.4696	0.8469	0.5918	0.1432

	ydum12	ydum13	ydum14	ydum15	ydum16	ydum17	ydum18
ydum12	1.0000						
ydum13	-0.0805	1.0000					
	0.0005						
ydum14	-0.0884	-0.0912	1.0000				
	0.0001	0.0001					
ydum15	-0.0909	-0.0938	-0.1030	1.0000			
	0.0001	0.0000	0.0000				
ydum16	-0.0983	-0.1014	-0.1113	-0.1145	1.0000		
	0.0000	0.0000	0.0000	0.0000			
ydum17	-0.0986	-0.1016	-0.1116	-0.1148	-0.1241	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0000		
ydum18	-0.0978	-0.1008	-0.1107	-0.1139	-0.1231	-0.1235	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
naics325411	0.0021	0.0001	-0.0216	-0.0231	-0.0271	-0.0273	-0.0268
	0.9283	0.9956	0.3485	0.3174	0.2399	0.2374	0.2449
naics325412	-0.0276	-0.0224	-0.0023	0.0073	0.0033	0.0017	-0.0002
	0.2314	0.3326	0.9191	0.7518	0.8863	0.9429	0.9925
naics325413	0.0451	0.0313	0.0012	-0.0063	-0.0136	-0.0188	-0.0211
	0.0504	0.1744	0.9593	0.7842	0.5570	0.4158	0.3617

	n~325411	n~325412	n~325413
naics325411	1.0000		
naics325412	-0.1145	1.0000	
	0.0000		
naics325413	-0.0544	-0.4439	1.0000
	0.0184	0.0000	

Table 6.6a Model #7 Signficant Interaction Effects (Final Model)

```
xtnbreg pat_app_yr_D1 DNvertical_n tot_prtpat prtcomm partnerstatus   lead1YRavgyrcol
brok_fixmis dens_fixmis InterDirect_Ind_t7 direct_t_7 ind_t_7 _10yrapp _10yrpatapp
EquityEventslead1YRstkprice_24_ yrcompst_C diversification_C lead1YRnet_inc_C lead1YREmploy_29_
lead 1YRr_d_46 ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12
ydum13 ydum14 ydum15 ydum16 ydum17 ydum18 naics325411 naics325412 naics325413 if yeardata 1992,
nolog

Random-effects negative binomial regression     Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

Random effects u_i ~ Beta                       Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        11

                                                Wald chi2(32)      =    477.33
Log likelihood  = -3082.5184                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
pat_app_yr~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
DNvertical_n |  -8.40e-06   3.23e-06    -2.60   0.009    -.0000147   -2.07e-06
  tot_prtpat |  -1.91e-06   .0000487    -0.04   0.969    -.0000974    .0000936
     prtcomm |  -.0067274   .0030131    -2.23   0.026     -.012633   -.0008219
partnersta~s |   .0000274   .0000493     0.56   0.578    -.0000692    .0001241
lead1YRavg~l |   -.066007   .0241826    -2.73   0.006     -.113404     -.01861
 brok_fixmis |  -.0005101    .000146    -3.49   0.000    -.0007961    -.000224
 dens_fixmis |   .0079127   .0036923     2.14   0.032     .0006759    .0151495
InterDirec~7 |  -.0006045   .0002343    -2.58   0.010    -.0010637   -.0001453
  direct_t_7 |   .0206266   .0054926     3.76   0.000     .0098612     .031392
     ind_t_7 |   .0019629   .0071485     0.27   0.784    -.0120478    .0159736
    _10yrapp |    .008684   .0041738     2.08   0.037     .0005035    .0168644
 _10yrpatapp |    .001044   .0001836     5.69   0.000     .0006841     .001404
 EquityEvents|   .0805304   .0322666     2.50   0.013      .017289    .1437718
lead1YRs~24_ |   .0013423   .0012967     1.04   0.301    -.0011992    .0038838
  yrcompst_C |  -.0352049   .0124981    -2.82   0.005    -.0597007   -.0107091
diversific~C |   .0420796   .0107697     3.91   0.000     .0209713    .0631879
lead1YRnet~C |  -.0000393   .0000666    -0.59   0.555    -.0001698    .0000912
lead1YRe~29_ |   .0062099   .0058363     1.06   0.287    -.0052291    .0176489
lead1YRr~46_ |   .0001218   .0001079     1.13   0.259    -.0000897    .0003333
      ydum08 |   .6186075   .2502034     2.47   0.013     .1282179    1.108997
      ydum09 |   .8174238   .2404626     3.40   0.001     .3461258    1.288722
      ydum10 |   1.161902   .2195317     5.29   0.000     .7316282    1.592177
      ydum12 |   .6061259   .2106015     2.88   0.004     .1933545    1.018897
      ydum13 |   1.030058   .1938579     5.31   0.000     .6501033    1.410012
      ydum14 |   1.067128   .1763683     6.05   0.000     .7214521    1.412803
      ydum15 |   1.187537    .156862     7.57   0.000     .8800934    1.494981
      ydum16 |   1.180704   .1442931     8.18   0.000     .8978949    1.463514
      ydum17 |   1.249145   .1334905     9.36   0.000      .987508    1.510781
      ydum18 |   .8167482   .1324618     6.17   0.000     .5571278    1.076369
 naics325411 |  -1.096861   .9379762    -1.17   0.242     -2.93526     .741539
 naics325412 |   .3271239   .1787794     1.83   0.067    -.0232772     .677525
 naics325413 |   .4112417   .2321296     1.77   0.076     -.043724    .8662073
       _cons |  -.2103831   .2967193    -0.71   0.478    -.7919423    .3711761
-------------+----------------------------------------------------------------
       /ln_r |   .2102015   .1057847                      .0028673    .4175356
       /ln_s |  -.4721007   .1125504                     -.6926954   -.2515059
-------------+----------------------------------------------------------------
           r |   1.233927   .1305305                      1.002871    1.518216
           s |   .6236907   .0701966                      .5002259    .7776288
------------------------------------------------------------------------------
Likelihood-ratio test vs. pooled: chibar2(01) =  1117.74 Prob>=chibar2 = 0.000
```

Table 6.6a Model #6 The Panel Negative Binomial Regression on Patenting Rates

```
xtnbreg pat_app_yr_D1 Uphorizontie_n2 DNhorizontie_n UPvertical_n2 DNvertical_n tot_prtpat
prtcomm partnerstatus   lead1YRavgyrcol   brok_fixmis  dens_fixmis  InterDirect_Ind_t7
direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C
diversification_C lead1YRnet_inc_C lead1YREmploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04
ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18
naics325411 naics325412 naics325413 if yeardata > 1992, nolog

Random-effects negative binomial regression     Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

Random effects u_i ~ Beta                       Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        11

                                                Wald chi2(35)      =    483.12
Log likelihood  = -3082.0396                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
pat_app_yr~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Uphorizont~2 |   1.05e-08   9.43e-08     0.11   0.911    -1.74e-07    1.95e-07
DNhorizont~n |  -.0002144   .0002278    -0.94   0.347    -.0006609    .0002321
UPvertical~2 |   3.39e-06    .000017     0.20   0.842    -.0000299    .0000367
DNvertical_n |  -7.38e-06   3.27e-06    -2.26   0.024    -.0000138   -9.77e-07
  tot_prtpat |  -.0000176   .0000707    -0.25   0.803    -.0001561    .0001209
     prtcomm |  -.0054468   .0034691    -1.57   0.116    -.0122461    .0013526
partnersta~s |   .0000298   .0000504     0.59   0.554    -.0000689    .0001285
lead1YRavg~l |  -.0655639   .0242107    -2.71   0.007     -.113016   -.0181117
 brok_fixmis |   -.000505   .0001459    -3.46   0.001    -.0007909   -.0002191
 dens_fixmis |   .0078295   .0036926     2.12   0.034      .000592    .0150669
InterDirec~7 |  -.0006357    .000238    -2.67   0.008    -.0011022   -.0001691
  direct_t_7 |   .0211042   .0055087     3.83   0.000     .0103074     .031901
     ind_t_7 |   .0022938   .0071653     0.32   0.749      -.01175    .0163376
    _10yrapp |   .0095468   .0043897     2.17   0.030     .0009431    .0181504
 _10yrpatapp |   .0010348   .0001838     5.63   0.000     .0006746    .0013949
 EquityEvents|   .0821158   .0323787     2.54   0.011     .0186548    .1455768
lead1YRs~24_ |   .0014317   .0013005     1.10   0.271    -.0011172    .0039805
  yrcompst_C |  -.0366163   .0126705    -2.89   0.004    -.0614501   -.0117825
diversific~C |   .0429679    .010796     3.98   0.000     .0218081    .0641278
lead1YRnet~C |  -.0000362    .000067    -0.54   0.589    -.0001676    .0000952
lead1YRe~29_ |    .006132    .005839     1.05   0.294    -.0053122    .0175763
lead1YRr~46_ |   .0001153   .0001086     1.06   0.288    -.0000976    .0003283
      ydum08 |   .6098399   .2499935     2.44   0.015     .1198615    1.099818
      ydum09 |   .8071017    .240742     3.35   0.001     .3352559    1.278947
      ydum10 |    1.14573   .2210922     5.18   0.000     .7123971    1.579062
      ydum12 |   .5957596   .2110371     2.82   0.005     .1821344    1.009385
      ydum13 |   1.032252   .1932293     5.34   0.000     .6535295    1.410974
      ydum14 |   1.054978   .1767479     5.97   0.000     .7085588    1.401398
      ydum15 |   1.179675   .1569388     7.52   0.000     .8720809     1.48727
      ydum16 |    1.17445   .1441725     8.15   0.000     .8918772    1.457023
      ydum17 |   1.244996   .1331698     9.35   0.000     .9839876    1.506004
      ydum18 |   .8163859   .1319209     6.19   0.000     .5578257    1.074946
 naics325411 |  -1.085821   .9382408    -1.16   0.247    -2.924739    .7530975
 naics325412 |   .3352316   .1791729     1.87   0.061    -.0159408    .6864039
 naics325413 |   .4187353   .2332414     1.80   0.073    -.0384096    .8758801
       _cons |  -.2096394    .297107    -0.71   0.480    -.7919584    .3726797
-------------+----------------------------------------------------------------
       /ln_r |   .2128228   .1059076                      .0052478    .4203979
       /ln_s |  -.4713505    .112543                     -.6919308   -.2507702
-------------+----------------------------------------------------------------
           r |   1.237165   .1310252                      1.005262    1.522567
           s |   .6241588   .0702447                      .5006086    .7782012
------------------------------------------------------------------------------
Likelihood-ratio test vs. pooled: chibar2(01) =  1104.92 Prob>=chibar2 = 0.000
```

Table 6.6a Model #5 Adding Exploration and Exploitation Networks

```
xtnbreg pat_app_yr_D1 tot_prtpat prtcomm partnerstatus   lead1YRavgyrcol   brok_fixmis
dens_fixmis InterDirect_Ind_t7 direct_t_7 ind_t_7 _10yrapp _10yrpatapp
EquityEventslead1YRstkprice_24_ yrcompst_C diversification_C lead1YRnet_inc_C lead1YREmploy_29_
lead1YRr_d_46_ ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12
ydum13 ydum14 ydum15 ydum16 ydum17 ydum18 naics325411 naics325412 naics325413 if yeardata > 1992,
nolog

Random-effects negative binomial regression     Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

Random effects u_i ~ Beta                       Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        11

                                                Wald chi2(31)      =    452.59
Log likelihood  = -3087.3706                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
pat_app_yr~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  tot_prtpat |  -.0000961   .0000434    -2.22   0.027    -.0001811   -.0000111
     prtcomm |  -.0058366   .0029741    -1.96   0.050    -.0116657   -7.57e-06
partnersta~s |   .0000331    .000051     0.65   0.517    -.0000669     .000133
lead1YRavg~l |  -.0686619    .024399    -2.81   0.005    -.1164831   -.0208408
 brok_fixmis |  -.0005005   .0001529    -3.27   0.001    -.0008002   -.0002008
 dens_fixmis |   .0078936   .0036925     2.14   0.033     .0006565    .0151307
InterDirec~7 |  -.0005133   .0002409    -2.13   0.033    -.0009854   -.0000411
  direct_t_7 |   .0203377   .0057778     3.52   0.000     .0090135    .0316619
     ind_t_7 |   .0003395   .0071829     0.05   0.962    -.0137388    .0144177
    _10yrapp |   .0068283   .0040477     1.69   0.092     -.001105    .0147615
 _10yrpatapp |    .001085   .0001906     5.69   0.000     .0007114    .0014586
 EquityEvents|   .0862571   .0328399     2.63   0.009     .0218921    .1506221
lead1YRs~24_ |    .001652   .0013122     1.26   0.208    -.0009198    .0042238
  yrcompst_C |  -.0309773    .012385    -2.50   0.012    -.0552515   -.0067031
diversific~C |   .0333773   .0103277     3.23   0.001     .0131353    .0536193
lead1YRnet~C |  -.0000399    .000065    -0.61   0.539    -.0001673    .0000874
lead1YRe~29_ |   .0071277    .005797     1.23   0.219    -.0042343    .0184897
lead1YRr~46_ |   .0001117   .0001088     1.03   0.304    -.0001015     .000325
      ydum08 |   .6556665   .2528661     2.59   0.010     .1600581    1.151275
      ydum09 |   .8493141   .2419535     3.51   0.000     .3750939    1.323534
      ydum10 |    1.19697   .2215134     5.40   0.000      .762812    1.631128
      ydum12 |   .6189643   .2123217     2.92   0.004     .2028215    1.035107
      ydum13 |   1.045966   .1964314     5.32   0.000     .6609675    1.430964
      ydum14 |   1.084702    .178213     6.09   0.000     .7354115    1.433993
      ydum15 |   1.197312   .1588214     7.54   0.000     .8860278    1.508596
      ydum16 |   1.193954   .1461351     8.17   0.000      .907534    1.480373
      ydum17 |   1.256658   .1355085     9.27   0.000     .9910661    1.522249
      ydum18 |   .8197716    .135001     6.07   0.000     .5551745    1.084369
 naics325411 |  -1.091672   .9384915    -1.16   0.245    -2.931082    .7477372
 naics325412 |   .2984906   .1789038     1.67   0.095    -.0521544    .6491355
 naics325413 |    .434981   .2329935     1.87   0.062    -.0216779    .8916398
       _cons |  -.1710878   .2982181    -0.57   0.566    -.7555846    .4134089
-------------+----------------------------------------------------------------
       /ln_r |   .1936852   .1052555                     -.0126118    .3999822
       /ln_s |  -.4854819   .1124179                     -.7058169   -.2651469
-------------+----------------------------------------------------------------
           r |   1.213714   .1277501                      .9874674    1.491798
           s |   .6154006    .069182                      .4937051    .7670933
------------------------------------------------------------------------------
Likelihood-ratio test vs. pooled: chibar2(01) =  1114.66 Prob>=chibar2 = 0.000
```

Table 6.6a Model #4 Adding Partners' Prominence and Tie Strength

```
xtnbreg pat_app_yr_D1 partnerstatus   lead1YRavgyrcol   brok_fixmis dens_fixmis
InterDirect_Ind_t7 direct_t_7 ind_t_7 _10yrapp _10yrpat app EquityEventslead1YRstkprice_24_
yrcompst_C diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_ ydum01 ydum02
ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17
ydum18 naics325411 naics325412 naics325413 if yeardata > 1992, nolog

Random-effects negative binomial regression     Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

Random effects u_i ~ Beta                       Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        11

                                                Wald chi2(29)      =    421.16
Log likelihood  = -3092.4975                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
pat_app_yr~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
partnersta~s |  -.0000517    .000045    -1.15   0.250    -.0001398    .0000365
lead1YRavg~l |  -.0692304   .0245644    -2.82   0.005    -.1173757    -.021085
 brok_fixmis |   -.000495   .0001618    -3.06   0.002    -.0008121   -.0001778
 dens_fixmis |   .0073688   .0036848     2.00   0.046     .0001468    .0145909
InterDirec~7 |  -.0006326   .0002448    -2.58   0.010    -.0011124   -.0001528
  direct_t_7 |   .0235665   .0059314     3.97   0.000     .0119411    .0351919
     ind_t_7 |   .0009166   .0071895     0.13   0.899    -.0131745    .0150077
    _10yrapp |   .0057251   .0039724     1.44   0.150    -.0020606    .0135109
 _10yrpatapp |   .0010808   .0001955     5.53   0.000     .0006976     .001464
 EquityEvents|   .0701441   .0321727     2.18   0.029     .0070867    .1332016
lead1YRs~24_ |   .0019539   .0013244     1.48   0.140    -.0006419    .0045497
  yrcompst_C |  -.0222399   .0116625    -1.91   0.057    -.0450979    .0006181
diversific~C |   .0251784   .0093286     2.70   0.007     .0068946    .0434621
lead1YRnet~C |   -.000028   .0000662    -0.42   0.673    -.0001578    .0001018
lead1YRe~29_ |   .0056647   .0058645     0.97   0.334    -.0058295     .017159
lead1YRr~46_ |   .0001078   .0001118     0.96   0.335    -.0001113    .0003269
       ydum08 |   .7218219   .2521099     2.86   0.004     .2276956    1.215948
       ydum09 |   .9277934   .2405815     3.86   0.000     .4562624    1.399324
       ydum10 |   1.252388   .2200856     5.69   0.000     .8210282    1.683748
       ydum12 |    .661679   .2126956     3.11   0.002     .2448032    1.078555
       ydum13 |   1.110338   .1956981     5.67   0.000     .7267772      1.4939
       ydum14 |   1.139388   .1781398     6.40   0.000     .7902403    1.488536
       ydum15 |   1.208708   .1600039     7.55   0.000     .8951056    1.522309
       ydum16 |   1.211045   .1473729     8.22   0.000     .9221992     1.49989
       ydum17 |   1.274829   .1368599     9.31   0.000     1.006589     1.54307
       ydum18 |   .8291072   .1368524     6.06   0.000     .5608814    1.097333
 naics325411 |  -1.090523   .9371208    -1.16   0.245    -2.927246    .7461999
 naics325412 |   .2754942   .1779112     1.55   0.122    -.0732053    .6241938
 naics325413 |   .4228799   .2334713     1.81   0.070    -.0347154    .8804752
       _cons |  -.2190679   .2986215    -0.73   0.463    -.8043554    .3662195
-------------+----------------------------------------------------------------
       /ln_r |   .1819824   .1048302                     -.0234811    .3874459
       /ln_s |  -.4842147   .1125804                     -.7048683   -.2635612
-------------+----------------------------------------------------------------
           r |   1.199593   .1257536                      .9767924    1.473213
           s |   .6161809   .0693699                      .4941737    .7683106
------------------------------------------------------------------------------
Likelihood-ratio test vs. pooled: chibar2(01) =  1107.51 Prob>=chibar2 = 0.000
```

Table 6.6a Model #3 Adding Brokerage and Density (Structural Holes)

```
xtnbreg pat_app_yr_D1 brok_fixmis  dens_fixmis InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp
_10yrpatapp EquityEvents lead1YRstkprice_ 24_ yrcompst_C diversification_C lead1YRnet_inc_C
lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09
ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411 naics325412 naics325413 if
yeardata > 1992, nolog

Random-effects negative binomial regression     Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

Random effects u_i ~ Beta                       Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        11

                                                Wald chi2(27)      =    403.69
Log likelihood  = -3097.0427                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
pat_app_yr~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 brok_fixmis |  -.0005627   .0001663    -3.38   0.001    -.0008886   -.0002369
 dens_fixmis |   .0072663   .0036716     1.98   0.048     .0000702    .0144624
InterDirec~7 |  -.0005648   .0002376    -2.38   0.017    -.0010305   -.0000991
  direct_t_7 |   .0268057   .0059843     4.48   0.000     .0150768    .0385346
     ind_t_7 |  -.0010204   .0070092    -0.15   0.884    -.0147582    .0127174
    _10yrapp |    .004714    .003768     1.25   0.211    -.0026713    .0120992
 _10yrpatapp |   .0010451   .0001952     5.35   0.000     .0006624    .0014277
 EquityEvents|   .0633755   .0324973     1.95   0.051     -.000318     .127069
lead1YRs~24_ |   .0019542   .0013625     1.43   0.152    -.0007163    .0046248
  yrcompst_C |  -.0180652   .0114159    -1.58   0.114      -.04044    .0043096
diversific~C |   .0202953   .0088922     2.28   0.022     .0028669    .0377236
lead1YRnet~C |  -.0000301   .0000662    -0.46   0.649    -.0001599    .0000996
lead1YRe~29_ |   .0042171   .0058775     0.72   0.473    -.0073026    .0157368
lead1YRr~46_ |   .0001419   .0001099     1.29   0.196    -.0000734    .0003573
      ydum08 |   1.141533   .2024722     5.64   0.000     .7446947    1.538371
      ydum09 |    1.35458    .185113     7.32   0.000     .9917654    1.717395
      ydum10 |   1.620489   .1684986     9.62   0.000     1.290238     1.95074
      ydum12 |   1.009976   .1666256     6.06   0.000     .6833958    1.336556
      ydum13 |   1.403053   .1522489     9.22   0.000      1.10465    1.701455
      ydum14 |   1.409533    .144049     9.79   0.000     1.127203    1.691864
      ydum15 |   1.434013    .140395    10.21   0.000     1.158844    1.709182
      ydum16 |   1.382042   .1363642    10.13   0.000     1.114773    1.649311
      ydum17 |    1.38853   .1335989    10.39   0.000     1.126681    1.650379
      ydum18 |     .89456   .1379432     6.48   0.000     .6241964    1.164924
 naics325411 |  -1.196964   .9552547    -1.25   0.210    -3.069228    .6753012
 naics325412 |    .289176    .173212     1.67   0.095    -.0503133    .6286653
 naics325413 |   .3998454   .2309624     1.73   0.083    -.0528326    .8525234
       _cons |   -.726916   .2166047    -3.36   0.001    -1.151453   -.3023785
-------------+----------------------------------------------------------------
       /ln_r |   .1643074   .1042573                     -.0400332    .3686481
       /ln_s |  -.4675312   .1127358                     -.6884893   -.2465731
-------------+----------------------------------------------------------------
           r |   1.178577   .1228753                      .9607575    1.445779
           s |   .6265472   .0706343                      .5023344    .7814742
------------------------------------------------------------------------------
Likelihood-ratio test vs. pooled: chibar2(01) =  1106.51 Prob>=chibar2 = 0.000
```

Table 6.6a Model #2 Adding Direct, Indirect, and Interaction Effects

```
xtnbreg pat_app_yr_D1 InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents
lead1YRstkprice_24_ yrcompst_C diversification_C lead1YRnet_inc_C lead1YRemploy_29_
lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12
ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411 naics325412 naics325413 if yeardata >
1992, nolog

Random-effects negative binomial regression     Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

Random effects u_i ~ Beta                       Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        11

                                                Wald chi2(25)      =    366.24
Log likelihood  = -3104.5273                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
pat_app_yr~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
InterDirec~7 |  -.0005418   .0002449    -2.21   0.027    -.0010218   -.0000618
  direct_t_7 |   .0130191   .0048577     2.68   0.007     .0034982      .02254
     ind_t_7 |    .002554    .006976     0.37   0.714    -.0111187    .0162268
    _10yrapp |    .004064   .0038096     1.07   0.286    -.0034026    .0115305
 _10yrpatapp |   .0005665   .0001308     4.33   0.000     .0003102    .0008228
 EquityEvents|   .0560026   .0326259     1.72   0.086    -.0079429    .1199482
lead1YRs~24_ |   .0022377    .001378     1.62   0.104    -.0004631    .0049385
  yrcompst_C |  -.0187445   .0117519    -1.60   0.111    -.0417777    .0042887
diversific~C |   .0243238   .0091534     2.66   0.008     .0063835    .0422642
lead1YRnet~C |  -.0000152   .0000693    -0.22   0.826     -.000151    .0001206
lead1YRe~29_ |   .0063436   .0061844     1.03   0.305    -.0057777    .0184648
lead1YRr~46_ |   .0000831   .0001182     0.70   0.482    -.0001486    .0003148
      ydum08 |   1.081761   .2120692     5.10   0.000     .6661132    1.497409
      ydum09 |   1.358356   .1893134     7.18   0.000     .9873082    1.729403
      ydum10 |   1.628204   .1708227     9.53   0.000     1.293397     1.96301
      ydum12 |   .9945969     .16921     5.88   0.000     .6629513    1.326242
      ydum13 |   1.366667   .1526627     8.95   0.000     1.067454     1.66588
      ydum14 |   1.385724   .1434492     9.66   0.000     1.104568    1.666879
      ydum15 |   1.436946   .1400293    10.26   0.000     1.162494    1.711399
      ydum16 |   1.390646   .1356597    10.25   0.000     1.124758    1.656535
      ydum17 |   1.395552   .1327963    10.51   0.000     1.135276    1.655828
      ydum18 |   .9022058    .137612     6.56   0.000     .6324912     1.17192
 naics325411 |  -1.257124   .9636443    -1.30   0.192    -3.145832    .6315843
 naics325412 |   .3082508   .1756227     1.76   0.079    -.0359634    .6524649
 naics325413 |   .3822653   .2319615     1.65   0.099     -.072371    .8369015
       _cons |  -.6841934   .2190041    -3.12   0.002    -1.113434   -.2549532
-------------+----------------------------------------------------------------
       /ln_r |   .1416497   .1039623                     -.0621126    .3454121
       /ln_s |  -.5004989   .1112929                     -.7186291   -.2823687
-------------+----------------------------------------------------------------
           r |   1.152173   .1197825                      .939777    1.412572
           s |   .6062281   .0674689                       .48742    .7539956
------------------------------------------------------------------------------
Likelihood-ratio test vs. pooled: chibar2(01) =  1162.06 Prob>=chibar2 = 0.000
```

Table 6.6a Model #1 Based Model with Control Variables

```
xtnbreg pat_app_yr_D1 _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C
diversification_C lead1YRnet_inc_C   lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03
ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18
naics325411 naics325412 naics325413 if yeardata > 1992, nolog

Random-effects negative binomial regression     Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

Random effects u_i ~ Beta                       Obs per group: min =         1
                                                               avg =       6.5
                                                               max =        11

                                                Wald chi2(22)      =    344.15
Log likelihood  = -3108.3407                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
pat_app_yr~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    _10yrapp |   .0045798   .0038215     1.20   0.231    -.0029102    .0120699
 _10yrpatapp |   .0005215   .0001208     4.32   0.000     .0002846    .0007583
 EquityEvents|   .0584627   .0328959     1.78   0.076    -.0060121    .1229375
lead1YRs~24_ |   .0019417   .0014117     1.38   0.169    -.0008251    .0047085
  yrcompst_C |  -.0206836    .011741    -1.76   0.078    -.0436955    .0023282
diversific~C |   .0285729   .0086929     3.29   0.001     .0115352    .0456106
lead1YRnet~C |  -.0000375   .0000679    -0.55   0.580    -.0001706    .0000955
lead1YRe~29_ |   .0082602   .0061795     1.34   0.181    -.0038513    .0203718
lead1YRr~46_ |    .000108   .0001152     0.94   0.349    -.0001179    .0003339
      ydum08 |   .9872497   .2101868     4.70   0.000     .5752912    1.399208
      ydum09 |   1.257656   .1869221     6.73   0.000     .8912952    1.624016
      ydum10 |   1.548486   .1694496     9.14   0.000     1.216371    1.880602
      ydum12 |   .9426369   .1698693     5.55   0.000     .6096992    1.275575
      ydum13 |   1.343738   .1538454     8.73   0.000     1.042207     1.64527
      ydum14 |   1.393633   .1451569     9.60   0.000      1.10913    1.678135
      ydum15 |   1.427702    .140236    10.18   0.000     1.152844     1.70256
      ydum16 |   1.389809   .1358721    10.23   0.000     1.123505    1.656114
      ydum17 |   1.394758   .1334021    10.46   0.000     1.133295    1.656222
      ydum18 |   .9056538   .1383363     6.55   0.000     .6345195    1.176788
 naics325411 |  -1.265631   .9668294    -1.31   0.191    -3.160581    .6293201
 naics325412 |   .3332541   .1751775     1.90   0.057    -.0100875    .6765958
 naics325413 |   .3949888   .2301752     1.72   0.086    -.0561463    .8461239
       _cons |  -.6488004   .2167581    -2.99   0.003    -1.073639   -.2239622
-------------+----------------------------------------------------------------
       /ln_r |   .1297473   .1037347                     -.0735689    .3330635
       /ln_s |  -.5132706   .1104122                     -.7296746   -.2968666
-------------+----------------------------------------------------------------
           r |   1.138541   .1181061                      .9290721    1.395236
           s |   .5985348   .0660856                      .4820658    .7431431
------------------------------------------------------------------------------
Likelihood-ratio test vs. pooled: chibar2(01) =  1215.57 Prob>=chibar2 = 0.000
```

Table 6.6b Model #7 Signficant Interaction Effects (Final Model)

```
zinb succmktapp_n UPvertical_n2 DNvertical_n tot_prtpat prtcomm partnerstatus   lead1YRavgyrcol
brok_fixmis  dens_fixmis direct_t_7 ind_t_7 _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_
yrcompst_C diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02
ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17
ydum18  naics325411 naics325412 naics325413 if yeardata > 1992,inf(_10yrapp _10yrpatapp)
cluster(focalcode) nolog

Zero-inflated negative binomial regression        Number of obs   =       1689
                                                  Nonzero obs     =        384
                                                  Zero obs        =       1305

Inflation model       = logit                     Wald chi2(32)   =    3150.26
Log pseudo-likelihood = -1362.158                 Prob > chi2     =     0.0000

                      (standard errors adjusted for clustering on focalcode)
------------------------------------------------------------------------------
             |               Robust
succmktapp_n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
succmktapp_n |
UPvertical~2 |  -.0000216    .000018    -1.20   0.232    -.0000569    .0000138
DNvertical_n |   7.14e-06   3.29e-06     2.17   0.030     6.85e-07    .0000136
  tot_prtpat |  -.0002678   .0001118    -2.40   0.017    -.0004869   -.0000488
     prtcomm |  -.0024936   .0045317    -0.55   0.582    -.0113755    .0063883
partnersta~s |   .0003109    .000125     2.49   0.013      .000066    .0005558
lead1YRavg~l |  -.0319799    .047566    -0.67   0.501    -.1252074    .0612477
 brok_fixmis |   .0004039   .0002743     1.47   0.141    -.0001337    .0009415
 dens_fixmis |  -.0123837   .0037433    -3.31   0.001    -.0197204   -.0050469
  direct_t_7 |  -.0234583   .0106634    -2.20   0.028    -.0443581   -.0025584
     ind_t_7 |   .0318586   .0120082     2.65   0.008     .0083229    .0553943
    _10yrapp |   .0373408   .0073128     5.11   0.000      .023008    .0516735
 _10yrpatapp |   3.07e-06   .0001722     0.02   0.986    -.0003344    .0003405
EquityEvents |  -.1132646   .0777855    -1.46   0.145    -.2657214    .0391923
lead1YRs~24_ |  -.0033032   .0025336    -1.30   0.192    -.0082689    .0016625
  yrcompst_C |   .0092313   .0183794     0.50   0.615    -.0267917    .0452543
diversific~C |   .0565555   .0112366     5.03   0.000     .0345321    .0785789
lead1YRnet~C |   .0001069   .0000959     1.11   0.265    -.0000811    .0002948
lead1YRe~29_ |  -.0137086   .0160116    -0.86   0.392    -.0450907    .0176736
lead1YRr~46_ |   .0004757   .0002933     1.62   0.105    -.0000991    .0010506
      ydum08 |  -.0465262   .3058394    -0.15   0.879    -.6459603    .5529079
      ydum09 |  -.1366327   .2947962    -0.46   0.643    -.7144227    .4411574
      ydum10 |  -.0975768   .3113604    -0.31   0.754    -.7078319    .5126783
      ydum12 |  -.2680911   .2821633    -0.95   0.342     -.821121    .2849387
      ydum13 |  -.3881654   .2518519    -1.54   0.123    -.8817861    .1054553
      ydum14 |  -.3117403   .2280646    -1.37   0.172    -.7587387    .1352581
      ydum15 |  -.1372946   .1914473    -0.72   0.473    -.5125244    .2379351
      ydum16 |   .0676464   .1452185     0.47   0.641    -.2169767    .3522695
      ydum17 |  -.0078119   .0898699    -0.09   0.931    -.1839538    .1683299
      ydum18 |   .0626574   .0760977     0.82   0.410    -.0864913    .2118062
 naics325411 |  -26.95281   .7482747   -36.02   0.000     -28.4194   -25.48622
 naics325412 |   1.445301   .2466934     5.86   0.000     .9617906    1.928811
 naics325413 |  -1.268514   .4945926    -2.56   0.010    -2.237898   -.2991308
       _cons |  -.3693585   .3786695    -0.98   0.329    -1.111537    .3728201
-------------+----------------------------------------------------------------
inflate      |
    _10yrapp |  -29.02719   .7306563   -39.73   0.000    -30.45925   -27.59513
 _10yrpatapp |   .0002622   .0035903     0.07   0.942    -.0067746     .007299
       _cons |   2.656669   .3536687     7.51   0.000     1.963491    3.349847
-------------+----------------------------------------------------------------
    /lnalpha |  -.9959479   .4754559    -2.09   0.036    -1.927824   -.0640716
-------------+----------------------------------------------------------------
       alpha |   .3693731   .1756206                      .1454643    .9379378
------------------------------------------------------------------------------
```

Table 6.6b Model #6 Zero Inflated Negative Binomial Regression on Marketed Drug Apps

```
zinb succmktapp_n Uphorizontie_n2 DNhorizontie_n UPvertical_n2 DNvertical_n tot_prtpat prtcomm
partnerstatus   lead1YRavgyrcol brok_fixmis dens_fixmis InterDirect_Ind_t7  direct_t_7  ind_t_7
_10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C diversification_C
lead1YRnet_inc_C lead1YREmploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06
ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411
naics325412 naics325413 if yeardata > 1992,inf(_10yrapp _10yrpatapp) cluster(focalcode) nolog

Zero-inflated negative binomial regression       Number of obs   =       1689
                                                 Nonzero obs     =        384
                                                 Zero obs        =       1305

Inflation model       = logit                    Wald chi2(35)   =    6034.79
Log pseudo-likelihood = -1358.656                Prob > chi2     =     0.0000

                       (standard errors adjusted for clustering on focalcode)
------------------------------------------------------------------------------
             |               Robust
succmktapp_n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Uphorizont~2 |   2.08e-07   2.02e-07     1.03   0.303    -1.88e-07    6.03e-07
DNhorizont~n |   .0004568   .0003079     1.48   0.138    -.0001467    .0010604
UPvertical~2 |  -.0000347   .0000177    -1.96   0.050    -.0000695   -2.62e-08
DNvertical_n |   7.63e-06   4.19e-06     1.82   0.068    -5.75e-07    .0000158
  tot_prtpat |   -.000308   .0001649    -1.87   0.062    -.0006311    .0000151
     prtcomm |   -.005874   .0035132    -1.67   0.095    -.0127598    .0010117
partnersta~s |   .0003108   .0001299     2.39   0.017     .0000562    .0005654
lead1YRavg~l |  -.0360327   .0482323    -0.75   0.455    -.1305662    .0585009
 brok_fixmis |   .0003685   .0002647     1.39   0.164    -.0001503    .0008873
 dens_fixmis |  -.0115662   .0034614    -3.34   0.001    -.0183504    -.004782
InterDirec~7 |   .0007753    .000869     0.89   0.372    -.0009279    .0024784
  direct_t_7 |  -.0309792   .0144491    -2.14   0.032    -.0592989   -.0026594
     ind_t_7 |   .0172391   .0153725     1.12   0.262    -.0128906    .0473687
    _10yrapp |   .0366667    .006877     5.33   0.000      .023188    .0501453
 _10yrpatapp |  -.0000209   .0001744    -0.12   0.905    -.0003628     .000321
EquityEvents |  -.1031862   .0720148    -1.43   0.152    -.2443327    .0379603
lead1YRs~24_ |  -.0032704   .0023899    -1.37   0.171    -.0079546    .0014138
  yrcompst_C |    .008724   .0204745     0.43   0.670    -.0314053    .0488532
diversific~C |     .05869   .0126975     4.62   0.000     .0338034    .0835766
lead1YRnet~C |   .0000617   .0001174     0.53   0.599    -.0001683    .0002917
lead1YRe~29_ |  -.0144736   .0159785    -0.91   0.365    -.0457909    .0168438
lead1YRr~46_ |   .0005591   .0003101     1.80   0.071    -.0000486    .0011669
      ydum08 |  -.1099063   .2878564    -0.38   0.703    -.6740944    .4542818
      ydum09 |  -.2016159   .2888061    -0.70   0.485    -.7676654    .3644336
      ydum10 |  -.1562746   .3177684    -0.49   0.623    -.7790892      .46654
      ydum12 |  -.3354701   .2847278    -1.18   0.239    -.8935264    .2225862
      ydum13 |  -.4373333   .2497697    -1.75   0.080    -.9268729    .0522062
      ydum14 |  -.3464489   .2312983    -1.50   0.134    -.7997851    .1068874
      ydum15 |  -.1564355     .18797    -0.83   0.405    -.5248498    .2119789
      ydum16 |   .0506718   .1379643     0.37   0.713    -.2197332    .3210769
      ydum17 |  -.0122161   .0898315    -0.14   0.892    -.1882827    .1638504
      ydum18 |    .057659   .0756243     0.76   0.446    -.0905619    .2058799
 naics325411 |   -25.0518   .7524307   -33.29   0.000    -26.52654   -23.57706
 naics325412 |   1.390892   .2434238     5.71   0.000     .9137899    1.867994
 naics325413 |   -1.21583   .4876133    -2.49   0.013    -2.171534   -.2601251
       _cons |  -.2252313   .3920044    -0.57   0.566    -.9935457    .5430832
-------------+----------------------------------------------------------------
inflate      |
    _10yrapp |  -27.87202   .7346722   -37.94   0.000    -29.31195   -26.43209
 _10yrpatapp |   .0001425   .0035701     0.04   0.968    -.0068548    .0071399
       _cons |   2.681367   .3574352     7.50   0.000     1.980807    3.381927
-------------+----------------------------------------------------------------
    /lnalpha |  -1.018142   .4606822    -2.21   0.027    -1.921063   -.1152218
-------------+----------------------------------------------------------------
       alpha |   .3612654   .1664285                      .1464512    .8911684
------------------------------------------------------------------------------
```

Table 6.6b Model #5 Adding Exploration and Exploitation Networks

```
zinb  succmktapp_n tot_prtpat prtcomm partnerstatus   lead1YRavgyrcol   brok_fixmis  dens_fixmis
InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_
yrcompst_C diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02
ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17
ydum18  naics325411 naics325412 naics325413 if yeardata > 1992,inf(_10yrapp _10yrpatapp)
cluster(focalcode) nolog

Zero-inflated negative binomial regression        Number of obs   =       1689
                                                  Nonzero obs     =        384
                                                  Zero obs        =       1305

Inflation model       = logit                     Wald chi2(31)   =    2560.79
Log pseudo-likelihood = -1363.988                 Prob > chi2     =     0.0000

                        (standard errors adjusted for clustering on focalcode)
------------------------------------------------------------------------------
             |               Robust
succmktapp_n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
succmktapp_n |
  tot_prtpat |  -.0000243   .0000853    -0.29   0.775    -.0001914    .0001428
     prtcomm |  -.0065459   .0051198    -1.28   0.201    -.0165805    .0034886
partnersta~s |   .0003412   .0001164     2.93   0.003     .0001131    .0005693
lead1YRavg~l |  -.0334595   .0476899    -0.70   0.483      -.12693    .0600111
 brok_fixmis |   .0003709   .0002746     1.35   0.177    -.0001672    .0009091
 dens_fixmis |  -.0114477   .0035639    -3.21   0.001    -.0184329   -.0044626
InterDirec~7 |   .0006324   .0008318     0.76   0.447    -.0009978    .0022627
  direct_t_7 |    -.02948   .0143444    -2.06   0.040    -.0575944   -.0013655
     ind_t_7 |   .0191656   .0150883     1.27   0.204     -.010407    .0487382
    _10yrapp |   .0379626   .0081708     4.65   0.000     .0219482    .0539771
 _10yrpatapp |  -.0000242   .0001749    -0.14   0.890     -.000367    .0003186
EquityEvents |  -.1178366    .067509    -1.75   0.081    -.2501517    .0144786
lead1YRs~24_ |  -.0036508   .0024294    -1.50   0.133    -.0084124    .0011108
  yrcompst_C |   .0103023   .0186081     0.55   0.580    -.0261689    .0467736
diversific~C |   .0572489   .0120414     4.75   0.000     .0336482    .0808496
lead1YRnet~C |   .0000812   .0001136     0.72   0.474    -.0001414    .0003038
lead1YRe~29_ |  -.0162521   .0156834    -1.04   0.300     -.046991    .0144869
lead1YRr~46_ |   .0005785   .0003134     1.85   0.065    -.0000358    .0011928
      ydum08 |  -.0823539   .2921088    -0.28   0.778    -.6548766    .4901689
      ydum09 |  -.2019319   .2921654    -0.69   0.489    -.7745655    .3707016
      ydum10 |  -.1678926    .305282    -0.55   0.582    -.7662344    .4304492
      ydum12 |  -.2368333   .2805537    -0.84   0.399    -.7867085    .3130419
      ydum13 |  -.4203142   .2468355    -1.70   0.089    -.9041029    .0634746
      ydum14 |  -.3496575   .2245295    -1.56   0.119    -.7897273    .0904124
      ydum15 |  -.1610792   .1886768    -0.85   0.393    -.5308789    .2087205
      ydum16 |   .0320502   .1383498     0.23   0.817    -.2391105    .3032108
      ydum17 |  -.0114921   .0893398    -0.13   0.898     -.186595    .1636107
      ydum18 |   .0594575   .0757647     0.78   0.433    -.0890385    .2079536
 naics325411 | -25.70703   .7507209   -34.24   0.000    -27.17841   -24.23564
 naics325412 |  1.418051   .2494936     5.68   0.000     .9290529     1.90705
 naics325413 | -1.327559    .453082    -2.93   0.003    -2.215583   -.4395345
       _cons |  -.2918483   .3865891    -0.75   0.450    -1.049549    .4658525
-------------+----------------------------------------------------------------
inflate      |
    _10yrapp |  -27.80858   .6919654   -40.19   0.000    -29.16481   -26.45236
 _10yrpatapp |   .0001058   .0035923     0.03   0.977     -.006935    .0071465
       _cons |   2.665789   .3550057     7.51   0.000      1.96999    3.361587
-------------+----------------------------------------------------------------
    /lnalpha |  -.9709221   .4388747    -2.21   0.027    -1.831101   -.1107434
-------------+----------------------------------------------------------------
       alpha |   .3787337   .1662166                      .1602371    .8951684
------------------------------------------------------------------------------
```

Table 6.6b Model #4 Adding Equity Partners and Tie Strength

```
zinb succmktapp_n partnerstatus   lead1YRavgyrcol brok_fixmis  dens_fixmis InterDirect_Ind_t7
direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C
diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum0
> 4 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18
naics325411 naics325412 naics325413 if yeardata > 1992,inf(_10yrapp _10yrpatapp)
cluster(focalcode) nolog

Zero-inflated negative binomial regression        Number of obs   =       1689
                                                  Nonzero obs     =        384
                                                  Zero obs        =       1305

Inflation model       = logit                     Wald chi2(29)   =    2359.67
Log pseudo-likelihood = -1365.425                 Prob > chi2     =     0.0000

                        (standard errors adjusted for clustering on focalcode)
------------------------------------------------------------------------------
             |               Robust
succmktapp_n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
succmktapp_n |
partnersta~s |   .0002775   .0000915     3.03   0.002     .0000982    .0004569
lead1YRavg~l |  -.0333326   .0475976    -0.70   0.484    -.1266222    .0599569
 brok_fixmis |   .0003757   .0002742     1.37   0.171    -.0001619    .0009132
 dens_fixmis |  -.0121401   .0033092    -3.67   0.000    -.0186261   -.0056542
InterDirec~7 |    .000611   .0008225     0.74   0.458     -.001001     .002223
  direct_t_7 |  -.0294114   .0140911    -2.09   0.037    -.0570294   -.0017934
     ind_t_7 |   .0202953   .0148828     1.36   0.173    -.0088744     .049465
    _10yrapp |   .0379894   .0082584     4.60   0.000     .0218033    .0541754
 _10yrpatapp |  -.0000101   .0001768    -0.06   0.955    -.0003565    .0003364
EquityEvents |  -.1256594   .0683352    -1.84   0.066     -.259594    .0082752
lead1YRs~24_ |  -.0036892   .0024856    -1.48   0.138    -.0085609    .0011824
  yrcompst_C |   .0106127   .0187331     0.57   0.571    -.0261035    .0473288
diversific~C |   .0564361   .0120764     4.67   0.000     .0327668    .0801054
lead1YRnet~C |   .0000732   .0001178     0.62   0.534    -.0001577    .0003041
lead1YRe~29_ |   -.016219   .0161053    -1.01   0.314    -.0477848    .0153468
lead1YRr~46_ |    .000585   .0003191     1.83   0.067    -.0000404    .0012104
      ydum08 |  -.0777762     .29224    -0.27   0.790    -.6505562    .4950038
      ydum09 |  -.2035886   .2947641    -0.69   0.490    -.7813155    .3741384
      ydum10 |  -.1573833   .3116836    -0.50   0.614     -.768272    .4535054
      ydum12 |  -.2522137   .2920617    -0.86   0.388     -.824644    .3202167
      ydum13 |  -.4053906   .2398524    -1.69   0.091    -.8754927    .0647115
      ydum14 |    -.32523   .2234734    -1.46   0.146    -.7632298    .1127698
      ydum15 |  -.1690341   .1878276    -0.90   0.368    -.5371694    .1991011
      ydum16 |    .015047   .1379823     0.11   0.913    -.2553934    .2854873
      ydum17 |  -.0111749   .0883695    -0.13   0.899     -.184376    .1620261
      ydum18 |   .0574786   .0760794     0.76   0.450    -.0916343    .2065916
 naics325411 |  -25.86051   .7508745   -34.44   0.000    -27.33219   -24.38882
 naics325412 |   1.41644   .2592875     5.46   0.000     .9082459    1.924634
 naics325413 |  -1.338307   .4619078    -2.90   0.004    -2.243629   -.4329839
       _cons |  -.2882424   .3964389    -0.73   0.467    -1.065248    .4887635
-------------+----------------------------------------------------------------
inflate      |
    _10yrapp |  -27.78007   .6846587   -40.58   0.000    -29.12198   -26.43817
 _10yrpatapp |   .0000996   .0035878     0.03   0.978    -.0069324    .0071315
       _cons |   2.665978   .3551954     7.51   0.000     1.969808    3.362148
-------------+----------------------------------------------------------------
    /lnalpha |  -.9663697   .4447043    -2.17   0.030    -1.837974   -.0947653
-------------+----------------------------------------------------------------
       alpha |   .3804617    .169193                      .1591395    .9095864
------------------------------------------------------------------------------
```

Table 6.6b Model #3 Adding Brokerage and Density (Structural Holes)

```
zinb  succmktapp_n brok_fixmis  dens_fixmis InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp
_10yrpatapp EquityEvents lead1YRstkprice_24_  yrcompst_C diversification_C lead1YRnet_inc_C
lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09
ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411 naics325412 naics325413 if
yeardata > 1992,inf(_10yrapp _10yrpatapp) cluster(focalcode) nolog

Zero-inflated negative binomial regression       Number of obs   =       1689
                                                 Nonzero obs     =        384
                                                 Zero obs        =       1305

Inflation model       = logit                    Wald chi2(27)   =    2006.76
Log pseudo-likelihood =  -1374.58                Prob > chi2     =     0.0000

                        (standard errors adjusted for clustering on focalcode)
------------------------------------------------------------------------------
             |               Robust
succmktapp_n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
succmktapp_n |
 brok_fixmis |   .0004132    .000284     1.45   0.146    -.0001434    .0009697
 dens_fixmis |  -.0119907   .0035964    -3.33   0.001    -.0190396   -.0049419
InterDirec~7 |   .0001296   .0008304     0.16   0.876     -.001498    .0017573
  direct_t_7 |  -.0245703   .0140408    -1.75   0.080    -.0520897    .0029492
     ind_t_7 |   .0299021   .0154569     1.93   0.053    -.0003929    .0601972
    _10yrapp |   .0387895    .009898     3.92   0.000     .0193899    .0581892
 _10yrpatapp |  -.0000538   .0001747    -0.31   0.758    -.0003963    .0002886
EquityEvents |  -.1280968   .0697845    -1.84   0.066     -.264872    .0086784
lead1YRs~24_ |   -.003281   .0026189    -1.25   0.210     -.008414    .0018521
  yrcompst_C |   .0142781   .0184536     0.77   0.439    -.0218902    .0504464
diversific~C |   .0569799   .0118386     4.81   0.000     .0337768    .0801831
lead1YRnet~C |   .0001165   .0001101     1.06   0.290    -.0000993    .0003323
lead1YRe~29_ |  -.0194794   .0157414    -1.24   0.216    -.0503321    .0113732
lead1YRr~46_ |   .0005593   .0003158     1.77   0.077    -.0000597    .0011783
      ydum08 |   .1652353   .3101609     0.53   0.594    -.4426689    .7731395
      ydum09 |     .06395    .288427     0.22   0.825    -.5013565    .6292566
      ydum10 |     .20778   .2971958     0.70   0.484     -.374713     .790273
      ydum12 |   .1431266   .2796032     0.51   0.609    -.4048855    .6911388
      ydum13 |   .0231705   .2067398     0.11   0.911    -.3820321     .428373
      ydum14 |   .0346298   .1769112     0.20   0.845    -.3121098    .3813695
      ydum15 |  -.0180265   .1583978    -0.11   0.909    -.3284806    .2924275
      ydum16 |   .1588149   .1104041     1.44   0.150    -.0575732     .375203
      ydum17 |   .0575411   .0772731     0.74   0.456    -.0939113    .2089935
      ydum18 |   .1008764   .0764692     1.32   0.187    -.0490005    .2507533
 naics325411 |  -25.16242   .7612197   -33.06   0.000    -26.65438   -23.67045
 naics325412 |   1.379252   .2880169     4.79   0.000     .8147495    1.943755
 naics325413 |  -1.375851   .5109555    -2.69   0.007    -2.377305   -.3743967
       _cons |  -.5966246   .4564478    -1.31   0.191    -1.491246    .2979966
-------------+----------------------------------------------------------------
inflate      |
    _10yrapp |  -27.25602   .7973782   -34.18   0.000    -28.81885   -25.69319
 _10yrpatapp |   .0001225   .0035977     0.03   0.973    -.0069289    .0071739
       _cons |   2.663331   .3584669     7.43   0.000     1.960749    3.365913
-------------+----------------------------------------------------------------
    /lnalpha |   -.919298   .4434984    -2.07   0.038    -1.788539   -.0500571
-------------+----------------------------------------------------------------
       alpha |   .3987989   .1768667                      .1672043    .9511751
------------------------------------------------------------------------------
```

Table 6.6b Model #2 Adding Direct, Indirect, and Interaction Effects

```
zinb  succmktapp_n InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents
lead1YRstkprice_24_ yrcompst_C diversification_C lead1YRnet_inc_C lead1YRemploy_29_
lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12
ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411 naics325412 naics325413 if yeardata >
1992,inf(_10yrapp _10yrpatapp) cluster(focalcode) nolog

Zero-inflated negative binomial regression       Number of obs   =       1689
                                                 Nonzero obs     =        384
                                                 Zero obs        =       1305

Inflation model       = logit                    Wald chi2(25)   =    2964.23
Log pseudo-likelihood = -1386.489                Prob > chi2     =     0.0000

                       (standard errors adjusted for clustering on focalcode)
------------------------------------------------------------------------------
             |               Robust
succmktapp_n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
succmktapp_n |
InterDirec~7 |   .0004237   .0007718     0.55   0.583    -.0010891    .0019365
  direct_t_7 |  -.0102149   .0154562    -0.66   0.509    -.0405084    .0200787
     ind_t_7 |   .0132386   .0154681     0.86   0.392    -.0170782    .0435554
    _10yrapp |   .0413808   .0124452     3.33   0.001     .0169886    .0657729
 _10yrpatapp |   .0000563   .0001707     0.33   0.742    -.0002783    .0003909
EquityEvents |  -.1072124   .0669656    -1.60   0.109    -.2384625    .0240378
lead1YRs~24_ |  -.0052621   .0028989    -1.82   0.069    -.0109439    .0004197
  yrcompst_C |   .0151121   .0177855     0.85   0.395    -.0197469    .0499711
diversific~C |   .0561901   .0121763     4.61   0.000      .032325    .0800551
lead1YRnet~C |   .0001429   .0001139     1.25   0.210    -.0000803    .0003661
lead1YRe~29_ |  -.0202348   .0150904    -1.34   0.180    -.0498115    .0093418
lead1YRr~46_ |   .0005363    .000301     1.78   0.075    -.0000536    .0011263
      ydum08 |   .0886147   .3081313     0.29   0.774    -.5153115    .6925409
      ydum09 |  -.0237622   .2809792    -0.08   0.933    -.5744713     .526947
      ydum10 |   .1225442   .2846492     0.43   0.667     -.435358    .6804465
      ydum12 |   .0542705   .2579564     0.21   0.833    -.4513147    .5598557
      ydum13 |   .0308722   .1982554     0.16   0.876    -.3577012    .4194455
      ydum14 |   .0185696   .1679772     0.11   0.912    -.3106596    .3477989
      ydum15 |  -.0722332   .1494836    -0.48   0.629    -.3652157    .2207493
      ydum16 |    .109646   .1063997     1.03   0.303    -.0988936    .3181856
      ydum17 |   .0280176   .0722997     0.39   0.698    -.1136872    .1697223
      ydum18 |   .0614116   .0678463     0.91   0.365    -.0715646    .1943878
 naics325411 |  -34.58631   .7591194   -45.56   0.000    -36.07416   -33.09846
 naics325412 |   1.357068   .2957671     4.59   0.000      .777375    1.936761
 naics325413 |   -1.32993   .4709584    -2.82   0.005    -2.252991   -.4068684
       _cons |  -.5714094    .448765    -1.27   0.203    -1.450973    .3081539
-------------+----------------------------------------------------------------
inflate      |
    _10yrapp |  -28.13163   .7894787   -35.63   0.000    -29.67898   -26.58428
 _10yrpatapp |   .0002665   .0036644     0.07   0.942    -.0069156    .0074486
       _cons |   2.645191   .3595282     7.36   0.000     1.940529    3.349853
-------------+----------------------------------------------------------------
    /lnalpha |   -.812132   .3692998    -2.20   0.028    -1.535946   -.0883177
-------------+----------------------------------------------------------------
       alpha |   .4439106   .1639361                      .2152519    .9154699
------------------------------------------------------------------------------
```

Table 6.6b Model #1 Based Model with Control Variables

```
zinb  succmktapp_n _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C
diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04
ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18
naics325411 naics325412 naics325413 if yeardata > 1992,inf(succmktapp_n  _10yrapp)
cluster(focalcode) nolog

Zero-inflated negative binomial regression       Number of obs   =       1689
                                                 Nonzero obs     =        384
                                                 Zero obs        =       1305

Inflation model       = logit                    Wald chi2(22)   =    1729.25
Log pseudo-likelihood = -1179.825                Prob > chi2     =     0.0000

                        (standard errors adjusted for clustering on focalcode)
------------------------------------------------------------------------------
             |               Robust
succmktapp_n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
succmktapp_n |
    _10yrapp |   .0402657   .0101124     3.98   0.000     .0204458    .0600855
 _10yrpatapp |   .0000628   .0001509     0.42   0.677    -.0002329    .0003586
EquityEvents |  -.1083547   .0781865    -1.39   0.166    -.2615974     .044888
lead1YRs~24_ |   -.006407   .0031428    -2.04   0.041    -.0125668   -.0002472
  yrcompst_C |   .0140547   .0163458     0.86   0.390    -.0179826     .046092
diversific~C |   .0534817   .0104985     5.09   0.000     .0329049    .0740585
lead1YRnet~C |   .0001624   .0000945     1.72   0.086    -.0000228    .0003477
lead1YRe~29_ |  -.0175325   .0147012    -1.19   0.233    -.0463463    .0112813
lead1YRr~46_ |    .000386   .0002844     1.36   0.175    -.0001715    .0009435
      ydum08 |   .0024009   .2556773     0.01   0.993    -.4987175    .5035192
      ydum09 |  -.1126675   .2243303    -0.50   0.615    -.5523469    .3270119
      ydum10 |   .0423912   .2216299     0.19   0.848    -.3919954    .4767778
      ydum12 |  -.0519635   .2049074    -0.25   0.800    -.4535746    .3496476
      ydum13 |  -.0759873   .1641147    -0.46   0.643    -.3976461    .2456715
      ydum14 |  -.0521969   .1612466    -0.32   0.746    -.3682344    .2638405
      ydum15 |  -.0677934    .142017    -0.48   0.633    -.3461416    .2105547
      ydum16 |    .095382    .104276     0.91   0.360    -.1089951    .2997591
      ydum17 |   .0316987   .0755672     0.42   0.675    -.1164103    .1798077
      ydum18 |   .0656417    .064509     1.02   0.309    -.0607937    .1920771
 naics325411 |   -9.52357    .711873   -13.38   0.000    -10.91882   -8.128324
 naics325412 |   1.286459   .2799125     4.60   0.000     .7378406    1.835077
 naics325413 |  -.7749272   .2590484    -2.99   0.003    -1.282653   -.2672015
       _cons |  -.3031928   .3990699    -0.76   0.447    -1.085356    .4789699
-------------+----------------------------------------------------------------
inflate      |
succmktapp_n |   -46.8954   .3088568  -151.84   0.000    -47.50074   -46.29005
    _10yrapp |  -1.373314   .3231917    -4.25   0.000    -2.006758   -.7398696
       _cons |   24.28152    .100284   242.13   0.000     24.08497    24.47807
-------------+----------------------------------------------------------------
    /lnalpha |  -.8600018    .381108    -2.26   0.024     -1.60696   -.1130439
-------------+----------------------------------------------------------------
       alpha |   .4231613   .1612702                      .2004963    .8931115
------------------------------------------------------------------------------
```

Table 6.6c Model#7 Test for Fixed-Effects on GLS Regression on Sales

```
xtreg sales_12_D2 Uphorizontie_n2 DNhorizontie_n UPvertical_n2 DNvertical_n tot_prtpat prtcomm
partnerstatus   lead1YRavgyrcol   brok_fixmis  dens_fixmis InterDirect_Ind_t7  direct_t_7
ind_t_7  _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C diversification_C
lead1YRnet_inc_C lead1YREmploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06
ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411
naics325412 naics325413 if yeardata > 1992, fe

Fixed-effects (within) regression               Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

R-sq:  within  = 0.5005                         Obs per group: min =         1
       between = 0.5451                                        avg =       6.5
       overall = 0.5747                                        max =        11

                                                F(31,1398)         =     45.19
corr(u_i, Xb)  = -0.8047                        Prob > F           =    0.0000

------------------------------------------------------------------------------
 sales_12_D2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Uphorizont~2 |    -.00138     .00029    -4.76   0.000    -.0019489    -.000811
DNhorizont~n |  -1.760333   .4941765    -3.56   0.000     -2.72974   -.7909253
UPvertical~2 |   .1312696   .0467447     2.81   0.005     .0395722    .2229669
DNvertical_n |   .0233909   .0048145     4.86   0.000     .0139464    .0328354
  tot_prtpat |   .3437352   .0973231     3.53   0.000     .1528202    .5346503
     prtcomm |   3.423298   3.844885     0.89   0.373    -4.119068    10.96566
partnersta~s |  -.3111221   .0869278    -3.58   0.000     -.481645   -.1405992
lead1YRavg~l |   57.90349   36.19582     1.60   0.110    -13.10047    128.9075
 brok_fixmis |   4.337319    .363116    11.94   0.000     3.625008     5.04963
 dens_fixmis |  -4.590208   5.269833    -0.87   0.384    -14.92784    5.747424
InterDirec~7 |  -2.178392   .7027059    -3.10   0.002    -3.556863   -.7999198
  direct_t_7 |  -62.80147   14.82938    -4.23   0.000     -91.8917   -33.71125
     ind_t_7 |   13.44535   11.32488     1.19   0.235    -8.770232    35.66093
    _10yrapp |   220.8077   25.04584     8.82   0.000     171.6763    269.9392
 _10yrpatapp |   12.69719   .7163475    17.72   0.000     11.29196    14.10242
 EquityEvents|   135.1334   53.48705     2.53   0.012     30.20986    240.0569
lead1YRs~24_ |  -5.354024   2.721076    -1.97   0.049    -10.69186   -.0161922
  yrcompst_C |   389.1471   995.1599     0.39   0.696    -1563.021    2341.315
diversific~C |  (dropped)
lead1YRnet~C |   -.192607   .1094867    -1.76   0.079    -.4073829     .022169
lead1YRe~29_ |   20.08055   13.48398     1.49   0.137    -6.370453    46.53156
lead1YRr~46_ |   .0953219   .1428758     0.67   0.505    -.1849521    .3755959
      ydum08 |    4252.51   9933.812     0.43   0.669    -15234.27    23739.29
      ydum09 |   3873.541   8940.039     0.43   0.665     -13663.8    21410.88
      ydum10 |   3641.765   7954.585     0.46   0.647    -11962.45    19245.97
      ydum12 |   3195.784   6963.903     0.46   0.646    -10465.04    16856.61
      ydum13 |   2741.212    5971.13     0.46   0.646    -8972.129    14454.55
      ydum14 |   2319.469   4976.782     0.47   0.641    -7443.297    12082.24
      ydum15 |   1899.311   3984.701     0.48   0.634    -5917.326    9715.948
      ydum16 |   1539.752   2989.371     0.52   0.607    -4324.385     7403.89
      ydum17 |    1068.15   1994.911     0.54   0.592    -2845.191    4981.491
      ydum18 |   529.4022   1002.544     0.53   0.598    -1437.251    2496.056
 naics325411 |  (dropped)
 naics325412 |  (dropped)
 naics325413 |  (dropped)
       _cons |  -6130.564   13316.57    -0.46   0.645    -32253.19    19992.06
-------------+----------------------------------------------------------------
     sigma_u |  4518.5232
     sigma_e |  1141.8332
         rho |  .93997546   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(259, 1398) =    25.16           Prob > F = 0.0000
```

Table 6.6c Model #6 GLS Regression on Sales (Final Model)

```
xtreg sales_12_D2 Uphorizontie_n2 DNhorizontie_n UPvertical_n2 DNvertical_n tot_prtpat prtcomm
partnerstatus   lead1YRavgyrcol   brok_fixmis  dens_fixmis InterDirect_Ind_t7  direct_t_7
ind_t_7  _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C diversification_C
lead1YRnet_inc_C lead1YREmploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06
ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411
naics325412 naics325413 if yeardata > 1992

Random-effects GLS regression                   Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

R-sq:  within  = 0.4883                         Obs per group: min =         1
       between = 0.6453                                        avg =       6.5
       overall = 0.6667                                        max =        11

Random effects u_i ~ Gaussian                   Wald chi2(35)      =   1799.73
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
 sales_12_D2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Uphorizont~2 |   -.001392   .0002963    -4.70   0.000    -.0019728   -.0008113
DNhorizont~n |  -1.707584   .5035213    -3.39   0.001    -2.694468   -.7207007
UPvertical~2 |   .1352774     .04743     2.85   0.004     .0423162    .2282385
DNvertical_n |   .0243462   .0047205     5.16   0.000     .0150941    .0335982
  tot_prtpat |   .3370022    .099349     3.39   0.001     .1422817    .5317227
     prtcomm |   4.045518    3.92254     1.03   0.302    -3.642519    11.73355
partnersta~s |  -.3571168   .0882778    -4.05   0.000     -.530138   -.1840955
lead1YRavg~l |   68.60646   31.86056     2.15   0.031     6.160901     131.052
 brok_fixmis |   5.314911   .3408769    15.59   0.000     4.646805    5.983017
 dens_fixmis |  -3.259564    5.24709    -0.62   0.534    -13.54367    7.024543
InterDirec~7 |  -2.260517   .6822488    -3.31   0.001      -3.5977    -.923334
  direct_t_7 |  -77.65044    14.2201    -5.46   0.000    -105.5213   -49.77956
     ind_t_7 |   17.62112   11.06872     1.59   0.111    -4.073176    39.31543
    _10yrapp |   103.9359   12.85762     8.08   0.000     78.73541    129.1363
 _10yrpatapp |   9.910993   .5341365    18.56   0.000     8.864104    10.95788
 EquityEvents|   116.3305    54.4288     2.14   0.033     9.652055     223.009
lead1YRs~24_ |  -6.917915   2.672342    -2.59   0.010    -12.15561   -1.680221
  yrcompst_C |  -18.26727   25.44801    -0.72   0.473    -68.14445    31.60991
diversific~C |   51.70613    23.8489     2.17   0.030     4.963138    98.44913
lead1YRnet~C |  -.1920691   .1059902    -1.81   0.070    -.3998061    .0156678
lead1YRe~29_ |   14.39227   11.28493     1.28   0.202    -7.725786    36.51032
lead1YRr~46_ |   .1278347   .1364687     0.94   0.349     -.139639    .3953084
      ydum08 |   12.87563   364.0772     0.04   0.972    -700.7025    726.4538
      ydum09 |    82.1373   337.1198     0.24   0.808    -578.6054      742.88
      ydum10 |   309.7905   305.5929     1.01   0.311    -289.1606    908.7416
      ydum12 |   278.2225   276.1658     1.01   0.314    -263.0526    819.4976
      ydum13 |    258.702   255.1258     1.01   0.311    -241.3354    758.7395
      ydum14 |   232.5283   223.8811     1.04   0.299    -206.2705    671.3271
      ydum15 |   260.3448   193.9865     1.34   0.180    -119.8618    640.5513
      ydum16 |   335.8041   164.8963     2.04   0.042     12.61336    658.9949
      ydum17 |   283.2339     140.81     2.01   0.044     7.251285    559.2164
      ydum18 |    138.014   124.9494     1.10   0.269    -106.8823    382.9104
 naics325411 |  -203.3507   1475.747    -0.14   0.890    -3095.762     2689.06
 naics325412 |   145.2666   344.4495     0.42   0.673    -529.8421    820.3753
 naics325413 |  -96.26103   460.2053    -0.21   0.834    -998.2468    805.7248
       _cons |  -577.0613   437.8939    -1.32   0.188    -1435.318    281.195
-------------+----------------------------------------------------------------
     sigma_u |  2313.5242
     sigma_e |  1141.8332
         rho |  .80412434   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table 6.6c Model #5 Adding Exploration and Exploitation Networks

```
xtreg sales_12_D2 tot_prtpat prtcomm partnerstatus   lead1YRavgyrcol   brok_fixmis  dens_fixmis
InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_
yrcompst_C diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02
ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17
ydum18  naics325411 naics325412 naics325413 if yeardata > 1992

Random-effects GLS regression                   Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

R-sq:  within  = 0.4688                         Obs per group: min =         1
       between = 0.6377                                        avg =       6.5
       overall = 0.6573                                        max =        11

Random effects u_i ~ Gaussian                   Wald chi2(31)      =   1678.37
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
 sales_12_D2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  tot_prtpat |   .4248523   .0848456     5.01   0.000     .2585579    .5911466
     prtcomm |   3.299094   3.710229     0.89   0.374    -3.972821    10.57101
partnersta~s |  -.3673773   .0879936    -4.18   0.000    -.5398415    -.194913
lead1YRavg~l |   68.89252   32.42258     2.12   0.034     5.345429    132.4396
 brok_fixmis |   4.743796   .3338277    14.21   0.000     4.089506    5.398086
 dens_fixmis |  -3.961754   5.321165    -0.74   0.457    -14.39105    6.467539
InterDirec~7 |  -2.385598   .6595395    -3.62   0.000    -3.678272   -1.092924
  direct_t_7 |  -70.14895   14.28533    -4.91   0.000    -98.14769   -42.15022
     ind_t_7 |   19.84345   11.07224     1.79   0.073    -1.857746    41.54464
    _10yrapp |   104.4588   13.16687     7.93   0.000     78.65217    130.2654
 _10yrpatapp |   10.28268   .5405355    19.02   0.000     9.223247    11.34211
 EquityEvents|   98.28409   55.05274     1.79   0.074    -9.617306    206.1855
lead1YRs~24_ |  -8.556451   2.699052    -3.17   0.002     -13.8465   -3.266406
  yrcompst_C |  -18.90357   26.21835    -0.72   0.471    -70.29058    32.48345
diversific~C |   54.59246   24.54008     2.22   0.026     6.494782    102.6901
lead1YRnet~C |  -.1994282   .1075157    -1.85   0.064    -.4101551    .0112988
lead1YRe~29_ |   12.87515   11.48274     1.12   0.262    -9.630613    35.38091
lead1YRr~46_ |   .1513368   .1383975     1.09   0.274    -.1199172    .4225908
      ydum08 |   16.84491    372.392     0.05   0.964      -713.03    746.7199
      ydum09 |   64.94555   344.6882     0.19   0.851     -610.631    740.5221
      ydum10 |   267.2338   312.0705     0.86   0.392     -344.413    878.8807
      ydum12 |   320.2409   281.9304     1.14   0.256    -232.3326    872.8144
      ydum13 |   251.1305   260.3975     0.96   0.335    -259.2392    761.5002
      ydum14 |   232.6085   228.4454     1.02   0.309    -215.1363    680.3533
      ydum15 |   269.8842   197.7775     1.36   0.172    -117.7525     657.521
      ydum16 |   333.9562   167.8907     1.99   0.047     4.896415     663.016
      ydum17 |   279.8893   143.1047     1.96   0.050    -.5908414    560.3694
      ydum18 |   131.0359   126.6865     1.03   0.301     -117.265    379.3369
 naics325411 |  -212.9803   1520.707    -0.14   0.889    -3193.511     2767.55
 naics325412 |   160.7174   355.0358     0.45   0.651    -535.1399    856.5748
 naics325413 |  -105.2315   474.5555    -0.22   0.825    -1035.343    824.8803
       _cons |  -588.0686   449.0971    -1.31   0.190    -1468.283    292.1455
-------------+----------------------------------------------------------------
     sigma_u |  2400.6119
     sigma_e |  1163.4312
         rho |  .80979832   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table 6.6c Model #4 Adding Prominence of Partners and Tie Strength

```
xtreg sales_12_D2 partnerstatus   lead1YRavgyrcol   brok_fixmis  dens_fixmis InterDirect_Ind_t7
direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C
diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04
ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18
naics325411 naics325412 naics325413 if yeardata > 1992

Random-effects GLS regression                   Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

R-sq:  within  = 0.4594                         Obs per group: min =         1
       between = 0.6348                                        avg =       6.5
       overall = 0.6539                                        max =        11

Random effects u_i ~ Gaussian                   Wald chi2(29)      =   1629.94
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
 sales_12_D2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
partnersta~s |   -.108801   .0709565    -1.53   0.125    -.2478732    .0302711
lead1YRavg~l |     68.024   32.63144     2.08   0.037     4.067559    131.9804
 brok_fixmis |   4.535541   .3338275    13.59   0.000     3.881251    5.189831
 dens_fixmis |  -4.216691   5.345892    -0.79   0.430    -14.69445    6.261065
InterDirec~7 |  -2.395103   .6618595    -3.62   0.000    -3.692324   -1.097882
  direct_t_7 |  -67.52081   14.33967    -4.71   0.000    -95.62605   -39.41557
     ind_t_7 |   18.54987   11.11441     1.67   0.095    -3.233976    40.33373
    _10yrapp |   102.9821   13.20725     7.80   0.000     77.09638    128.8679
 _10yrpatapp |   10.39945   .5427897    19.16   0.000       9.3356     11.4633
 EquityEvents|   92.50702   55.39283     1.67   0.095    -16.06093     201.075
lead1YRs~24_ |  -8.465844   2.720937    -3.11   0.002    -13.79878   -3.132906
  yrcompst_C |  -19.12055   26.26817    -0.73   0.467    -70.60521    32.36412
diversific~C |   56.16242   24.58734     2.28   0.022     7.972117    104.3527
lead1YRnet~C |  -.2090845   .1083741    -1.93   0.054    -.4214939    .0033249
lead1YRe~29_ |   14.03145   11.55251     1.21   0.225    -8.611047    36.67395
lead1YRr~46_ |   .1557312   .1395148     1.12   0.264    -.1177128    .4291752
      ydum08 |   28.76239   373.8538     0.08   0.939    -703.9775    761.5023
      ydum09 |   75.96487   346.1495     0.22   0.826    -602.4757    754.4055
      ydum10 |   232.4236    313.403     0.74   0.458     -381.835    846.6823
      ydum12 |   329.4986   283.3215     1.16   0.245    -225.8013    884.7984
      ydum13 |   218.3699   261.7171     0.83   0.404    -294.5863     731.326
      ydum14 |   198.0712   229.6138     0.86   0.388    -251.9636     648.106
      ydum15 |   263.9178   198.9091     1.33   0.185    -125.9368    653.7724
      ydum16 |   338.6596   168.9893     2.00   0.045      7.44676    669.8725
      ydum17 |   272.8918   144.1348     1.89   0.058    -9.607259    555.3908
      ydum18 |   122.2852    127.708     0.96   0.338    -128.0178    372.5883
 naics325411 |  -232.2859   1523.585    -0.15   0.879    -3218.458    2753.886
 naics325412 |   173.1746   355.6234     0.49   0.626    -523.8344    870.1836
 naics325413 |  -116.3141   475.3171    -0.24   0.807    -1047.918    815.2902
       _cons |  -590.8986   450.4557    -1.31   0.190    -1473.776    291.9784
-------------+----------------------------------------------------------------
     sigma_u |  2403.5701
     sigma_e |  1173.3739
         rho |  .80754615   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table 6.6c Model #3 Adding Brokerage and Density (Structural Holes)

```
xtreg sales_12_D2 brok_fixmis  dens_fixmis InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp
_10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C diversification_C lead1YRnet_inc_C
lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09
ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411 naics325412 naics325413 if
yeardata > 1992

Random-effects GLS regression                   Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

R-sq:  within  = 0.4578                         Obs per group: min =         1
       between = 0.6328                                        avg =       6.5
       overall = 0.6527                                        max =        11

Random effects u_i ~ Gaussian                   Wald chi2(27)      =   1618.57
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
 sales_12_D2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 brok_fixmis |   4.483722   .3319732    13.51   0.000     3.833066    5.134377
 dens_fixmis |  -4.293583   5.348312    -0.80   0.422    -14.77608    6.188916
InterDirec~7 |  -2.204573   .6559913    -3.36   0.001    -3.490292   -.9188534
  direct_t_7 |  -65.97067   14.32134    -4.61   0.000    -94.03997   -37.90137
     ind_t_7 |   17.61214   11.12159     1.58   0.113    -4.185782    39.41006
    _10yrapp |   103.3026   13.23318     7.81   0.000       77.366    129.2391
 _10yrpatapp |   10.51712   .5417947    19.41   0.000     9.455219    11.57902
 EquityEvents|   91.72782   55.34879     1.66   0.097     -16.7538    200.2095
lead1YRs~24_ |  -8.465141   2.722154    -3.11   0.002    -13.80046   -3.129818
  yrcompst_C |  -22.90999   26.28789    -0.87   0.383     -74.4333    28.61332
diversific~C |   54.91073   24.59394     2.23   0.026     6.707484     103.114
lead1YRnet~C |  -.2166733   .1084079    -2.00   0.046    -.4291489   -.0041977
lead1YRe~29_ |   16.15137   11.52641     1.40   0.161    -6.439976    38.74272
lead1YRr~46_ |   .1341321    .139354     0.96   0.336    -.1389968     .407261
      ydum08 |  -374.8914   319.1205    -1.17   0.240    -1000.356    250.5734
      ydum09 |  -317.0595   291.1758    -1.09   0.276    -887.7535    253.6345
      ydum10 |  -150.4706   258.4378    -0.58   0.560    -656.9995    356.0582
      ydum12 |  -42.28621   230.2358    -0.18   0.854      -493.54    408.9676
      ydum13 |  -161.8171    207.315    -0.78   0.435     -568.147    244.5128
      ydum14 |  -119.7604   184.0991    -0.65   0.515     -480.588    241.0673
      ydum15 |    25.6283   166.2379     0.15   0.877     -300.192    351.4486
      ydum16 |   154.1279   146.6094     1.05   0.293    -133.2212     441.477
      ydum17 |   151.5726    132.874     1.14   0.254    -108.8557    412.0009
      ydum18 |   63.70452   124.6685     0.51   0.609    -180.6412    308.0503
 naics325411 |  -152.4179   1526.972    -0.10   0.920    -3145.228    2840.392
 naics325412 |   158.9315   356.4694     0.45   0.656    -539.7357    857.5987
 naics325413 |  -84.68573   476.3387    -0.18   0.859    -1018.292     848.921
       _cons |  -128.2834   395.8478    -0.32   0.746    -904.1307     647.564
-------------+----------------------------------------------------------------
     sigma_u |  2408.0712
     sigma_e |   1173.818
         rho |  .80800966   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table 6.6c Model #2 Adding Direct, Indirect, and Interaction Effects

```
xtreg sales_12_D2 InterDirect_Ind_t7  direct_t_7  ind_t_7  _10yrapp _10yrpatapp EquityEvents
lead1YRstkprice_24_ yrcompst_C diversification_C lead1YRnet_inc_C lead1YRemploy_29_
lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04 ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12
ydum13 ydum14 ydum15 ydum16 ydum17 ydum18  naics325411 naics325412 naics325413 if yeardata > 1992

Random-effects GLS regression                   Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

R-sq:  within  = 0.4210                         Obs per group: min =         1
       between = 0.5738                                        avg =       6.5
       overall = 0.5952                                        max =        11

Random effects u_i ~ Gaussian                   Wald chi2(25)      =   1284.92
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
 sales_12_D2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
InterDirec~7 |  -.1441807    .667138    -0.22   0.829    -1.451747    1.163386
  direct_t_7 |   34.39097   12.85661     2.67   0.007     9.192475    59.58947
     ind_t_7 |  -20.85847   11.20318    -1.86   0.063    -42.81631    1.099365
    _10yrapp |    138.423   13.98308     9.90   0.000     111.0167    165.8294
 _10yrpatapp |   13.39031   .5347872    25.04   0.000     12.34215    14.43847
 EquityEvents|   121.0456   57.80947     2.09   0.036     7.741101    234.3501
lead1YRs~24_ |  -9.405718    2.84942    -3.30   0.001    -14.99048   -3.820958
  yrcompst_C |  -45.01601   28.49346    -1.58   0.114    -100.8622    10.83014
diversific~C |   28.32991   26.61958     1.06   0.287    -23.84351    80.50334
lead1YRnet~C |  -.2843486   .1135208    -2.50   0.012    -.5068454   -.0618519
lead1YRe~29_ |   19.21932   12.18443     1.58   0.115    -4.661714    43.10036
lead1YRr~46_ |   .1588877   .1460787     1.09   0.277    -.1274213    .4451968
      ydum08 |  -560.1483   341.6311    -1.64   0.101    -1229.733    109.4364
      ydum09 |  -523.4991   311.3455    -1.68   0.093    -1133.725    86.72686
      ydum10 |  -355.8772   276.2594    -1.29   0.198    -897.3357    185.5813
      ydum12 |  -228.4984   245.7884    -0.93   0.353    -710.2348    253.2379
      ydum13 |  -264.9213   221.1014    -1.20   0.231    -698.2722    168.4295
      ydum14 |  -248.5346   195.9756    -1.27   0.205    -632.6396    135.5705
      ydum15 |  -200.5463   175.6483    -1.14   0.254    -544.8107     143.718
      ydum16 |  -45.52497   154.3039    -0.30   0.768     -347.955    256.9051
      ydum17 |  -5.750086   139.3104    -0.04   0.967    -278.7934    267.2932
      ydum18 |  -43.76022   130.3602    -0.34   0.737    -299.2615     211.741
 naics325411 |   442.6905   1657.279     0.27   0.789    -2805.517    3690.898
 naics325412 |   108.4723   387.3931     0.28   0.779    -650.8042    867.7487
 naics325413 |  -54.75043   517.9598    -0.11   0.916    -1069.933    960.4321
       _cons |   78.79576   428.5584     0.18   0.854    -761.1633    918.7548
-------------+----------------------------------------------------------------
     sigma_u |  2591.8767
     sigma_e |  1212.9576
         rho |  .82033828   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table 6.6c Model #1 Based Model with Control Variables

```
xtreg sales_12_D2 _10yrapp _10yrpatapp EquityEvents lead1YRstkprice_24_ yrcompst_C
diversification_C lead1YRnet_inc_C lead1YRemploy_29_ lead1YRr_d_46_  ydum01 ydum02 ydum03 ydum04
ydum05 ydum06 ydum07 ydum08 ydum09 ydum10 ydum12 ydum13 ydum14 ydum15 ydum16 ydum17 ydum18
naics325411 naics325412 naics325413 if yeardata > 1992

Random-effects GLS regression                   Number of obs      =      1689
Group variable (i): focalcode                   Number of groups   =       260

R-sq:  within  = 0.4206                         Obs per group: min =         1
       between = 0.5698                                        avg =       6.5
       overall = 0.5878                                        max =        11

Random effects u_i ~ Gaussian                   Wald chi2(22)      =   1256.88
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
 sales_12_D2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    _10yrapp |   147.4105   14.09149    10.46   0.000     119.7917    175.0293
 _10yrpatapp |   13.89577    .515741    26.94   0.000     12.88494     14.9066
 EquityEvents|   112.9404   57.63146     1.96   0.050    -.0151582     225.896
lead1YRs~24_ |   -9.42003   2.846084    -3.31   0.001    -14.99825   -3.841808
  yrcompst_C |  -44.39761   29.14083    -1.52   0.128    -101.5126    12.71738
diversific~C |   29.64311   27.19807     1.09   0.276    -23.66414    82.95035
lead1YRnet~C |  -.2797467   .1135167    -2.46   0.014    -.5022354    -.057258
lead1YRe~29_ |   19.08259   12.23247     1.56   0.119    -4.892611    43.05779
lead1YRr~46_ |   .1623298   .1459582     1.11   0.266     -.123743    .4484025
      ydum08 |  -567.7345   344.0461    -1.65   0.099    -1242.053    106.5835
      ydum09 |  -531.6636   312.5407    -1.70   0.089    -1144.232    80.90494
      ydum10 |  -361.3806   277.3745    -1.30   0.193    -905.0245    182.2634
      ydum12 |  -217.3975   247.5779    -0.88   0.380    -702.6413    267.8463
      ydum13 |  -228.6986   222.9251    -1.03   0.305    -665.6237    208.2265
      ydum14 |  -202.9676   197.9272    -1.03   0.305    -590.8978    184.9627
      ydum15 |  -152.7979   176.3383    -0.87   0.386    -498.4146    192.8187
      ydum16 |  -2.857297   154.4009    -0.02   0.985    -305.4775    299.7629
      ydum17 |   27.41674   139.0993     0.20   0.844    -245.2129    300.0463
      ydum18 |  -27.44256   130.1356    -0.21   0.833    -282.5036    227.6185
 naics325411 |   368.4936   1697.746     0.22   0.828    -2959.028    3696.016
 naics325412 |   30.06931   396.9428     0.08   0.940    -747.9242    808.0628
 naics325413 |  -79.32542   531.5456    -0.15   0.881    -1121.136    962.4849
       _cons |   130.3243   437.9175     0.30   0.766    -727.9781    988.6267
-------------+----------------------------------------------------------------
     sigma_u |  2670.4126
     sigma_e |  1214.4722
         rho |  .82861553   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

APPENDIX C

BIOSCAN FIELDS AND THEIR DESCRIPTIONS

Company records: include only those fields for which information has been obtained. Dates are included, when possible, to reflect the approximate occurrence of events.

Company Name and Address: Displays main address, telephone, fax, web site, and e-mail address, if known. Second addresses are given for major research facilities or U.S. facilitates of non-U.S. companies. (Fax, e-mail, and second addresses are not searchable fields.)

Key Personnel: Displays management involved in relevant marketing and R&D areas, including chairperson of the board, president, chief operating officer (COO), chief executive officer (CEO), executive or senior vice presents, director of R&D (research and development), and director of marketing. Also includes names of senior scientists and researchers.

Employees: Displays total number of employees, along with a breakdown of the number of PhDs/MDs/DVMs on staff, if known.

History: Displays information on founders, founding date, name changes, major acquisitions, previous subsidiaries or investments, and organization memberships.

Facilities: Includes type and location of facilities involved in biotechnology, including size (in square feet or square meters).

Stock-Financial History: Contains information on public/private status; initial funding; stock exchange and ticker symbol; and public offerings, including date, price of stock at issuance, number of shares offered, and value. For public companies, it also includes financial for the most recently competed fiscal year, compare with the corresponding figures for the previous year.

Private Placements: Lists arrangements made through investment firms to fund clinical research for products in development. Information may include date, dollar value, and designation of funds.

Subsidiaries/Divisions: Lists subsidiaries of biotechnology companies and, for non-biotechnology companies, only those subsidiaries involved in biotechnology. The address, management, and research interests are listed, if readily available. (A company usually is considered a subsidiary if 51% or more is owned by the parent company.) Also included are divisions of large companies that focus on biotechnology.
Subsidiary of: Lists the parent company.

Investments: Lists investments by biotechnology companies. For non-biotechnology companies, data generally are limited to investments in the biotechnology industry. Joint ventures also are listed here.

Principal Investors: Lists the principal investors in the biotechnology company.

Financial Information: Lists general information, which may include R&D budget, nonprofit offshoots, or investment arms of the company.

Business Strategy: Lists general corporate goals and missing statement.

Agreements: Lists a brief summary of the product(s) and content of the agreement, and the date the agreement commenced. Also includes federal grants awarded, such as SBIR grants. Agreements are arranged alphabetically by company/ organization. Parentheses after a company name may contain geographic qualifiers or the name of its parent company.

Research and Development: Lists general research interests and technologies worked on by the company or its subsidiaries. Research conducted through agreements with other companies also is included.

Products on the Market: Lists 1) all products of biotechnology companies; and 2) biotechnology products of nonbiotechnology (e.g., chemical and pharmaceutical) companies.

Product in developments: Lists generic, trade name, and uses of the product. The status refers to standard stages for a U.S. drug or other product in development. For Human Therapeutics, they are, in order:

- Preclinicals;
- IND (Investigational New Drug Application);
- Phase I;
- Phase II;
- Phase III;
- NDA (New Drug Application) –for biologicals, the PLA (Product License Approval is analogous to the NDA;
- Market

APPENDIX D

FREQUENTLY ASKED QUESTIONS OF DRUG@FDA DATABASE

1. What is the purpose of Drugs@FDA, and what are its main uses?

Drugs@FDA is a Web site where you can search for official information about FDA approved brand name and generic drugs.

The main uses of Drugs@FDA are:

- Finding labels for approved drug products.
- Finding generic drug products for a brand name drug product.
- Finding therapeutically equivalent drug products for a brand name or generic drug product.
- Finding consumer information for drugs approved from 1998 on.
- Finding all drugs with a specific active ingredient.
- Viewing the approval history of a drug.

2. What Drug Products are in Drugs@FDA?

Drugs@FDA contains prescription and over-the-counter human drugs currently approved for sale in the United States. Drugs@FDA also contains discontinued drugs.

Drugs@FDA contains the following biological therapeutic products:

- Monoclonal antibodies for in-vivo use
- Cytokines, growth factors, enzymes, immunomodulators; and thrombolytics
- Proteins intended for therapeutic use that are extracted from animals or microorganisms, including recombinant versions of these products (except clotting factors)
- Other non-vaccine therapeutic immunotherapies

Not all biologic therapeutic products are in Drugs@FDA.

Drugs@FDA contains most of the drug products approved since 1939. The majority of labels, approval letters, reviews, and other information are available for drug products approved from 1998 to the present.

3. What Drug Products are not in Drugs@FDA?

Drugs@FDA does not include:

- **Dietary supplements**.
- **Drugs for animals.** FDA's Center for Veterinary Medicine is responsible for the agency's oversight of these products.
- Drugs **withdrawn** for reasons of safety or effectiveness.

- Over-the-counter products that are approved for marketing through a process other than submitting a New Drug Application.
- Prescription drugs **sold in countries other than the United States**.
- Prescription drugs **sold (illegally)** in the United States without FDA approval.
- Drugs that are under review at FDA for which **no action regarding approval** has occurred.
- **Biological products** including bacterial and viral vaccines; human blood products; certain blood products produced by biotechnology; and gene therapy. FDA's Center for Biologics Evaluation and Research is responsible for the agency's oversight of these products.

4. Why doesn't Drugs@FDA include dietary supplements?

- Dietary supplements do not require FDA approval to be sold in the United States. FDA's Center for Food Safety and Applied Nutrition is responsible for the agency's oversight of these products.

5. How can I find out if a generic drug is available for a brand name drug?

- Find the **"Drug Details"** page for your drug by following Instructions to Finding Health Information.
- If a generic drug is available, you will see the link "**Therapeutic Equivalence**" in the middle of the **Drug Details** page. Click on this link to see the generic and other therapeutically equivalent drug products for your drug.
- Be sure to read the definitions for Generic Drug and Therapeutic Equivalents.

6. What information is available for each drug product in Drugs@FDA?

Search results for all drug products include:

- drug name (brand name or generic name)
- active ingredient
- dosage form or route of administration
- strength
- marketing status (prescription, over-the-counter, or discontinued)
- company that sponsored an application for approval
- FDA action date
- Supplement type (type of regulatory action)

Many, but not all drug products have links to:

- current FDA approved labels
- older labels
- approval letters
- reviews (scientific analyses of new drug applications that provide the basis for approval)

7. How can I search Drugs@FDA?

You can search by:

- drug name
- generic name
- active ingredient
- drug name and FDA Action Date range
- application number (NDA, ANDA, BLA)
- action dates of approvals and supplements in one, two, or three month blocks

Detailed instructions for searching Drugs@FDA are available.

8. How do searches work in Drugs@FDA?

The drugs that are listed on the "Search Results" page are not always related in terms of their chemical makeup or the conditions they treat, and are not necessarily substitutable. They appear together because their drug names or active ingredient names contain the words or parts of words you entered in the search box. The text you searched for appears in bold letters in the search results.

Even if drug products have the same active ingredient, dosage form, and strength, it might not be safe to use one in place of the other. You should always consult a health care professional to determine if one drug can be safely substituted for another, that is, if they are therapeutically equivalent.

How searches work:

- When you enter a string of characters to search Drugs@FDA, you are searching for that string of characters in the exact order you typed them, anywhere in a drug name or an active ingredient name.
    - ***Example***:
      If you enter "**proz**" you will retrieve drug products that have that four-letter string somewhere in their drug names or active ingredient names:
        - CEF**PROZ**IL [from the "Active Ingredient" column]
        - OXA**PROZ**IN POTASSIUM [from the "Active Ingredient" column]
        - **PROZ**AC [from the "Drug Name" column]
        - **PROZ**AC WEEKLY [from the "Drug Name" column]

    - ***Tip***: Enter as much of the name as you know to focus your results. For example, if you know you want to retrieve the records for Prozac, enter the entire word.

- If you enter **two or more words separated by a space**, Drugs@FDA will look for records containing both of the words, whether they occur together or apart, in either a drug name or an active ingredient name.

- ***Example***:
  If you enter "**claritin pseudoephedrine**" you will retrieve drug products that have either one of those words in either their drug names or active ingredient names:
  - **CLARITIN**-D (LORATADINE; **PSEUDOEPHEDRINE** SULFATE)
  - **CLARITIN**-D 24 HOUR (LORATADINE; **PSEUDOEPHEDRINE** SULFATE)

9. How often do you update Drugs@FDA?

We add new drug approvals every day, sometimes several times throughout the day.

10. Where does the information in Drugs@FDA come from?

The information in Drugs@FDA comes from:

- Approved Drug Products with Therapeutic Equivalence Evaluations (Orange Book)
- **C**enter-wide **O**racle-based **M**anagement **I**nformation **S**ystem (COMIS). COMIS is used by FDA staff to track information about the receipt and review status of investigational new drug applications (INDs), new drug applications (NDAs), and abbreviated new drug applications (ANDAs).

11. How can I get further assistance?

- For general drug information:
  - Call 301-827-4573 or 888-INFO-FDA (1-888-463-6332)
  - E-mail your questions to druginfo@cder.fda.gov
- For technical questions about this site, please use our Drugs@FDA Comments and Feedback form.

FDA/Center for Drug Evaluation and Research
Division of Library and Information Services
Page Last Updated: March 2, 2004

VITA

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