Resource Spillover from Academia to High Tech Industry:

Evidence from New Nanotechnology-Based Firms in the U.S.

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Resource Spillover from Academia to High Tech Industry:

Evidence from New Nanotechnology-Based Firms in the U.S.

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LIST OF ABBREVIATIONS

Abbreviation	Full Name
ATP	Advanced Technology Program
BECON	Bioengineering Consortium
CRADA	Cooperative Research and Development Agreement
DHHS	Department of Health and Human Services
DHS	Department of Homeland Security
DOC	Department of Commerce
DOD	Department of Defense
DOE	Department of Energy
DOJ	Department of Justice
DOT	Department of Transportation
EPA	Environmental Protection Agency
FLC	Federal Laboratory Consortium
GOCOs	Government-owned, Contractor-operated Laboratories
GOGOs	Government-owned, Government-operated Laboratories
IWGN	Interagency Working Group on Nanotechnology
NASA	National Aeronautics and Space Administration

NBRE	Negative Binomial Regression Equation
NCTTA	National Competitiveness Technology Transfer Act
NNBF	New Nanotechnology-based Firms
NNI	National Nanotechnology Initiative
NSF	National Science Foundation
NSTI	Nano Science and Technology Institute
OLS	Ordinary Least Squares
ORTAs	Office of Research, Technology and Applications
RaDIUS	RAND Database for Research and Development in the U.S.
SBIR	Small Business Innovation Research
SCI	Science Citation Index
STTR	Small Business Technology Transfer Research
USDA	The United States Department of Agriculture
USPTO	The United States Patent and Trademark Office

SUMMARY

The role of universities in supporting economic development has been explored in numerous studies emphasizing the mechanisms of technology transfer and knowledge spillover. However, in addition to these forms of intellectual capital, university scientists bring other resources into research collaboration and contribute to firm partnerships in both direct and indirect ways. This thesis proposes the concept of resource spillover, which captures the various ways in which university scientists can benefit collaborating firms. The study first analyzes firms, university scientists, and collaboration along with the concepts of ego, alter, and network ties in social capital theory; then it categorizes the resources possessed by university scientists into human capital, social capital, and positional capital, and tests the impact of each on the performance of a firm. The study finds that firms benefit from research collaboration in terms of both increased research capability and research output and improved public relations and research credibility.

The study is carried out using a sample of new nanotechnology-based firms in the United States. As the U.S. government recognizes nanotechnology as providing scientific and technological opportunities with immense potential, this industry has become the recipient of significant federal R&D funding. In turn, because academic research has proven to be important to not only overall nanotechnology R&D but also industrial R&D, it necessitates appropriate policy programs that support successful resource spillover from academia and promote the development of industry.

CHAPTER 1: INTRODUCTION

1.1 University-industry relationship

The history of the university-industry relationship in the United States can be divided into three periods: from the mid-1800s to WWII; from the early 1940s to the mid-1970s; and from the late 1970s to the present (Abramson, Encarnacao et al. 1997). During the first period, university research was more immediately practical and applied, and tailored to support the technical needs of local or regional industries, in particular the agriculture industry. About 40 percent of federal research funds went to university-based agriculture research in the mid-1930s.

After the Second World War, the reputation of academic research in meeting national goals was greatly enhanced because it served the war effort. Federal agencies became the major source of research funding, and the orientation of university research shifted to more basic or long-term applied research. The difference between academic research and industrial research was reinforced during this period, with one labeled "basic research" and the other "applied research." (Ibid)

The current phase is characterized by a renewed interest in collaborative research between academia and industry. The emergence of technology-intensive industries, such as information technology, biotechnology, and micro-electronics, has generated a surge in interest in academic research. Increased R&D costs have also compelled universities to seek not only federal but also private funding. (Ibid) Therefore, according to Gibbons et al. (1994), university research transited from Mode 1: traditional researcher-initiated and interest driven research, to Mode 2: context focused and problem driven research. The social structure of this era is also represented by the concept of the triple helix, given the close linkages among the government, universities, and industry (Etzkowitz and Leydesdorff 2000).

University-industry interactions were also fostered by a series of federal technology transfer legislatives authorized in the 1980s (Table 1.1). The most notable legislation were the 1980 Bayh-Dole Patent and Trademark Act and a 1984 amendment to this act that allowed universities to own the patents of their inventions that resulted from federally-funded research and license them to industry. This legislation created financial incentives for universities to market technologies and to encourage them to actively engage in technology transfer (Cooke and Morgan 1998). However, Mowery et al. (2001) cautioned that the Bayh-Dole act might not be as effective as it seems since it doesn't significantly change university patent portfolios and research content.

Table 1.1 Selected federal technology transfer legislation since 1980

Year	Name	Key Points
1980	Stevenson-Wydler Technology Innovation Act	Made technology transfer a mission of the federal government and established the Office of Research, Technology and Applications (ORTAs)
1980	Bayh-Dole Patent and Trademark Act	Allowed universities, not-for-profit organizations, and small businesses to retain certain rights related to inventions they developed under funding agreements with the government

Table 1.1 continued

1982	Small Business Innovation Development Act	Required federal agencies to provide special set aside funds for small business R&D
1984	Amendment to Bayh-Dole Patent and Trademark Act	Deleted term limitations on exclusive licenses and designated the Secretary of Commerce to determine "exceptional circumstances" when contractor rights might be overruled
1984	National Cooperative Research Act	Encouraged joint R&D ventures among competing private firms to enhance U.S. industrial competitiveness by allowing an exemption from treble damages in private antitrust legislation for registered ventures
1986	Federal Technology Transfer Act	Amended the Stevenson-Wydler Act to authorize the Cooperative Research and Development Agreement (CRADA) for government-owned, government-operated laboratories (GOGOs) and formed the Federal Laboratory Consortium (FLC) for Technology Transfer
1988	Executive Order 12591 and 1218	Required federal agencies to delegate authority to government-operated laboratories to enter into cooperative agreements; provided the authority to enhance the global trade position of the U.S.
1988	Omnibus Trade and Competitiveness Act	Established regional university-based Manufacturing Technology Centers for the transfer of advanced manufacturing techniques to small & medium-size firms
1989	National Competitiveness Technology Transfer Act (NCTTA)	Amended the Stevenson-Wydler Act to establish technology transfer as a federal laboratory mission and permit CRADAs for government-owned, contractor-operated laboratories (GOCOs)
1991	American Technology Preeminence Act	Extended the FLC mandate through 1996, allowed the exchange of intellectual property between participants in a CRADA, and allowed laboratory directors to gift excess equipment to not-for-profit organizations
1992	Small Business Technology Transfer Act	Established the Small Business Technology Transfer Research (STTR) Program

Source: (NTTC 1996; Bozeman 2000)

Currently, higher education and university research are regarded as the essential driver of high technology-based economic development and an essential aspect of the innovation system (Nelson and Rosenberg 1993; Siegel, Waldman et al. 2003; Rosenbloom 2004). After all, technological development is more likely to take place in universities instead of in companies, as universities are more likely to pursue scientific knowledge independent of commercial applications, and pure science is more effective at stimulating advanced innovations than applied research (Kaufmann and Todtling 2001). Mansfield (1991) found that about one-tenth of the new products and processes commercialized between 1975 and 1985 in some high tech industries would not have been developed without the support of university research. In general, innovative or learning regions contain both top universities and firms that have access to their knowledge (Cooke, Uranga et al. 1997). Regions such as San Jose (CA), Boston (MA), Raleigh-Durham (NC), and Austin (TX) are well known for their strategies of using universities to attract high tech industries.

Universities and industry cooperate in various modes: from informal information transfer such as consulting, training, and undirected cooperate gifts to more structured cooperation such as contract research, research consortia, business incubators, and research centers (Geisler 1995). See Table 1.2 for the variety of university-firm links.

Table 1.2 University-firm links

	Types of university-firm links
1	Ad hoc or regular consultations among firm employees at universities
2	Presentations by faculty members at firms, or by firm employees at universities
3	Discussions between faculty members and firm employees at professional association meetings, conferences, and seminars
4	Purchases of university research results (patents) on an ad hoc basis
5	Training of firm employees by university researchers
6	Joint supervision of Ph.D. and master's theses by university and firm members
7	Access to special equipment of a firm/university with or without the assistance of the owner's organizations
8	Investment in university facilities
9	Regular acquisition of university research
10	Joint publications by university researchers and firm employees
11	Formal R&D cooperation such as contract research or joint research projects
12	Creation of business incubators and research centers
13	Permanent or temporary mobility from universities to firms
14	Spin-off formations of new enterprises

Source: (Inzelt 2004)

Several factors stimulate university cooperation with industry: the commercialization of technology, the seeking of research funding, the exposure of faculty and students to practical questions and intellectually challenging research programs, and access to firm technologies (Geisler, Furino et al. 1991; Etzkowitz, Webster et al. 1998). The collaboration between U.S. researchers from academia and those from other sectors is one of the indicators of the usefulness of academic research (NSB 2004). On the other hand, the motivation for firms to cooperate with academicians include having access to knowledgeable researchers and well-educated graduates, university facilities, state-of-the-art information and knowledge, assistance with education and training and outsourcing R&D activities; obtaining solutions to technical problems; and gaining prestige and enhancing their image (Evan and Olk 1990; Geisler 1995; Allan 2001; Geisler 2001). The government can also benefit from university-industry interaction by correcting any market failure in R&D investment, speeding up technological innovation, and increasing technological information exchange among various sectors (Hagedoorn, Link et al. 2000).

1.2 University-industry technology transfer

Technology and technical change is one of the main driving forces behind the structure of production, opportunities for trade, increases in international competitiveness, and growth of the national income (Dahlman and Nelson 1995). Accounting for a substantial share of worker productivity growth (Solow 1957; Denison 1962), it is regarded as a key driver of economic growth (Schumpeter 1911). As the key problem of technology policy is not so much in generating new ideas but more in ensuring that the ideas are effectively used (Ergas 1987), the emphasis has shifted from building research capabilities to promoting technology transfer with the intention of generating more spin-offs from public R&D and more fully exploiting commercialization opportunities (Shapira 2001). More than 200 universities in the United States were involved in technology transfer-related activities by 1990 (Jamison and Jansen 2000). In 1999, the commercialization of university research generated more than $40 billion in revenue and supported over 270,000 jobs (AUTM 2003).

Technology transfer refers to the movement of technology and know-how from one organization to another. However, the acquisition of the know-how accompanying hard technology is not only more important but also more difficult in the technology transfer process (Audretsch, Bozeman et al. 2002). Although extensive literature on the topic of technology transfer is available, the majority focuses on international technology transfer before 1980, when the research agenda shifted to domestic technology transfer (Bozeman 2000). Technology-related interactions occur between organizations across institutional boundaries at different levels, such as governmental agencies, universities, federal labs, and firms. Technology transfer occurs in the form of 1) embodied technology flows: through the purchase of products and intermediate goods; 2) technical interactions: through patenting, citations of patents and scientific publications in other sectors, and joint research activities; and 3) personnel mobility: through flows of skilled workers (OECD 1997). The latter two forms are more common in university-industry relationships, as firms are attracted by the scientific knowledge and human resources that universities generate.

1.3 Purpose and structure of thesis

In addition to benefiting from knowledge and technology transfer, always the main theme in university-industry literature, high tech firms can profit from collaboration with university scientists in other aspects as well. For example, firms can gain the trust of university scientists, building a strong base for other activities; they can also become more embedded into scientific community, which opens even more opportunities for acquiring high quality knowledge; and finally, they can enhance their social credentials through links with prestigious universities. Evidence of these benefits can be found in social capital theory. This thesis attempts to explore these various resources inherent in academia and track the spillover effects of interactions with university scientists on high tech firms. The term "resource spillover" is used in this thesis to indicate the resources diffused from university to industry through collaboration. The core research question in this thesis is as follows:

How do new technology-based small firms benefit from resources spillovers associated with university scientist collaborations?

By identifying the resources of university scientists that have potential benefits to high tech firms and clarifying how these benefits affect firm performance, this study provides a reference point from which policy scientists can begin to design appropriate programs that assure successful resource spillover and promote high tech industry development.

Due to its knowledge-intensive nature and close connection with academia, the nanotechnology industry is used as a case study in this thesis, the structure of which is organized as follows: Chapter 2 reviews the development of nanotechnology and the nanotechnology industry, and Chapter 3 describes its involvement in research activities and interactions with university. Chapter 4 reviews social capital theory, which this thesis proposes as a way of explaining firm-university collaborative behavior, including its origins and applications, and then introduces a research framework and applies concepts of social capital theory to explain resource spillover that results from university-firm interactions. Chapter 5 explains the methodology used in this study, including data collection and variable construction, and Chapter 6 discusses the model specifications and econometric results. Chapter 7 presents the conclusions, policy implications, and limitations of the study.

CHAPTER 2: NANOTECHNOLOGY AND THE NANOTECHNOLOGY INDUSTRY IN THE UNITED STATES

This chapter briefly defines the nature of nanotechnology and debates surrounding it and then reviews the history of nanotechnology and significant breakthroughs in instrumentation that have led to its industrialization. The chapter ends by discussing the commercialization of nanotechnology and the development of the nanotechnology industry.

2.1 Nanotechnology and its applications

Associated with nanotechnology, at the leading-edge of knowledge, are state-of-the-art techniques, revolutionary technology opportunities, and a promise of successful economic development. A wide range of disciplines such as physics, chemistry, biology, materials, mathematics, and engineering have contributed to developments in nanotechnology (NSTC 1999). Due to the diversity of these fields, no existing definition captures the full range of its applications. The National Nanotechnology Initiatives (NNI)'s version of the definition (PCAST 2005) of nanotechnology is the "science, engineering, and technology related to the understanding and control of matter at the length scale of approximately 1 to 100 nanometers." The essence of nanotechnology is that it allows one to work at the nanometer level to generate larger structures with novel and significantly improved properties and functions. Currently known nanostructures include carbon nanotubes, proteins, DNA, and single-electron transistors operating at room temperature (NSTC 1999).

Since the 1990s, numerous applications of nanotechnology have emerged in the market. Three organizations have played an important role in assisting firms with translating underlying research into valuable products: the US NanoBusiness Alliance, the Europe Nanobusiness Association, and the Asia-Pacific Nanotechnology Forum. Firms that lead in incorporating nanotechnologies into products already being used by consumers are the paints and cosmetics (e.g., shampoos, skin creams, and sunscreens) industries (Wood , Jones et al. 2003). Other commercial applications of nanotechnology already in use include hard-disks for computers and improvements to telecommunications (Ibid). Table 2.1 lists the top ten nanotech products in 2003, published in the *Forbes & Wolfe Nanotech Report*. However, it has been acknowledged that nanotechnology is still in its early stage of development, as was information technology in the 1960s and biotechnology in the 1980s (Arnall 2003), and its applications did not make a significant impact on industry until 2006 (Miles and Jarvis, 2001).

2.2 The history of nanotechnology

The concept of nanotechnology was envisioned early in 1959 by Nobel laureate physicist Richard Feynman in his lecture “There is Plenty of Room at the Bottom” (NSTC 1999). He predicted that materials and devices at the atomic or molecular scale would bring about new discoveries and opportunities, and new sets of miniaturized instruments would be needed to operate on these nano structures. The term ”nanotechnology" was first coined in 1974 by Japanese researcher Nobuhiko Taniguchi to describe the precision manufacture of materials on a nanometer scale and then extended by Eric Drexler (1992) as the fabrication of materials and products with the precise positioning of molecules in accordance with an explicit engineering design (Smith 1998).

Table 2.1 Top 10 nanotech products in 2003

Product	Tech Company	Manufacturer
High-Performance Ski Wax	Cerax Nanowax	Nanogate
Breathable Waterproof Ski Jacket	Nano-Tex	Franz Ziener GmbH & Co
Wrinkle-Resistant, Stain-Repellent Threads	Nano-Tex	Eddie Bauer
Deep-Penetrating Skin Cream	L'Oréal	L'Oréal
World's First OLED Digital Camera	Kodak	Kodak
Nanotech DVD and Book Collection		
Performance Sunglasses	Nanofilm	
Nanocrystalline Sunscreen	BASF	NuCelle
High-Tech Tennis Rackets	Nanoledge	Babolat
High-Tech Tennis Balls	InMat	Wilson

Source: Forbes & Wolfe Nanotech Report 2003 (Link: www.forbes.com)

In 1981, Gerd Binnig and Heinrich Rohrer invented the Scanning Tunneling Microscope, capable of displaying images of individual atoms, which led to the inventors' winning the Nobel Prize in 1986 and their induction into the US National Inventors Hall of Fame in 1994. Another exemplary breakthrough is the 1986 invention of the atomic force microscope, which could display images of non-conducting surfaces, including biological entities, and was later used in machining and cutting operations (Smith 1998).

These inventions mark the birth of the nanotechnology industry (NSTC 1999), and since then, nanotechnology research has begun to take on a clearer definition. Starting in the 1990s, advances in nanotechnology research took place in various areas, including miniature medical robotics, the organic chemistry of molecular machinery, DNA structures, the treatment of proteins as modular devices, and cellular conveyor systems (Smith 1998). As a result of such revolutionary breakthroughs, together with the potential social and economic benefits, nanotechnology has also attracted the attention of governments. It has been listed as one of six priority areas by the National Science Foundation (NSF) in the United States; it was one of the themes in the Sixth EU Framework Program for Research and Technological Development in Europe; and it has been the focus of research in countries worldwide. The United States government has expedited its support of nanotechnology since the approval of National Nanotechnology Initiative (NNI) in 2001. Table 2.2 presents a brief review of the milestones in the history of nanotechnology.

Table 2.2 Milestones in the development of nanotechnology

Year	Event
1959	Richard Feynman delivers his “There is Plenty of Room at the Bottom” talk.
1974	The term “nanotechnology” is coined by Japanese researcher Nobuhiko Taniguchi.
1981	Gerd Binnig and Heinrich Rohrer invent the Scanning Tunneling Microscope, capable of displaying images of individual atoms.
1986	Drake, Prater, Weisenhorn, Gould, Albrecht, Quate, Cannell, H. G. Hansma, and P. K. Hansma develop the atomic force microscope, which can display images of non-conducting surfaces including biological entities.
1987	Eric Drexler and Chris Peterson found the Foresight Institute, which promotes and advances nanotechnology.
1990	The Institute of Physics publishes the first issue of *Nanotechnology*.
1991	Nanotubes are manufactured for the first time by Sumio Iijima and P. M. Ajayan of NEC in Japan.
1997	The U.S. Department of Defense Task Force on the Future of Military Healthcare (MHSS2020) forms the Committee on Nanotechnology and Biotechnology.
1997	NSF issues an “Initiative Announcement” for research proposals in molecular nanotechnology.
1998	The Interagency Working Group on Nanotechnology (IWGN) is formed to coordinate federal work on the nanoscale.
2001	NNI is set up.

Reference: Smith (1998)

2.3 Debates surrounding nanotechnology

Nanotechnology has economically valuable applications in a diverse range of industries, such as materials and manufacturing, as it has "the ability to synthesize nanoscale building blocks with precisely controlled size and composition and then to assemble them into larger structures with unique properties and functions will revolutionize segments of the materials manufacturing industry," nanoelectronics and computer technology, medicine and health, aeronautics and space exploration, environment and energy, national security, global trade and competitiveness (NSTC 1999). The benefits that nanotechnology could proffer include greatly improved coatings, higher strength and hardness for materials, greater ductility and toughness, enhanced efficiency in optics, improved catalysis, and novel magnetic properties (Smith 1998). It is believed that nanotechnology will lead to the next industrial revolution. The US NSF predicts that "the entire semiconductor industry and half of the pharmaceutical industry will rely on nanotechnology in 10 years and that, by 2015, the global market will be 1 trillion US dollars" (ETC-Group 2002).

Various sources have made the following remarks on nanotechnology (NSTC 1999):

- NSF started the initiative – Synthesis and Processing of Nanoparticles – in 1991 and "the National Nanofabrication User Network in 1994, and highlighted Nanoscale science and engineering in its fiscal year 1998 budget."

- The Department of Defense identified nanotechnology as a strategic research objective in 1997.

- At a congressional hearing in April 1998, Dr. Neal Lane, the former NSF director, recognized nanotechnology as the area that would most likely produce the break-throughs of tomorrow

- In March 1998, the President's Science Advisor, Dr. John H. Gibbons, identified nanotechnology as one of the six technologies that would determine economic development in the next century.

- The National Institutes of Health identified nanobiotechnology as a topic of interest in its 1999 Bioengineering Consortium (BECON) program.

However, alongside the commendations has been dissention on the promising future created by nanotechnology. This difference of opinion is reflected in the debate between the Foresight Institute and *Scientific American* in 1996-1997 (Foresight 1997). The first concern involves the amount of fanfare that nanotechnology has received, and whether it is worthy of such publicity. After all, since many scientists believe that not all the blueprints are realizable, they are cautious about just how much nanotechnology can achieve. For example, NNI has been criticized for "using nano as a convenient tag to attract funding for a whole range of new science and technologies" (Roy 2002; Arnall 2003). Advocates of nanotechnology are labeled as nanoenthusiasts and asked to be responsible for "recklessly setting impossibly high expectations for the economic benefits" (*Economist*, 2002). Some highly-respected nano scientists such as George M. Whitesides, Richard E. Smalley, and Philip Ball, are also skeptical about the feasibility of nanoscale manufacturing, arguing that the concept of nanotechnology does not fit laws of physics and chemistry (Wood , Jones et al. 2003). They are worried that the fanfare resulting from advances in nanotechnology may become a barrier to commercial involvement if companies form an unrealistic impression of the applications of nanotechnology (DTI 2002).

Other scientists have raised concerns about social equity, environmental, and ethical issues. Although this group does not question the ability of nanotechnology to change the future, they suggest an alternative future transformed by nanotechnology in an apocalyptic way (Wood , Jones et al. 2003). Wood et al. argued that nanotechnology has the potential to be used for harmful purposes, leading to destructive rather than constructive results if the knowledge is abused. For example, the convergence of nanotechnology with robotics and genetics will generate greater power and consequently more danger. In addition, nanotechnology may have some unexpected consequences, such as drug resistance to certain viruses, chemical pollution, and nuclear accidents, which other technologies have produced. New classes of nanosubstances could adversely affect the stability of cell walls or disturb the immune system when inhaled or digested (Freitas 2003). In other words, technologists might not be able to fully control nanotechnology and nanomachines. Bill Joy (2000) has an extreme dystopian view on this issue, warning that nanotechnology could result in “our own extinction” as the world is destroyed by technological accidents and human beings are replaced by robotic technologies. Thus, he has recommended the complete relinquishment of nanotechnology such as the cancellation of research on biological weapons in the 1970s.

2.4 New nanotechnology-based firms

Nanotechnology creates a market by replacing the current market and provides exponential improvements in the value perceived and received by the customer. However, since nanotechnological innovations are incremental but discontinuous, and the discoveries break through typical technology capabilities, nanotechnology is referred to as a potentially disruptive technology (Anderson and Tushman 1990; Libaers 2004). Large established firms are poor producers of disruptive technologies, as they tend to externalize research by acquiring small external start-up companies (Ferrary 2003). Even when in-house research is carried out in large firms, research activities are not part of the core business. Instead of focusing on developing and marketing nano-related products, established companies typically invest in nanotechnology in order to integrate it into their existing technology platforms (Miller, Serrato et al. 2005). Hence, this thesis does not consider these established companies as nanotechnology companies.

As in other emerging high technologies, start-up enterprises account for the majority of firms working in the nanotechnological field (Darby and Zucker 2003; Miller, Serrato et al. 2005). Because they are always the main actors in the transfer and commercialization of disruptive technologies through the process of discontinuous innovation, these new technology-based firms are of particular interest to policy scientists (Mansfield 1968). Besides, they play a critical role in maintaining a dynamic economy, generating employment growth, and bringing new technologies to market (Utterback, Meyer et al. 1988; Heirman and Clarysse 2004). Over a five-year period, entry in manufacturing industries accounted for half of the increase in employment in the U.S. (Baldwin and Johnson 1999). For this reason, this thesis focuses on new nanotechnology-based firms

(NNBFs), defined as those established based on nano-related technologies, and on the development of nanotechnological processes, materials, tools, and devices, and their introduction to the market. Figure 2.1 illustrates the growth in the number of NNBFs in the last 15 years.[1] Although a few companies were established before 1990, the majority were formed up in the late 1990s.

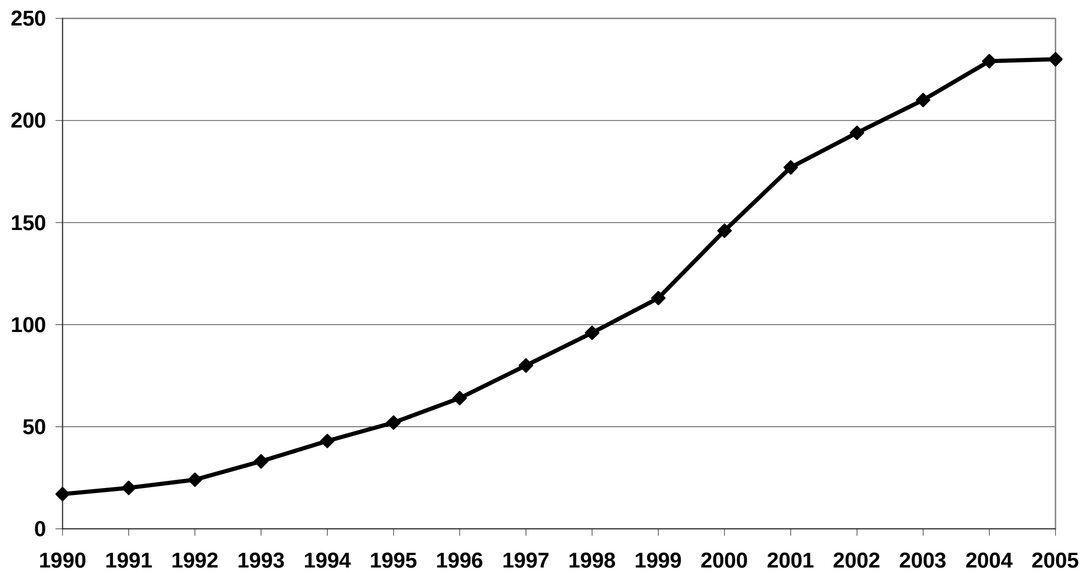

Figure 2.1 Number of new nanotechnology-based firms, 1990-2005

These NNBFs are mostly young, small, and still in the early stage of development. The age of these firms ranges from 1 to 26, the average age in 2007 being 9. Seventy-two percent of these firms are under 10 years old. The number of employees working in the

[1] The search strategy of NNBFs is explained in Chapter 5.

firms varies from 1 to 190, the average being 21. Eighty percent of the firms have fewer than 30 employees. Firm performance varies a lot in terms of sales, from \$18,000 to \$34.7 million, while the medium sales in 2005 were \$2.2 million.[2] However, the distribution of firms is rather even, 26 percent with sales of less than \$0.5 million, 19 percent with \$0.5-\$1 million, 44 percent with \$1-5 million, and 11 percent with over \$5 million.

These firms work in different areas of nanotechnology (Figure 2.2). Nanomaterials and nanodevices & nanoelectronics are the main focus of the nanotechnology industry in this stage, accounting for almost 77 percent of the production of the firms, followed by nanobiotechnology, accounting for 22 percent of production. Another 1 percent of firms work in other areas, such as nanochemistry and nano-clean-energy. The areas are defined in Table 2.3.

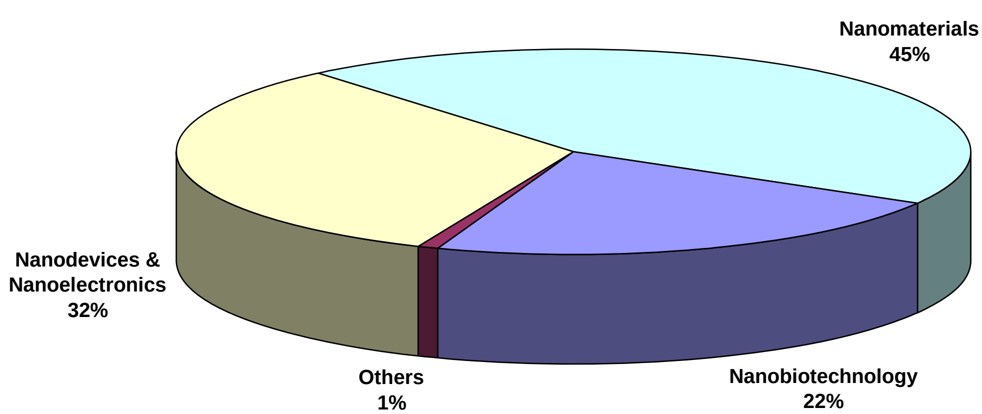

Figure 2.2 Composition of the nanotechnology industry

[2] The sales information of 37 firms is missing. Therefore, the statistics on sales are calculated based on the remaining 193 firms.

Table 2.3 Areas of nanotechnology research

Area of Nanotechnology	Key Terms
Nanomaterials	• Nanowires • Nanotubes • Nanocrystals • Quantum dots • Nanopolymers • Fullerenes • Nanodots
Nanobiotechnology	• Biomolecular devices • Biosensors • Molecular motors • Biomolecular fabric • Cellular biology • Drug discovery and delivery
Nanodevices & Nanoelectronics	• Nanocomputers • Semiconductors • Nanolithography • Thin films

Source: Modified from Porter, Youtie et al. (2007 forthcoming)

The NNBFs, indicated by the purple dots in Figure 2.3, are distributed in 33 states, mostly along the east and west coasts. The states leading in terms of hosting NNBFs are California and Massachusetts, home to 18 percent and 11 percent of NNBFs respectively, followed by Texas (7 percent) and New York (6 percent). The green dots in Figure 2.3 represent universities with nanotechnology R&D, measured as having at least ten publications on nanotechnology. As expected, most of the NNBFs are located close to universities.

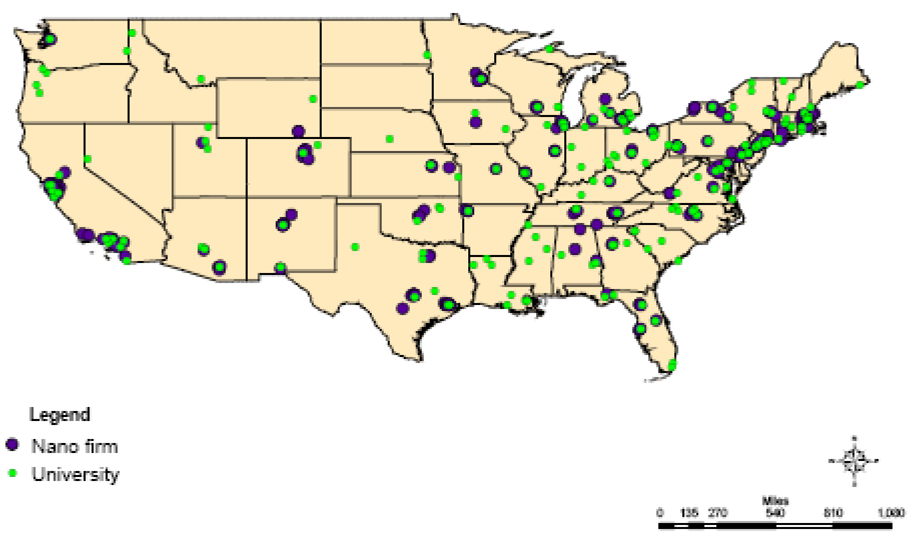

Figure 2.3 Geographical distribution of NNBFs in the U.S.

CHAPTER 3: R&D ACTIVITY IN NANOTECHNOLOGY

Due to its knowledge-intensive nature, R&D plays a key role in the development of nanotechnology, in which university-industry interaction is relatively active. This chapter reviews the input and output of nanotechnology R&D in the United States and compares industrial and university R&D activities. This chapter discusses input in terms of funding sources for nanotech R&D and research output in terms of publications and patents for both academia and industry.

3.1 Funding for nanotech R&D

In 2005, a total of $9.6 billion in R&D funding was devoted to nanotechnology worldwide (Luxresearch, 2006). The main source was government funding, $4.6 billion, followed by corporate R&D, $4.5 billion, and venture capital, $0.497 billion (Figure 3.1). Not surprisingly, the United States has provided the most funding: $1.6 billion from the government, $1.8 billion from corporations, and $0.46 billion from venture capitalists.

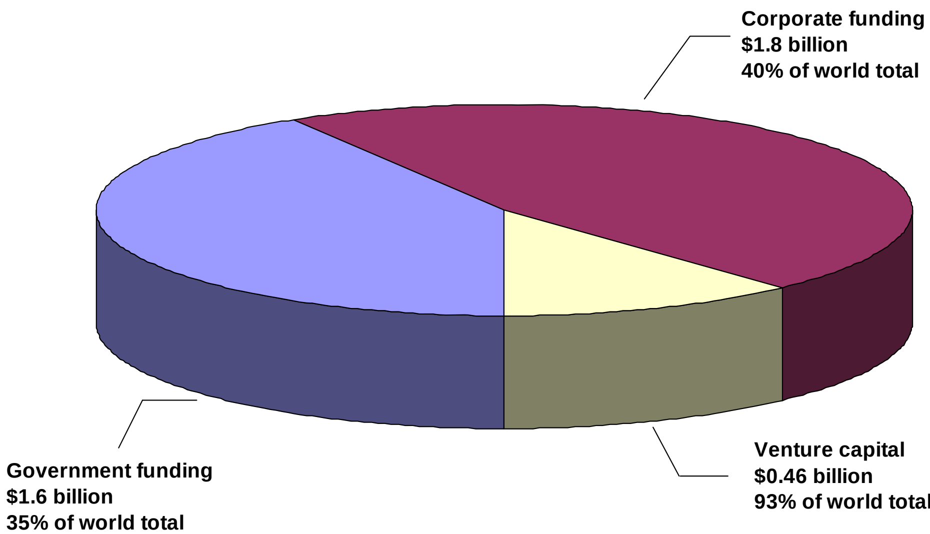

Figure 3.1 Funding for nanotech R&D in the U.S. in 2005

Source: Computed from Luxresearch (2006)

While corporate funding is available primarily from large firms with sufficient funds and venture capital is highly concentrated in a small number of start-up firms, of which only ten percent received 43 percent of the funding (Luxresearch 2006), government funding has gone to general start-up firms.

3.1.1 Government funding for nanotechnology

The U.S. and Japan, accounting for more than half of the world total, have been the largest government R&D spenders on nanotechnology. The EU and the other regions of the world shared the remainder. In 1997-2005, the United States government has spent $5 billion on nanotechnology R&D, with an average annual growth rate of 34 percent (Figure 3.2).

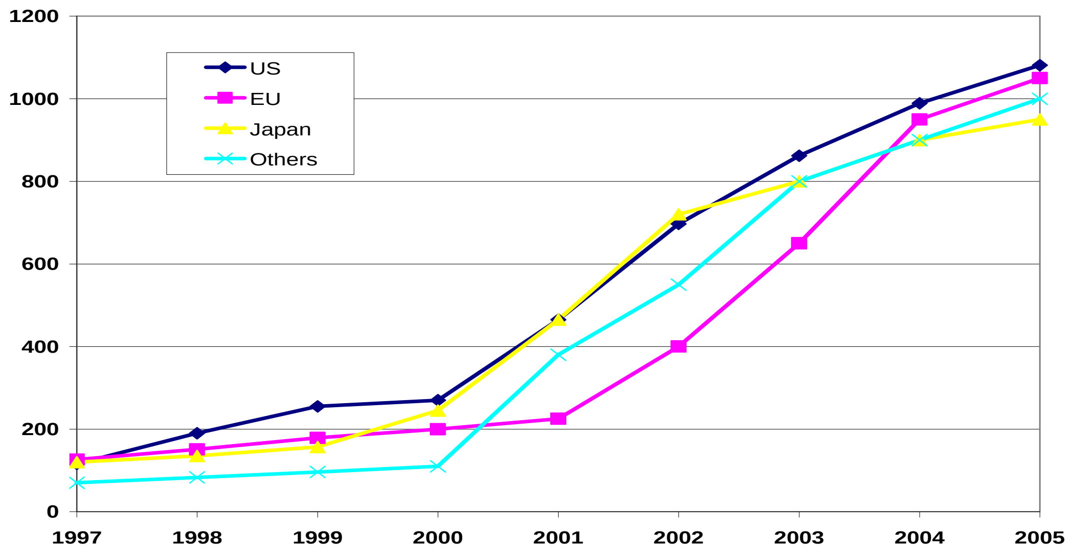

Figure 3.2 Government nanotechnology R&D investments (in millions of US dollars), 1997-2005

Source: PCAST (2005)

Since 2001, the National Nanotechnology Initiative (NNI) has been the primary program coordinating federal investment in nanotechnology. The principal federal agencies that provide research funds for nanotechnology include the Department of Defense (DOD), the National Science Foundation (NSF), the Department of Energy (DOE), the Department of Health and Human Services (DHHS), the Department of Commerce

(DOC), the National Aeronautics and Space Administration (NASA), the Environmental Protection Agency (EPA), the Department of Agriculture (USDA), the Department of Homeland Security (DHS), the Department of Justice (DOJ), and the Department of Transportation (DOT). Among these agencies, the DOD (30%), the NSF (27%), the DOE (18%) and the DHHS (12%) were the leading contributors, jointly providing 88 percent of the funds. Among the remaining agencies, the DOC accounted for 7 percent of nanotechnology R&D investment, NASA 3 percent, the EPA 0.6 percent, the USDA 0.3 percent, the DOJ 0.12 percent, the DHS 0.11 percent, and the DOT 0.03 percent. Figure 3.3 presents the NNI budget for nanotechnology from main funding agencies between 2001 and 2006 and estimations for 2007 and 2008.

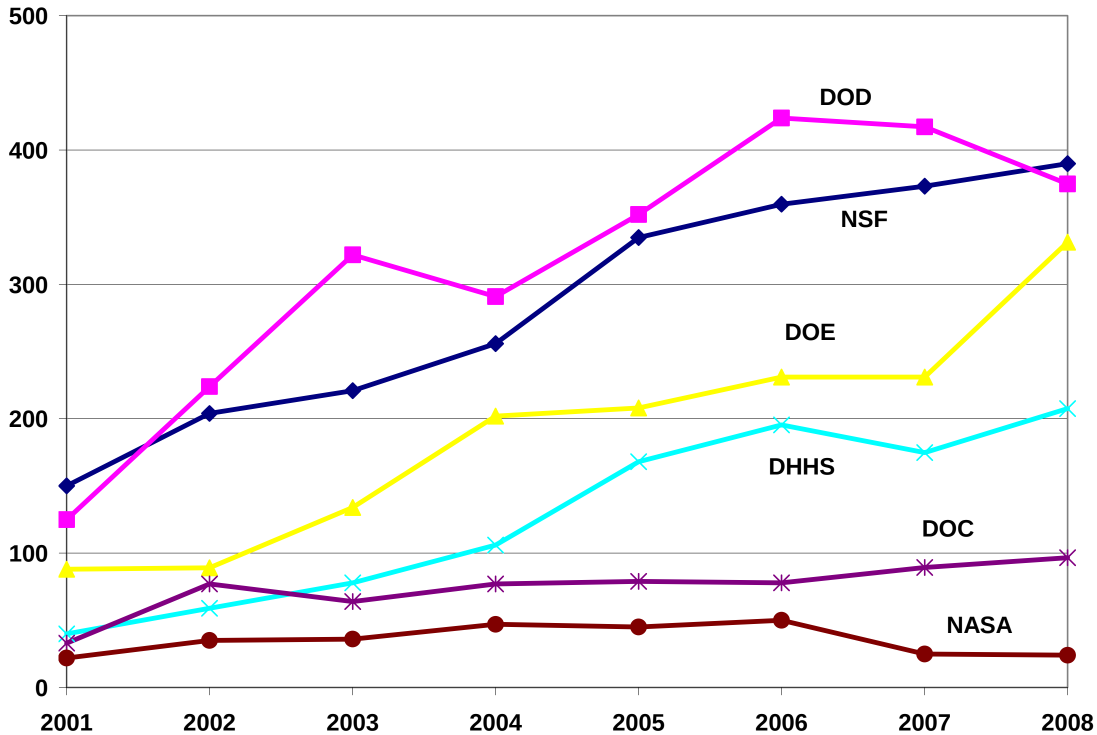

Figure 3.3 Estimated federal investments in nanotechnology (in millions of dollars), 2001-2008

Source: The NNI budget (http://www.nano.gov/html/about/funding.html)

The DOD is the largest contributor to nanotechnology, but its budget has fluctuated over the years. In 2004, the budget dropped by 10, and in 2007 and 2008, the budget is expected to drop again by 2 and 10 percent, respectively. The budget of the NSF, the second largest contributor to nanotechnology, has grown steadily at an average of 15 percent between 2001 and 2008. The budgets of the DOE and the DHHS have exhibited a similar trend as that of the NSF, but increasing at an even faster rate of 23 percent and 28 percent, respectively. By contrast, the budgets of the DOC and NASA appear to have stabilized over time.

3.1.2 Destination of government funding in nanotechnology

Since the last decade, around three quarters of all federal funding for nanotechnology has gone to academia. The other sectors that have received funds are industry (14.1 percent), non-profit organizations (non-educational) (2.7 percent), the federal government (1.7 percent), the state government (0.3 percent), and other sectors (6.3 percent), including the National Academy of Sciences, and national labs and hospitals (Figure 3.4). Most firms that have received federal funding are new technology-based firms supported through programs such as Small Business Innovation Research (SBIR), Small Business Technology Transfer (STTR), and the Advanced Technology Program (ATP).

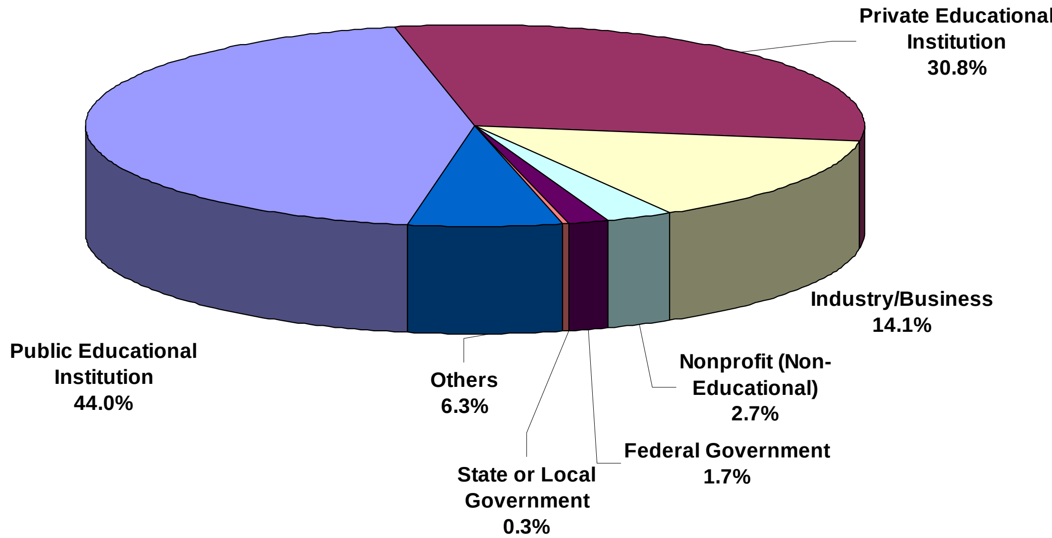

Figure 3.4 Destination of federal funding in nanotechnology, 1993-2005

Source: RaDIUS database (https://radius.rand.org/)

3.2 Publications

Since 1990, the number of publications on nanotechnology has increased exponentially. Using the search terms developed by the Georgia Tech team working on the CNS-ASU project (Porter, Youtie et al. 2007 forthcoming), the number of publications on nanotechnology by U.S. authors in the Science Citation Index (SCI) reached 15,000 in 2005, 34 times that in 1990. As shown in PCAST (2005), the United States continues to dominate publications on nanotechnology in both general SCI journals or in a subset of high-impact journals, more than twice the number from the second highest country, China. However, the gap between the United States and other countries is closing. The proportion of nanotechnology publications by U.S. authors declined from 40 percent in the early 1990s to 30 percent in 2004.

As in other disciplines, publications from universities play an important role in the development of nanotechnological research. University scientists have contributed over 80 percent of publications in nanotechnology (Figure 3.5), and this share has increased over the years. In contrast, although sustaining slow but steady growth, industry has contributed a much smaller proportion of publications, about 10 percent in the 2000s.

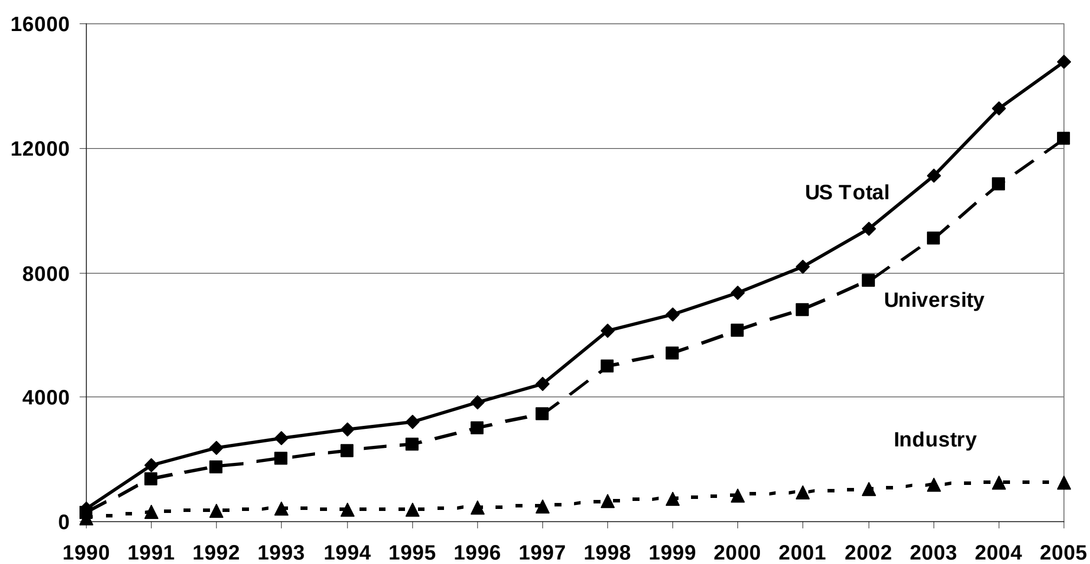

Figure 3.5 SCI publications on nanotechnology in the U.S. by year

As expected, most of the institutions that lead in the number of publications in nanotechnology are academic (Table 3.1). The United States Navy and Oak Ridge National Lab are the only non-university organizations that have been productive in publishing. By 2006, approximately 700 universities had published at least one paper in nanotechnology. Most universities perform well in terms of publications partly due to the fact that they are home to the top scientists in the field of nanotechnology, the main authors of publications. As shown in Table 3.2, these scientists alone contributed 20% to 25% of the publications in their respective institutions.

Table 3.1 Top institutions in terms of SCI publications in nanotechnology in the U.S., 1990-2006

Rank	University	Number of Publications
1	University of Illinois – Urbana Champaign	2,950
2	University of California – Berkeley	2,947
3	Massachusetts Institute of Technology	2,578
4	University of California – Santa Barbara	2,437
5	Pennsylvania State University	1,954
6	Harvard University	1,857
7	Northwestern University	1,834
8	US Navy	1,813
9	Oak Ridge National Laboratory	1,795
10	University of Michigan – Ann Arbor	1,634
11	Georgia Institute of Technology	1,594
12	Stanford University	1,594

Table 3.2 The top 10 authors of SCI publications in nanotechnology in the U.S., 1990-2006

Rank	Author	Affiliation	Number of Pubs
1	Gossard, Arthur C.	University of California – Santa Barbara	355
2	Whitesides, George M.	Harvard University	308
3	Dresselhaus, Mildred S.	Massachusetts Institute of Technology	305
4	Wang, Zhonglin	Georgia Institute of Technology	277
5	Petroff, Pierre M.	University of California – Santa Barbara	229
6	Pfeiffer, Loren N.	Lucent Technology	211
7	Smalley, Richard E.	Rice University	201
8	Ferry, David K.	Arizona State University	197
9	Lieber, Charles M.	Harvard University	194
10	Mirkin, Chad A.	Northwestern University	192

In addition to the large share of publications from academia, university science also plays an important role in industry research. In the industry sector, while over 3,000 firms have published at least one paper in nanotechnology, two-thirds of them, 70 percent of which were NNBFs, collaborated with university scientists. In other words, nearly half of the publications from the industry sector were affiliated with university addresses (Figure 3.6).

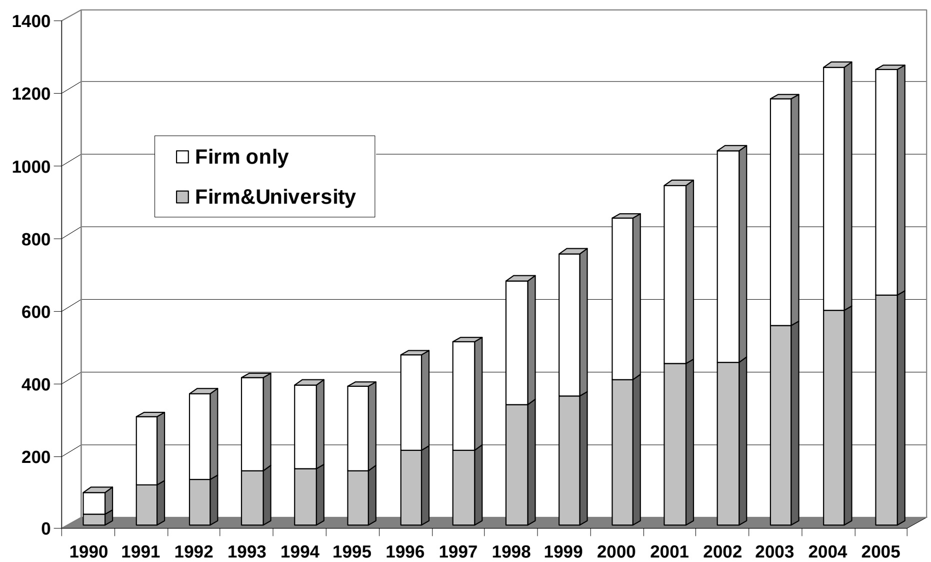

Figure 3.6   Publications on nanotechnology from firm scientists, 1990-2005

Out of the 700 universities that engage in nanotechnology research, approximately 290 collaborate with industry. Table 3.3 presents the universities and firms that most actively collaborate in university-industry research. Not surprisingly, over half represent those with the most publications, listed in Table 3.1.

Table 3.3 The top 10 university/industry collaborators and the number of collaborative publications, 1990-2006

Rank	**Most Active Universities**	**# of Co-Pubs**	Rank	**Most Active Firms**	**# of Co-Pubs**
1	Massachusetts Institute of Technology	172	1	IBM Corp.	643
2	University of California – Berkeley	168	2	Lucent Technology	129
3	Stanford University	165	3	Dupont Co. Inc.	92
4	University of Illinois – Urbana Champaign	156	4	Intel Corp.	90
5	University of Minnesota	132	5	Motorola Inc.	88
6	North Carolina State University	114	6	Eastman Kodak Co.	79
7	Arizona State University	112	7	Xerox Corp.	72
8	Cornell University	104	8	ExxonMobil Co.	71
9	University of Florida	103	9	Dow Chemical Co. USA	68
10	Pennsylvania State University	99	10	Procter & Gamble Co.	44

Interestingly, universities active in collaborating with industry partners work mostly with large established companies. However, the list of the universities most interested in working with NNBFs significantly differs (Table 3.4). The only universities that appear on both lists are the University of Florida and Pennsylvania State University.

Table 3.4 The top 10 university/NNBF collaborators and the number of collaborative publications, 1990-2006

Rank	Most Active Universities	# of Co-Pubs	Rank	Most Active NNBFs	# of Co-Pubs
1	Rutgers University	23	1	Zyvex Corp.	23
2	University of Connecticut	21	2	Hysitron Inc.	21
3	University of Florida	17	3	Material Modification Inc.	20
4	University of New Mexico	15	4	Inframat Corp.	17
5	University of Texas – Austin	14	5	NEI Inc.	14
6	Pennsylvania State University	12	6	Evans E Inc.	10
7	University of Maryland – College Park	11	7	BioForce Nanoscience Inc.	9
8	Princeton University	11	8	Epion Corp.	9
9	University Arkansas	11	9	Zia Laser Inc.	9
10	University of North Carolina – Chapel Hill	10	10	Asylum Research	8

3.3 Patents

Whereas publications are used as indicators of research output, patents are often used as indicators of technology innovation. Similar to publications, the number of nanotechnology-related patents has grown rapidly. According to PCAST (2005), the number of such patents issued by the U.S. Patent and Trademark Office (USPTO) increased by 50 percent between 2000 and 2003. More than 60 percent of nanotechnology patents issued by the USPTO between 1997 and 2003 were awarded to industry, universities, and other organization in the United States. Japan, Germany, Canada, and France represent the other top patent holders.

Broken down by sector, around eighty percent of the patents issued by the USPTO[3] were assigned to industry between 1990 and 2005, ten percent to universities, and ten percent to other organizations such as national labs, research institutes, hospitals, and so forth (Figure 3.7). In spite of the large number of patents from industry, the growth in industry patents is slow compared with that in the other two sectors. The average annual growth rate between 1990 and 2005 was 12 percent for industry patents, 30 percent for university patents, and 20 percent for patents from other organizations. Correspondingly, the share of industry patents decreased from 88 percent in 1990 to 68% in 2005. The lost share was taken largely by universities, whose proportion increased from 6 percent to 22 percent, and partly by other organizations, whose proportion increased from 6 percent to 10 percent.

[3]Between 2000 and 2005, more than half of nanotechnology patents issued by the USPTO had no assignee information. They were either assigned to individuals or not yet assigned. Thus, these patents are not included in this study.

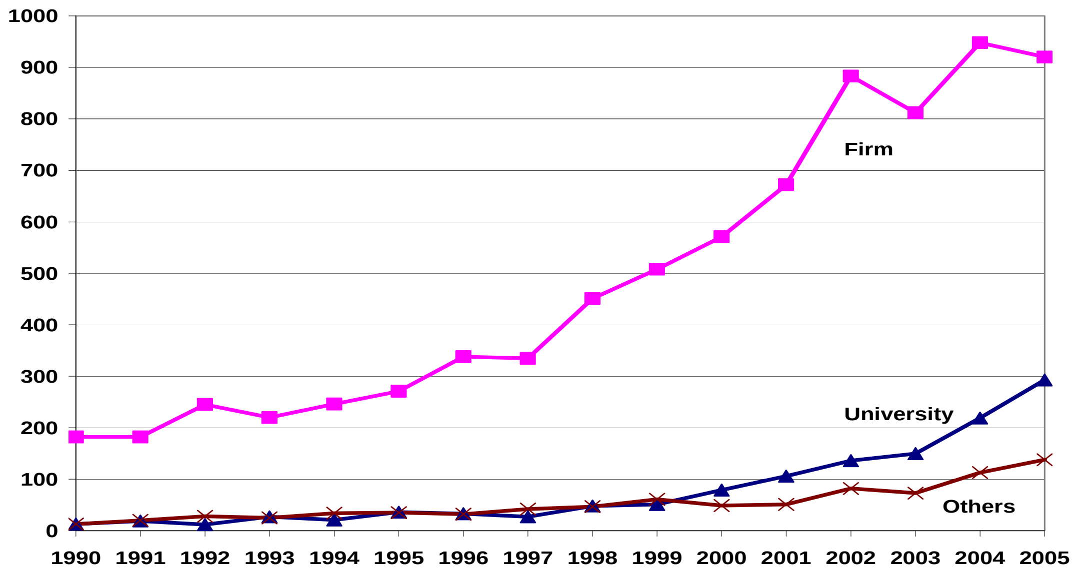

Figure 3.7 USPTO patents in nanotechnology by publication year, 1990-2005

Among the thirteen assignees holding more than 100 patents in nanotechnology in 1990-2005, eleven were large companies, two exceptions being the University of California and the U.S. Navy (Table 3.5). These top thirteen institutions were awarded 24 percent of the nanotechnology patents issued by the USPTO. In addition to these giant patent holders, around 2,000 companies, including 138 NNBFs and 200 universities, have been granted nanotechnology patents by the USPTO. Table 3.6 presents a list of universities that hold at least 20 nanotechnology patents. Due to the regulation of intellectual property, patents are assigned to the university system instead of individual university campuses, so the list compares university systems, which differs from the other tables.

Table 3.5 The top assignees of USPTO patents in nanotechnology, 1990-2005

Rank	Assignee	# Patents
1	International Business Machines Corporation	388
2	Xerox Corporation	259
3	University of California	238
4	Eastman Kodak Company	225
5	L'Oreal S.A	196
6	Micron Technology, Inc.	190
7	General Electric Company	173
8	NEC Corporation	144
9	Motorola, Inc.	139
10	Advanced Micro Devices, Inc.	133
11	Intel Corporation	128
12	3M Innovative Properties Company	119
13	United States of America, Navy	101

Table 3.6 Universities active in nanotechnology patenting, 1990-2005

Rank	Assignee	# Patents
1	University of California	238
2	Massachusetts Institute of Technology	79
3	California Institute of Technology	53
4	Rice University	43
5	University of Texas	37
6	University of Michigan	28
7	Cornell University	26
8	University of Chicago	26
9	Stanford University	24
10	Harvard University	23
11	University of Illinois	23
12	North Carolina State University	21

Although universities are not the principal holders of nanotechnology patents, their contribution to the development of nanotechnology should not be underestimated. After all, 35 universities are co-assignees with firms on nanotechnology patents, and numerous university professors are the sole inventors in firm patents (Table 3.7). In addition to invention, university scientists play an important role in the commercialization of nanotechnology. The majority of intellectual property licensed by nanotech startups comes from universities (Waitz and Bokhari 2003), and 70 percent of university nanotechnology-related inventions cannot be properly commercialized without the involvement of inventors (Darby and Zucker 2003). The important role of universities in nanotech R&D can also be evidenced in the Top 5 nanotech breakthroughs reported by *Forbes*. Most of the researchers involved in the breakthroughs have been affiliated with universities (Table 3.8).

Table 3.7 Universities active in co-patenting with firms, 1990-2005

Rank	Assignee	# Co-Patents
1	Duke University	11
2	University of California	6
3	University of Tennessee	4
4	University of Arizona	3
4	Iowa State University	3
6	University of Chicago	2
6	Boston University	2
6	California Institute of Technology	2
6	Massachusetts Institute of Technology	2
6	Northwestern University	2
6	Rutgers University	2
6	Stanford University	2
6	University of Michigan	2
6	University of Washington	2

Table 3.8 The top 5 nanotech breakthroughs in 2006 (Wolfe 2006)

Breakthroughs	Researchers	Affiliations
DNA Origami	Paul W. K.Rothemund	California Institute of Technology
Nanomagnets to clean up drinking water	Vicki Colvin, Amy Kan, William Yu, J.T.Mayo, Arjun Prakash, Joshua Falkner, Sujin Yean, Lili Cong, Cafer T. Yavuz, Mason Tomson, Doug Natelson and Heather Shipley	Rice University
Arrays connect nanowire transistors with neurons	Charles Lieber, Fernando Patolsky, Brian Timko, Guihua Yu, Ying Fang, Andrew Greytak, and Gengfeng Zheng	Harvard University
Single nanotube electrical circuits	Phaedon Avouris, Zhihong Chen, Joerg Appenzeller, Yu-Ming Lin, Paul Solomon; Jennifer Sippel-Oakley and Andrew Rinzler; Jinyao Tang and Shalom Wind	IBM; University of Florida; Columbia University
Nanoparticles destory prostate cancer	Robert Langer; Omid Farokhzad, Benjamin Teply, Ines Sherifi, Jerome Richie; Jianjun Cheng; Sangyong Jon; Philip Kantoff	Massachusetts Institute of Technology; BWH; Harvard University; Gwangju Institute of Science and Technology, South Korea; Dana Farber Cancer Institute

CHAPTER 4: SOCIAL CAPITAL AND RESOURCE SPILLOVER

Although university-industry interaction has been a focus of research for many years, the rationale behind the motivation for such interaction has not received much attention. This study notes the importance of several concepts in social capital theory that motivate firms to collaborate with universities and reap the associated benefits. This chapter begins by reviewing the origin of social capital theory and the various definitions of social capital and continues with a discussion of the basic concepts of social capital and their applications to university-industry relationships. It follows with a discussion of research hypotheses and variable measurement. The chapter ends with a brief summary.

4.1 Overview of social capital theory

Classical economists have always regarded land, labor, and physical capital as the three main resources shaping economic growth. However, if they are owned solely by individuals, these resources have a limited impact unless people can access each other's resources and disseminate their information and knowledge. Thus, as the quality of workers was found to play an important role in determining how productivity of the other factors, Neo-classical economists of the 1960s recognized the importance of a new resource: human, or social capital (Woolcock 1998).

Social capital originates from relationships in civil society, such as family, schools, local communities, firms, associations, gender, and ethnicity (OECD 2001). The family is the primary source of social capital, as family members receive both materials and emotional support from each other. Schools and firms are the formal institutions that provide education and work experience for the accumulation of human capital and also build social networks based on the relationships of classmates, schoolmates, and colleagues. Communities, neighborhoods, and associations also provide a social network that benefits its members. Social interaction among neighbors and group members provides opportunities for them to work together toward a common good. Social capital can also be built on gender and ethnicity, both of which provide members with opportunities to share common values and culture and bond for their mutual benefit. The importance of trust, partnerships, and collaborative ventures have been increasingly emphasized in the new economic literature, in which innovation is regarded as dependent on collaborative activities across different sectors such as industry and academia.

The concept of social capital was initiated in the late 1970s and the early 1980s. Bourdieu proposed the term "culture capital" and used it to describe the resources available through the network (Bourdieu 1986). In his work, Bourdieu stated that social capital has two elements: social relationships, which allow people to access resources possessed by other people, and the amount and quality of these resources (Portes 1998). Coleman further analyzed the generation of social capital and its consequences (Coleman 1988). He also stressed that social capital complements human capital (OECD 2001). Putnam emphasized the role of social capital in improving the efficiency of society and fostering social cohesion (Putnam 1993). Nahapiet and Ghoshal (1998) explained social capital in terms of three dimensions: the existence of connections, trust developed across these connections, and shared understanding among members. This concept emphasizes shared norms and values, which promote communication. While Coleman and Putnam claimed that dense networks were major components of social capital, Granovetter (1973) and Burt (1992) highlighted the role of weak ties or the absence of social ties, or the "structural hole." They argued that weak ties provide new sources of ideas and information and additional opportunities, and the number of holes indicates the volume of resources that can be brokered from different sides of the holes. Table 4.1 presents the various statements of social capital.

These various elaborations of social capital theory differ mainly in their treatment of the social network versus the resources acquired through it, the number of resources versus the ability to obtain them, the dense network versus the loose network, individual human capital versus collective social capital, and the possessors of social capital versus the sources of social capital. Despite their differences, they share the notion that social capital is relational instead of individual and that it represents the ability of actors to obtain resources by being members of social structures (Portes 1998; OECD 2001).

Table 4.1 Various definitions of social capital

Definition	Author
"The aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition."	(Bourdieu 1986)
"A variety of entities with two elements in common: They all consist of some aspect of social structures, and they facilitate certain actions of actors – whether persons or corporate actors – within the structure."	(Coleman 1988)
"Social capital is the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition."	(Burt 1992)
"Social capital refers to features of social organization, such as trust, norms, and networks, which can improve the efficiency of society by facilitating coordinated actions."	(Putnam 1993)
"The sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit. It comprises both the network and the assets that may be mobilized through the network."	(Nahapiet and Ghoshal 1998)
"Social capital is an instantiated informal norm that promotes cooperation between two or more individuals."	(Fukuyama 2000)
"Networks together with shared norms, values and understandings that facilitate co-operation within or among groups."	(OECD 2001)

The positive consequence of social capital is apparent. It can be seen as a complement to human capital (Coleman 1988) and expands the scope and scale of resources that an individual can mobilize. Its usefulness has been proven in various studies on access to employment, mobility through occupational ladders, and entrepreneurial success (Portes 1998). On a societal level, it builds trust, encourages acceptance of norms and shared values, reduces uncertainty and risk, promotes exchange, savings, and investment (Fukuyama 2002), and improves the efficiency of society through coordinated action (Putnam 1993).

However, critics argue that the benefits that social capital confers upon its group members are accompanied by the loss of outsiders. An empirical study conducted by Robert Cushing found that regions ranked high on an innovation index ranked low on Putnam's measures of social capital (Florida 2002). Cushing and other scholars argued that social ties may promote inward-seeking social interactions, exclude outsiders, and impede the building of trust and cooperation on the wider community level (Portes and Landolt 1996; Portes 1998; OECD 2001). It can also be used by one group against other groups (OECD 2001). Nevertheless, it is important to note that most of these problems occur in dense networks and can be remedied by weaker ties, a looser network, or a wide radius of trust (Fukuyama 2000). Unlike strong ties, which consume more time and energy, weak ties require less investment and are more manageable (Granovetter 1973). In addition, they have a lower entry threshold and allow people to move in and out easily. Therefore, places with looser networks and weaker ties are more open to novel combinations of resources and ideas (Florida 2002).

Other negative consequences of social capital have also been discussed. For example, some components of social capital such as public or private goods, which are dominated by externalities, risk underinvestment due to the free-rider impact since people can benefit from the contribution of others, and the contributors do not fully appreciate its benefit (OECD 2001). Social capital also restricts individual freedom and personal autonomy, so successful group members are pressured to assist other members (Portes 1998).

4.2 Applications of social capital theory

Social capital theory has popular applications in social studies, such as school attrition, academic performance, children's intellectual development, employment and occupational attainment, juvenile delinquency and its prevention, and immigrant and ethnic enterprises (Portes 1998). The literature emphasizes the norms of society and the sources of human motivation (OECD 2001). Social capital theory has also been applied to economic and political studies with a focus on the investment strategies and the role of institutions and social arrangements, respectively (OECD 2001). Also under study has been the question of whether or not the stock of social capital will be enhanced or destroyed by the intervention of the state, or government (Woolcock 1998).

In the science and technology policy area, social capital is regarded as a facilitator of the creation of human capital. Studies have explored the use of social capital to promote scientific research productivity and suggested that social capital be added to evaluation models (Bozeman, Dietz et al. 2001) so that instead of concentrating solely at the immediate outcomes of a project, one should devote more attention to sustained knowledge capabilities the project generates. Furthermore, social capital theory has been tested in a regional growth model that examines whether social capital can account for innovation and economic growth (Florida 2002). This thesis applies social capital theory to the area of the university-industry partnership.

4.3 Theoretical framework

As social capital comprises both social networks and resources that can be mobilized through networks, concepts will be explained within the context of these two variables. The concept "resource spillover" refers to the spillover effects of various resources of university scientists such as the human capital, social capital, and positional capital on collaborating firms. Based on the resources in these three dimensions, three hypotheses are proposed.

4.3.1 Network structure

Social capital resides in social networks in which actors and social ties are the primary elements. Actors, which refer to the social entities under study, can be people, groups, organizations, regions, or events (Wasserman and Faust 1999). A social tie, by definition, is a link between a pair of actors, such as kinship (family members), an emotional relationship (friendships), the transfer of material resources (buying or selling), the transfer of non-material resources (lecturer and audience), and an organization attachment (colleagues) (Ibid). One social tie can represent different relationships. For example, the relationship between a university scientist and a firm scientist can be an emotional relationship, or a friendship, or it can involve the transfer of material resources, when the firm scientist uses the equipment of the university scientist, or it could involve a transfer of non-material resources, when the university scientist learns the marketing information of the technology from the firm scientist, or sharing memberships in the same association.

Network structures fall into different categories, such as the one-mode network, the two-mode network, and the ego-centered network (Wasserman and Faust 1999). The mode indicates the number of sets of entities in the structure. A one-mode network is the basic type of network with only a single set of actors. A two-mode network consists of two sets of actors, each of which can be either the same type or different types. For example, one set of actors can consist of people, and the other set of actors the affiliations of the people. The relationships among the people and their affiliations and between the people and the affiliations comprise the network. Although the networks could be a three-mode or even higher-mode networks, so far, no network analysis method can analyze such a complicated structure. Another type of the social network is an ego-centered network, which contains a focal actor "ego" and other actors, or "alters," which are linked to ego. Social ties exist between the ego and the alters, and also among the alters.

Since firms are the focus of this study, the ego-centered network is used to model the relationship between high tech firms and university scientists. In this structure, the firm is the ego and university scientists are the alters. However, as stated above, because firms and university scientists can form numerous types of relationships, this thesis cannot cover all the types or compare one type with another. Instead, it will focus on the most important relationship: research collaboration. As co-publishing is the typical outcome of collaboration on research between university scientists and firm scientists, the remainder of the thesis will use co-authorship to measure scientific ties between firms and university scientists.

4.3.2 Resources and resource spillover

Resources, defined as normatively valued goods in a society, can be either ascribed or acquired. Ascribed resources are those one inherits, such as race, gender, or wealth, and parental resources. Acquired resources are those invested or obtained by oneself, such as education, employment, and reputation (Lin 2003). Not surprisingly, ascribed resources are strongly correlated with acquired resources. After all, those from wealthier families have more opportunities to obtain a strong education; or those with more parental resources are more likely to gain better employment.

All of the resources owned by the alter can be taken advantage of by the ego through their connections. For example, the ego can ask for financial assistance from the alter if the alter is wealthy; the ego can also ask the alter to solve technical problems if the alter is knowledgeable; the alter can introduce the ego to some groups if the alter has any membership; or at least the ego can learn some information from the alter. Hence, resources owned by a person benefits not only the owner but also other people who have a link to the owner. This thesis refers to this phenomenon as "resource spillover."

The term "resource spillover" better captures the beneficial relationship between academia and industry than and other terms such as technology transfer or knowledge diffusion because it encompasses various factors that take part in the diffusion process. Such factors include not only technology and knowledge, the most prevailing in current knowledge, but also all the other resources of university scientists, including affiliation, social standing, reputation, power and network. Resource spillover can also occur both intentionally and unintentionally once a relationship is established. In some cases, resources are utilized by other people, even without the consent of the owner, because of symbolic utility. Simply by mentioning that one has a close relationship with a well-respected person, an individual may gain the trust of other people without having to inform the well-respected person whose reputation is borrowed without his or her knowledge. As Lin (2003) pointed out, letting others know about one's social ties is sufficient for promoting his or her social standing.

As an assumption of social capital theory, resources are distributed unequally in a society, where an individual in a higher position possesses greater social capital. Social structure, a pyramid shape, is comprised of positions that are rank-ordered according to the resources available to each position. There are fewer positions in the upper level, which has better resources and more positions than in the lower level, which has poorer resources and fewer positions. The higher the position a person can attain, the fewer competitors, the more accessible resources, and the better view of the structure he or she has. A position closer to the top not only includes more valued resources but also allows greater accessibility to resources attached to other positions, especially those in lower ranks (Lin 2003).

An ego has several advantages if it has access to an alter with better resources. First, the alter has well-embedded and commanded resources that benefit the ego. Second, in the pyramid structure of resource distribution, the alter with more resources has both a higher position and an advantageous view of the structure; thus, the alter can provide the ego with better information. In addition, the alter with a higher social position possesses stronger social credentials, and the alter's willingness to be linked with the ego ensure the ego's credentials. Finally, the ability to access the better-positioned alter enhances the ego's confidence in further interactions and actions (Ibid).

4.3.3 Resource spillover from university to industry

Given the fact that resource spillover is positively associated with resources possessed by the alter, or university scientists in our case, NNBFs naturally look for better-positioned scientists in the social structure when they collaborate with university scientists. The collaboration between firms and university scientists is measured by the number of co-authored publications. Co-authorship has been used as an indicator of research collaboration in many studies (Otte and Rousseau 2002) since it is the most tangible way to structure scientific activities (Peters and van Raan 1991).

One needs to be aware that co-authorship is not a perfect indicator of collaboration due to honorific co-authorship, by which co-authorship credits appear to be irresponsible (Cason 1992). Cases also exist where researchers work closely together but decide to publish their results separately or researchers who have not worked together but decide to pool their findings and write jointly (Katz and Martin 1997). Nevertheless, co-authorship is found to be positively correlated with collaborative activities (Glanzel and Schubert 2004) and "co-authorship credits cover all collaborators that substantially and technically contribute to their co-authored papers" (Yoshikane, Nozawa et al. 2006). By establishing collaborative relationships with university scientists through the active publication of papers, firm researchers can earn their trust and gain access to the tacit knowledge that is not codified, but otherwise accessible (Hicks 1995).

The remainder of this chapter compares the quantity and quality of the resources owned by university scientists and their impact on related NNBFs through research collaboration as indicated by co-authored publications.

4.3.3.1 Firm performance

4.3.3.1.1 Innovation capability

The impact of collaboration with university scientists on NNBFs was measured in two ways: by the direct contribution to a firm's innovation capabilities and the indirect contribution to a firm's perceived technology potential and external investment potential. A university, as a producer of advanced knowledge, is the most favorable working partner when a firm wants to enhance its research capabilities and output.

Patent indicators are the most frequently used indicators for innovation capability among the few others such as publications, new products, and total factor productivity (Dernis, Dominique et al. 2000). Patent indicators show their strength in that patents are directly linked to inventions, and patent data are publicly available via patent offices and relatively easy to access. In addition, patent documents provide rich and categorized information of invention, which is allowed to be aggregated at different levels such as by assignee, region, or industry for the different purposes of each study. Therefore, patent data, as an indicator of technological innovation, have been widely used in various studies (Griliches 1984; Pavitt 1985; Schmoch 1997).

As discussed in the OECD (2005) and innumerable studies in the literature (Pavitt 1985; Dernis, Dominique et al. 2000), patent indicators as a measure of innovation output are not without their drawbacks. First of all, patents do not represent all inventions. Some inventions are protected by other means such as trade secrecy, and others are simply not patentable. Secondly, the value of patents varies as some patents may have no industrial value while others can be used in a number of applications. Patent indicators are also critiqued for their inconsistency across countries and across industries.

These disadvantages of patent indicators, however, are not important in the context of this study. Since this thesis studies only patent statistics of firms in the nanotechnology industry in the United States, they do not vary across industries and countries. Furthermore, most innovations in nanotechnology are patentable. Since high-tech firms often use patents to build technical credibility in order to participate in knowledge exchange and win orders (Waitz and Bokhari 2003), the patents capture most of the inventions in nanotechnology.

4.3.3.1.2 Perceived technology potential and investment potential

On the other hand, by exhibiting collaboration with universities, firms implicitly announce their research capabilities at the benchmark level of their university collaborators. As the costs of labor and setting up a laboratory are often prohibitive, NNBFs have significant capital requirements. They must continuously seek external financial support. Raising funds requires the company to persuade investors or funding agencies to give them money under conditions of information asymmetry and uncertainty. Since nanotechnology and its related technologies are typically state-of-the-art and the technology too complex for the lay person, the long-term benefits of investment are difficult for the funding agencies to assess (Waitz and Bokhari 2003). Thus, lacking the ability to thoroughly evaluate a technology, funding decision makers must often rely on perceived signals of quality (Gregorio and Shane 2003). As shown in several studies, researchers who have strong technical reputations tend to have more access to the external sources of high-quality knowledge and collaborate with other top-rated researchers (Hicks 1995; Furucawa and Goto 2005). Thus, the choice of collaborators can signal the potential and improve the reliability of a firm. Therefore, firms with ties with prolific university scientists are more likely to acquire investment.

As described in Chapter 3, government funding and venture capital are the main sources of funding for NNBFs. While government programs emphasize technology capabilities, venture capitalists are more interested in the marketing potential and profitability of a firm since they invest for return. In other words, the ability to obtain funding from the government depends on the perceived technology potential of the firm.

4.3.3.2 Resources of university scientists

The resources of university scientists are examined in three dimensions: human capital, which consists of resources possessed by an individual; social capital, which includes resources embedded in the networks possessed by the individual; and positional capital, which refers to resources represented by one's affiliation or associations.

4.3.3.2.1 Human capital

Human capital refers to the knowledge, skills, wealth, and reputation that an individual possesses. In addition to the three types of resources accessible through social ties, as suggested by Lin (2003)—wealth, or economic assets, power, or political assets, and reputation, or social assets, this study adds a fourth type—intellectual capital, or knowledge assets, which are characterized by relationships between a student and a teacher, those among conference participants, those among members of a study group, and others. These relationships carry no expectations of economic or political gain, but instead foster the exchange of ideas and skills, and broaden the scope and viewpoints of the participants.

To maintain an advantage in competition, high tech firms must conduct ongoing R&D and develop advanced and marketable products. R&D not only creates new knowledge but also enhances firms' absorptive capacity, which is the ability to recognize and exploit external information that is critical to firms' innovative capabilities (Cohen and Levinthal 1990). Considering the importance of intellectual capital to the establishment of NNBFs, knowledge is not only the most prominent asset but also the most desirable return that firms expect from their collaboration with university scientists (Zucker, Darby et al. 1998). After all, the scientific knowledge of university scientists can be transformed into technological capability within the firm through collaboration, training, and other experiences. Investors tend have higher expectation of firms collaborating with star scientists because intellectual capital is reflected in their valuation of firms' assets (Darby, Liu et al. 1999). The most productive university scientists tend to be more active in research activities and are more likely to deliver their knowledge to partners, leading to the following hypotheses.

H1: NNBFs that collaborate with more productive university scientists are more likely to have more research output.

H2: NNBFs that collaborate with more productive university scientists are more likely to have higher perceived technology potential.

H3: NNBFs that work with more productive university scientists are more likely to have higher external investment potential.

Many studies have used the number of papers published in scientific journals as a measurement of the productivity of academic scientists. However, this measurement does not account for the fact that some scientists might have more publications simply because they have been working in the field for many years and not necessarily because they are more productive than others. By contrast, newcomers are at a disadvantage if their research output is compared with that of senior scientists without taking into account the effort they have expended. Instead, the publication rate, or the amount of publications in a certain time window, better indicates a scientist's research capability and productivity. In this thesis, the time window is set as one year, and the publication rate refers to the average number of publications that a scientist has per year. It is calculated as the total number of publications divided by the length of the scientist's career.

4.3.3.2.2 Social capital

Providing the basis for trust, cooperation, and collective action, social capital constitutes a valuable resource. Social networks provide access to more information and opportunities through contacts and connections, such as the "invisible college" (Price 1963; Crane 1972), weak ties (Granovetter 1973), and friends of friends (Boissevain 1974). A dense network (i.e., or strong ties), which refers to close relationships such as family or colleagues, tend to have an overlapping network and share common sources of information. They are more likely to gain new information from weak ties, which are located in distant parts of the network. Relationships that constitute a loose network, or weak ties, can refer to those that don't have frequent contact or to those from a different working class or cultural background. Therefore, establishing contact with people who are directly connected, or a "structure hole," can greatly reduce the redundancy of resources (Burt 1992). Nahapiet and Ghoshal (1998) suggest that these information channels reduce both the amount of time and investment required to gather information. An empirical study conducted by Crane (1969) shows that scientists with more social ties tend to have higher research productivity.

As Burt (1992) pointed out, the ego can benefit from a network with a large number of indirect ties without too high of a network maintenance cost. For a collaborating company, a scientific network of university scientists represents indirect social ties, one of the more desirable benefits of collaboration (Pavitt 1995). The firm can translate such a tie into its own network, so the firm becomes embedded in the scientific community (Murray 2004) and has more opportunities to learn high quality knowledge.

H4: Collaborating with university researchers who have more social capital enhances the research productivity of NNBFs.

H5: Collaborating with university researchers who have more social capital has a positive impact on the perceived technology potential of NNBFs.

H6: Collaborating with university researchers who have more social capital has a positive impact on the external investment potential of NNBFs.

The scientific network of university researchers can be indicated by the number of collaborators or by the size of the scientific community in which they work. As most information typically travels through a maximum of one intermediary (Scott 1991), this study will take into account only direct contact between a university scientist and a firm. Co-authorship is again used to measure the amount of collaboration between a university scientist and other researchers.

Figure 4.1 illustrates how the firm Transgenex Nanobiotech, Inc. is linked to the scientific community through its connection with the University of South Florida. On the map, the links refer to co-publications.[4] In this network, Transgenex Nanobiotech has direct access to only one university, the University of South Florida, which is its primary contact. However, all the contacts of the University of South Florida represent secondary contacts to Transgenex Nanobiotech. Having established a connection with the University of South Florida, the firm can also indirectly benefit from the resources of the secondary contacts.

[4] To simplify the diagram, only American institutions having more than 1 co-publication with University of South Florida are listed in the map.

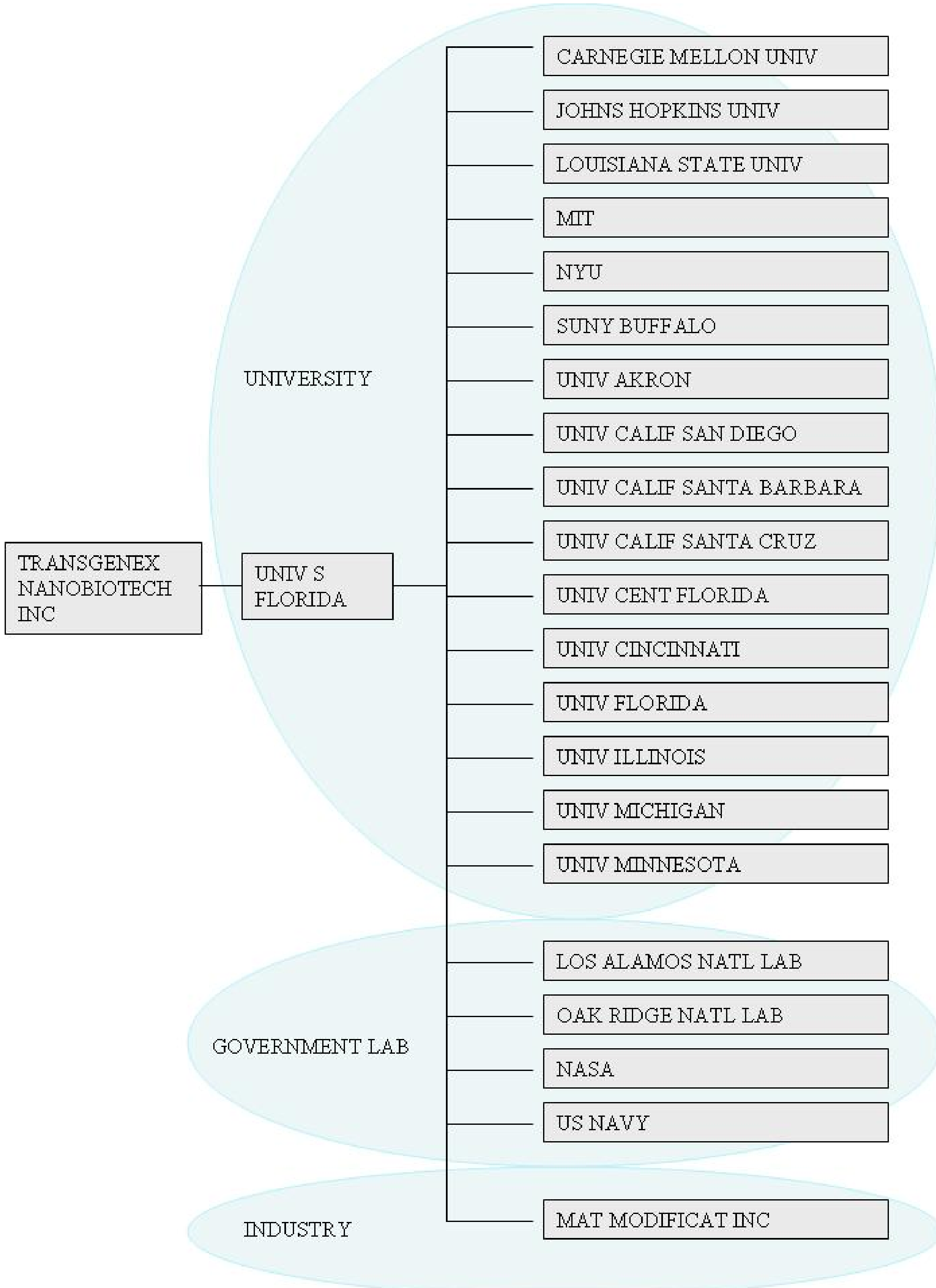

Figure 4.1 Map of networks in the scientific community

4.3.3.2.3 Positional capital

By establishing social ties with university scientists, high tech firms not only acquire more know-how and information from these scientists but also benefit from their positional capital. According to Lin (2003), the positional capital of social ties can be more useful than human capital because it not only evokes “the resources embedded in positions in the organization, but also the power, wealth, and reputation of the organization itself."

In this context, the university with which the scientists are affiliated represents an invaluable asset. A prestigious university tends to have the best faculty, students, instruments and equipment and to generate new ideas and innovations. It is believed that more eminent universities or researchers produce higher quality technology that is more worthy of funding and that the alumni can get more prestigious jobs in which they then construct valuable social ties. All these attributes enable these universities to procure funding and support from both public and private sources. As a result of their increased economic and political resources, they are wealthier, and thus better able to invest in research and attract human resources, all of which builds a positive feedback loop. Thus, even if two scientists are equally knowledgeable and have the same research productivity, they possess different positional capital if they are in universities with clearly different reputations.

Correspondingly, working with scientists from prestigious universities provides more opportunities for a firm to access university resources, including instruments and students, both of which are helpful in improving a firm’s research capabilities. Furthermore, the current reputation of the academic institutions with which scientists are affiliated affects their reputation in their fields of study (Long, Bowers et al. 1998; Cable and Murray 1999), which in turn adds to their firms' perceived development potential through collaboration.

H7: NNBFs linked to universities with a higher reputation tend to have more research output.

H8: NNBFs linked to universities with a higher reputation are more likely to have higher perceived technology potential.

H9: NNBFs linked to universities with a higher reputation are more likely to have higher external investment potential.

University reputation is measured by a national ranking reported by the *U.S. News and World Report*, which publishes the mostly widely accepted ranking of universities and colleges. Universities often cite the ranking when they report their prestigiousness and progress. Among the various rankings provided by the *U.S. News and World Report*, the list of the best national universities is used as a measurement since it reflects the recognition of the university both inside and outside of the scientific community.

4.5 Summary

To summarize, this chapter proposes research framework and hypotheses and explains measurements of dependent and independent variables. With regard to dependent variables, research output is measured by the number of patents granted to the firm, perceived technology potential is measured by the value of SBIR/STTR awards received by the firm, and perceived investment potential is measured by venture capital invested on the firm. In terms of independent variables, research productivity is determined by the publication rate of a university scientist, network size is measured by the number of collaborators of the scientist, and university reputation is indicated by the national ranking. The process is illustrated in Figure 4.2.

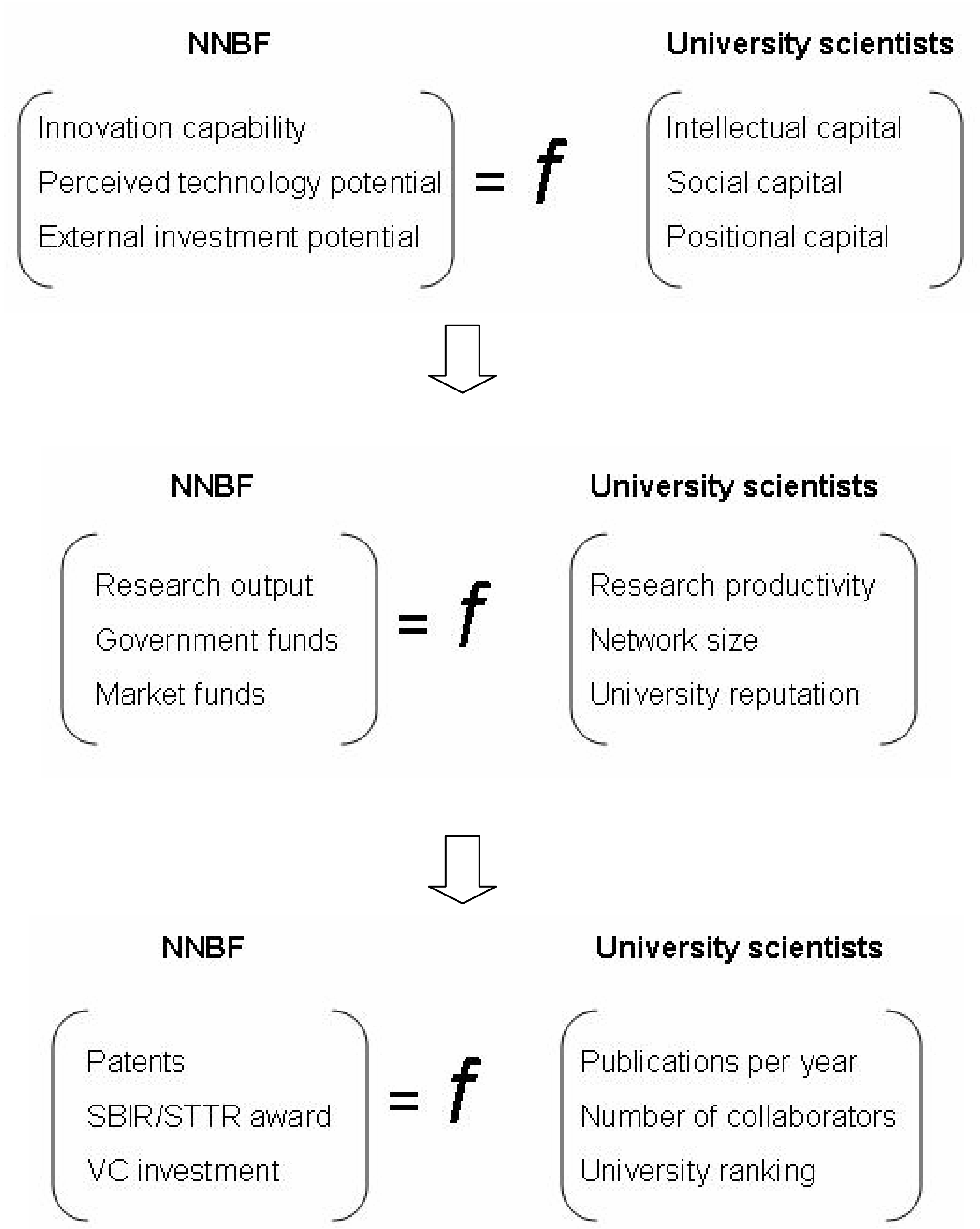

Figure 4.2 Research model

CHAPTER 5: SAMPLING STRATEGY AND DATA COLLECTION

This chapter begins by introducing a sample collection strategy, including data sources, criteria for identifying NNBFs, and the selection process, and it is followed by three sections that describe dependent variables, network ties, and independent variables. Each section explains data sources, collection processes, and data distribution patterns.

5.1 Sample collection

The analysis is conducted on a sample of NNBFs, as described in Chapter 2. The partial list of NNBFs came from a nanotechnology firm directory provided by the Nano Science and Technology Institute (NSTI) (website: www.nsti.org). NSTI was founded in 1997 as a result of the merging of several scientific societies that promote nanotechnology and integrate it with other advanced technologies. The institute maintains a database of more than 3,000 firms and organizations that conduct R&D or business in the field of nanotechnology. Additional firms were obtained from the directories provided by two other main databases of nanotechnology firms: the International Nanotechnology Business Directory (website: www.nanovip.com) and the International Small Technology Network (website: www.nanotechnology.com). The final list for this study contained around four thousand firms.

From this list, NNBFs were identified by a manual check of the product portfolios and company histories and backgrounds for all 4,000 firms from their websites and press releases. A firm is qualified as an NNBF if it was an independent entity, established based on nanotechnology or a related technology or product, and still in business by the time this search was complete (May 2006). Eleven firms were found to have changed their names and were listed under their current names as well as their original names, which were then removed from the list. As a result, 244 NNBFs were identified.

Since most of the websites of the NNBFs do not provide complete information of their profiles (e.g., address, size, number of employees, net sales, the founding year, and founder information) these data had to be obtained from other sources. As mentioned before, NNBFs are mostly young and small, so they are not covered by the primary sources of the company directory. The main databases used to search for information about the NNBFs were Dun & Bradstreet, CorpTech, and Plunkett. Containing over 100 million business records and covering 132 NNBFs, Dun & Bradstreet is the most comprehensive of the sites (website: www.dnb.com). CorpTech, specifically targeting high tech industries and profiling more than 95,000 companies (website: www.corptech.com), was the source for 89 NNBFs. Plunkett, which does market research and industry analysis, is among the few databases that have a separate category for nanotechnology companies (website: www.plunkettresearch.com). The category "Nanotechnology and MEMs Industry Companies" covers 316 firms, including 40 NNBFs.

In addition to the above websites, several other sources including Reference USA (website: www.referenceusa.com), Hoovers (website: www.hoovers.com), and ThomasNet (website: www.thomasnet.com), were accessed for information. Although these databases contain information mainly about established, large, or public companies, they do provide additional information about a few NNBFs. A search for information about the firms that had changed their names was conducted in databases with both the new and old names. After the search, basic firm information was still missing for 14 of the 244 NNBFs, so they were dropped from the following analysis. Thus, the final sample is comprised of 230 NNBFs.

In addition to basic firm information, other data related with dependent and independent variables need to be collected from various other sources for these NNBFs, which is explained below.

5.2 Dependent variables: innovation output and research credibility

The hypotheses in Chapter 4 proposed three dependent variables: innovation capability, perceived technology potential, and external investment potential.

5.2.1 Innovation capability

5.2.1.1 Patents

As mentioned by the NSF (2004), in the U.S., unless inventors are self-employed or independent, they generally assign ownership of their patents to their employers. Hence, the number of patents granted to an NNBF is a good indicator of technology innovation and invention activities in a firm. Since this study focuses on NNBFs in the United States, in which the domestic market is most important, only patents granted by the USPTO are taken into account. In addition, in order to reduce variations in quality across applications, patent grants are used instead of patent applications. The date of the patent application is recorded for each patent grant because it better indicates the time when a technology is invented.

5.2.1.2 Data description

Among the 230 NNBFs, 122 firms had patent activities by 2005. As shown in Figure 5.1, 200 firms have no more than eleven patents and only three have over 50 patents. The maximum number of patents awarded to an NNBF was 232.[5] Together, the NNBFs contributed a total of 1,474 patents.

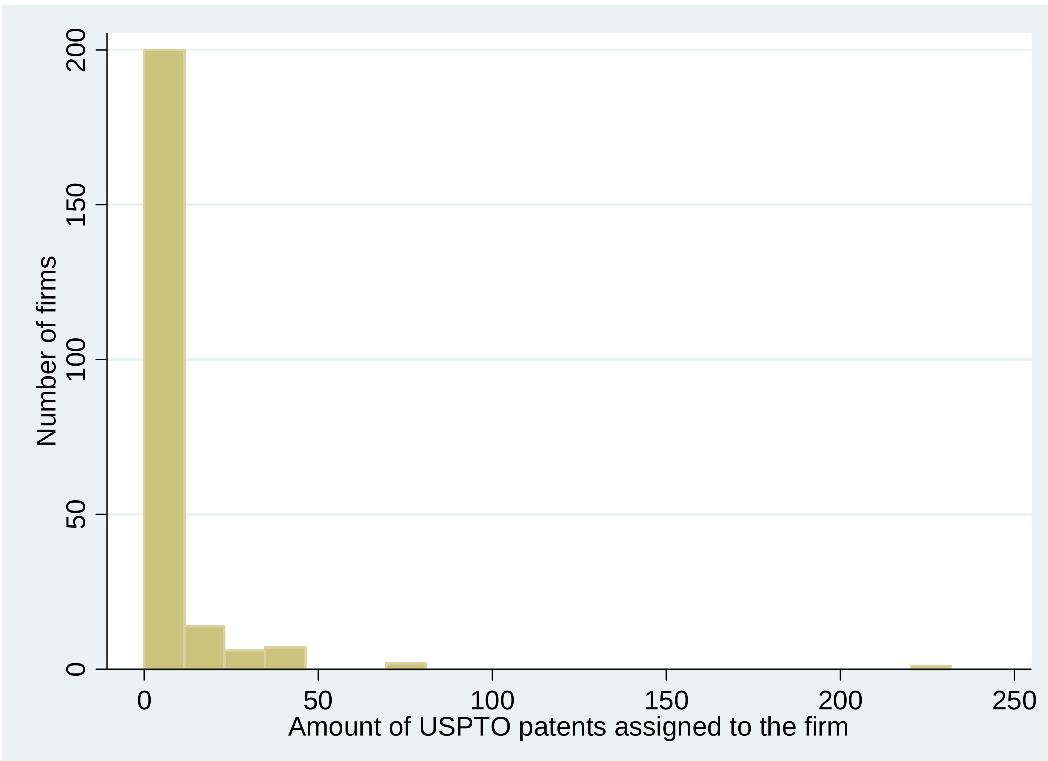

Figure 5.1 Frequency distribution of assigned patents

[5] The number of assigned patents presented here is different from the number presented Chapter III, which is due to different search strategies. In Chapter 3, the number of patents was searched using a set of nanotechnology keywords while patent statistics presented here refer to the total amount of patents assigned to the firm, which includes but does not limit to patents retrieved with nano keywords.

5.2.2 Perceived technology potential

5.2.2.1 Federal funding

To provide R&D funds to small businesses with no more than 500 employees, the federal government has established the SBIR and STTR Programs. The SBIR program, established in 1982, provides funds for small businesses at their startup and development stages and enables them to compete with larger businesses. The program is most helpful to firms with a high degree of technical and market uncertainty since they are less likely to obtain private funds (Toole and Czarnitzki 2005). The SBIR requires ten agencies to reserve R&D funds for small business: the DOA, the DOC, the DOD, the ED, the DOE, the DHHS, the DOT, the EPA, NASA, and the NSF. The STTR, established in 1992, emphasizes the public-private sector partnership and supports joint venture opportunities for small businesses and the nation's premier nonprofit research institutions. This program requires five federal departments and agencies to reserve a portion of their R&D funds for small business-nonprofit research institution partnerships: the DOD, the DOE, the DHHS, NASA, and the NSF.

Information on the amounts of the SBIR/STTR award to small businesses is publicly available via the gateway Tech-Net (Link: tech-net.sba.gov), a search engine that provides information and resources about and for small high-tech businesses. The system provides information on a firm's name, state, zip code, ownership, principle investigator, keywords, phase applications, and so forth. A firm starts with a Phase 1 application and if the scientific and technical merit and feasibility of the idea is acknowledged, it can be awarded up to $100,000. The recipients of a Phase 1 award are eligible for a Phase 2 award, which can net the company up to $750,000 to further develop the idea (Wallsten 2000). As a part of this study, awards information for each firm was obtained in January 2007.

5.2.2.2 Data description

After the search in the above system of the 230 NNBFs by their firm names, 141 were found to have been awarded SBIR/STTR in Phase 1 and 93 succeeded in Phase 2. In Phase 1, the 141 firms received a total of 1,854 awards. The number of awards received by firms is highly skewed toward the right (Figure 5.2). Three firms received over 100 awards, 36 firms at least 10 awards, (but fewer than 100), a majority (191 firms) fewer than 10 awards, and 89 firms no awards at all.

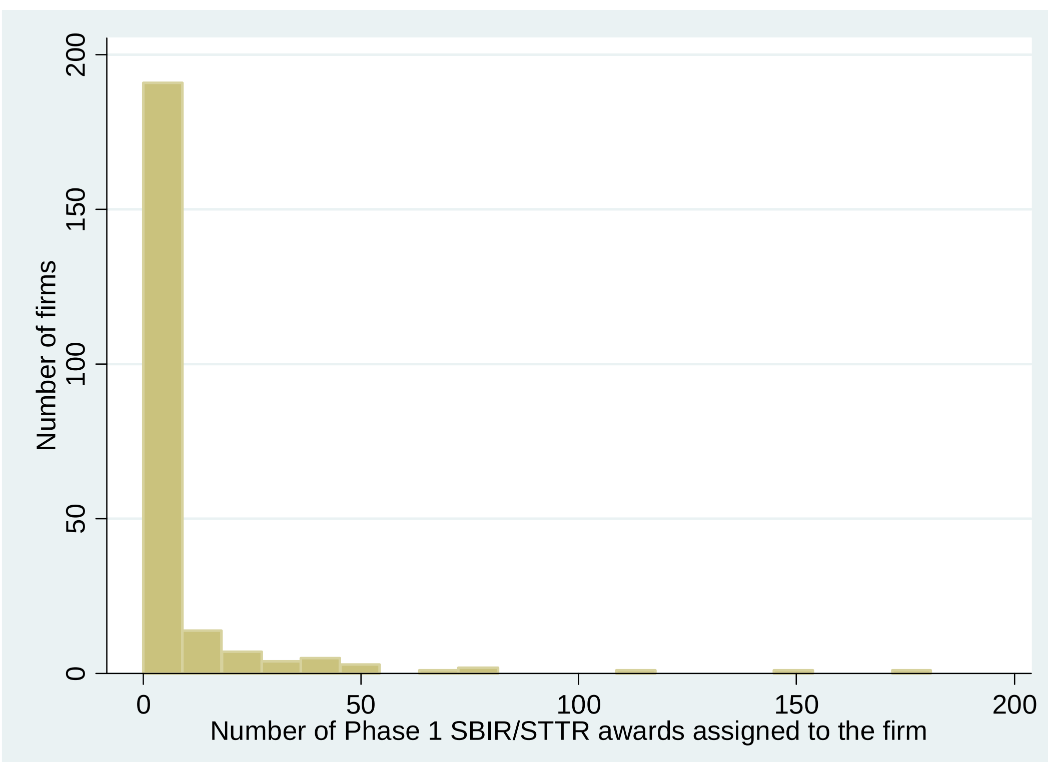

Figure 5.2 Frequency distribution of SBIR/STTR awards in Phase 1

The number of awards in Phase 2 was 579, less than one-third the number in Phase 1. Nineteen firms had at least ten Phase 2 awards and the maximum number was 76. One hundred and ninety-six firms received fewer than four awards in Phase 2, with 31 firms having only one award and 137 firms having none.

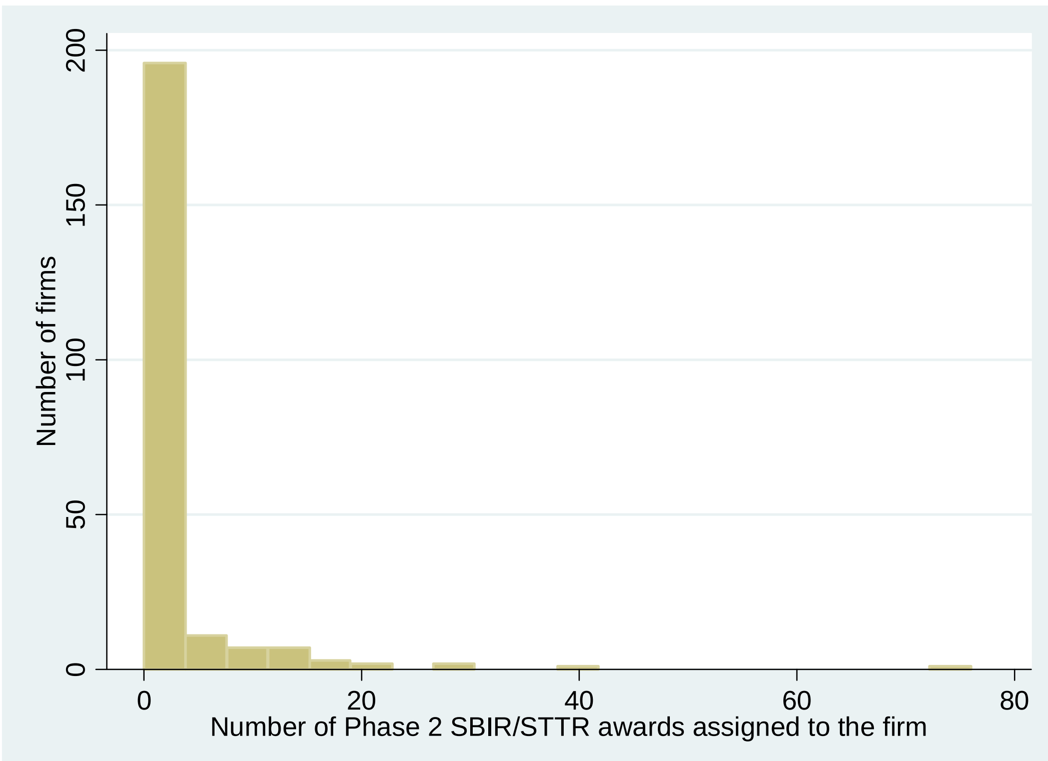

Figure 5.3 Frequency distribution of SBIR/STTR awards in Phase 2

On average, 27 percent of the awards in Phase 1 successfully moved into Phase 2. As shown in Table 5.1, 48 firms that had been granted Phase 1 awards failed to enter Phase 2. In the remaining 93 firms, around half managed to receive an average of 29 percent of Phase 1 awards renewed in Phase 2. Nine firms achieved a 100 percent success rate in renewing Phase 1 awards. However, none of these nine firms had more than three awards in phase 1.

Table 5.1   Success rate of Phase 1 awards in Phase 2

Success Rate	Number of Firms (total 141)
0	48
0< and <=25%	27
25%< and <=50%	46
50%< and <=75%	11
75%< and <100%	0
100%	9

The value of the SBIR/STTR awards is even more skewed to a small number of firms. The overall value of SBIR/STTR Phase 1 awards to NNBFs is $268 million. The left-most bar in Figure 5.4 shows that 168 firms received less than $1.08 million in SBIR/STTR Phase 1 awards. Four firms received awards worth over $10 million, and the maximum value was $21.5 million.

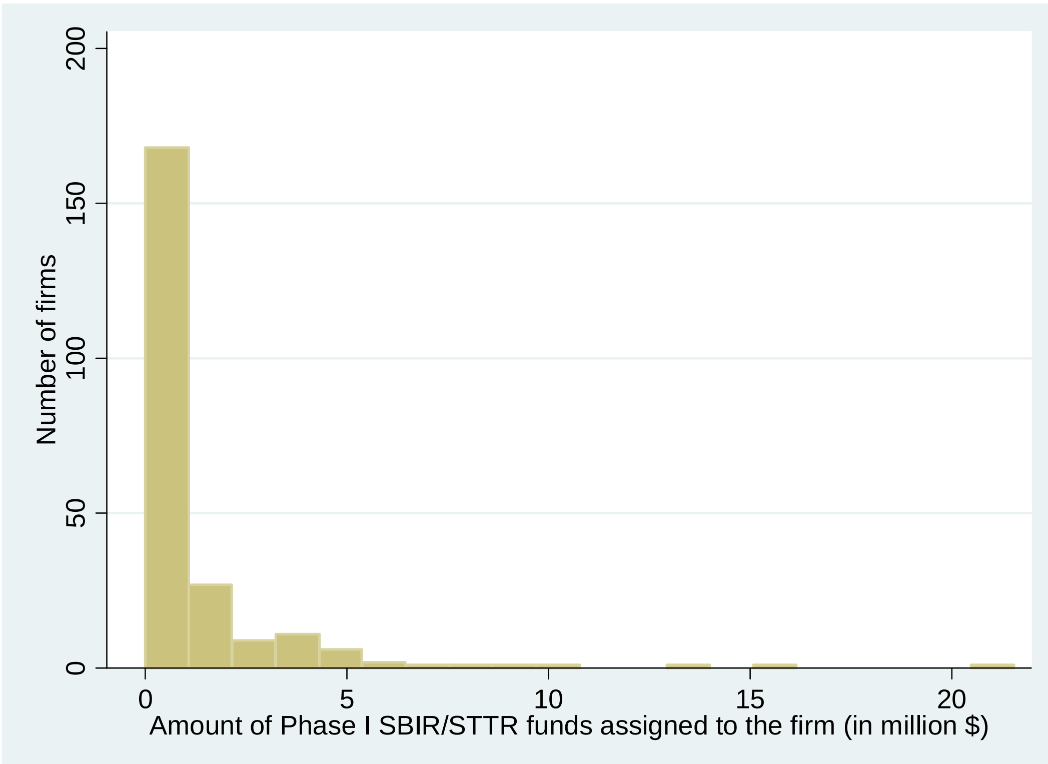

Figure 5.4 Frequency distribution of value of SBIR/STTR Phase 1 awards

Although fewer awards were conferred in Phase 2 than in Phase 1 (579 and 1,854, respectively), the value of the Phase 2 awards was much larger. The total value of awards was $268 million in Phase 1 and $608 million in Phase 2. Considering that the number of awardees in Phase 2 was only 66 percent of that in Phase 1, the funding received by each firm was substantial. Whereas the average award received by each firm in Phase 1 was $1.9 million, it was $6.5 million in Phase 2. In Phase 2, 15 firms awarded over $10 million in funding and 59 firms received over $1 million (but less than $10 million).

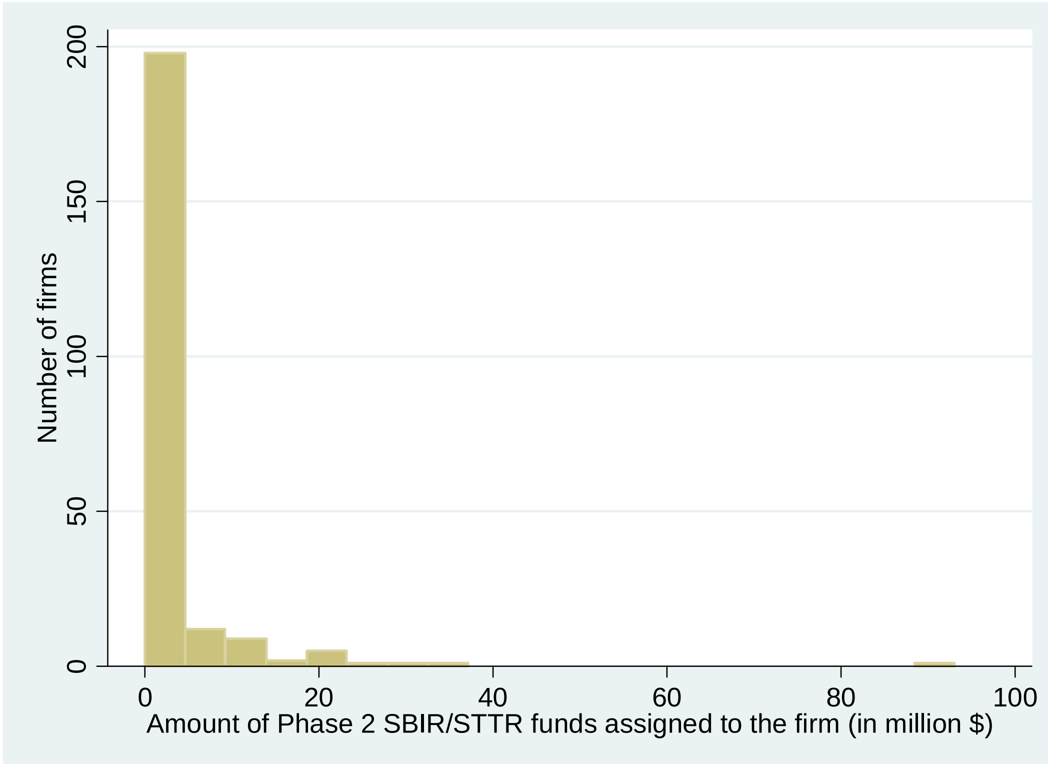

Figure 5.5 Frequency distribution of the value of SBIR/STTR Phase 2 awards

5.2.3 External investment potential

5.2.3.1 Venture capital

Data on venture capital investment was obtained from PricewaterhouseCoopers / Thomson Venture Economics / National Venture Capital Association MoneyTree(tm) Survey (Link: https://www.pwcmoneytree.com/MTPublic/ns/index.jsp). The MoneyTree Report is a quarterly study of venture capital investment published by Pricewaterhouse-Coopers and the National Venture Capital Association using data from Thomson Financial, who surveys venture capital practioners on a quarterly base. The report provides information from 1995 to present on cash-for-equity venture capital (VC) investment in the

U.S. The database contains information about the amount of VC investment and the number of VC deals by region, industry, investee firms, investors, and investment stages. Each NNBF was searched in the database using the firm name in January 2007.

5.2.3.2 Data description

The search of 230 firms in the MoneyTree Report database produced only 60 firms with VC investment activities since 1995. The total VC investment in these NNBFs was $1.3 billion, more than the sum of SBIR/STTR Phase 1 and Phase 2 awards, which was $876 million. Therefore, although VC funding does not have as broad coverage as government funding, it is plays a significant role in the financing of NNBFs. Among the 60 firms receiving VC investments, 184 firms receive less than $5 million in VC investment as indicated by the left bar in Figure 5.6. Six firms receive over $50 million, accounting for 35 percent of total investment.

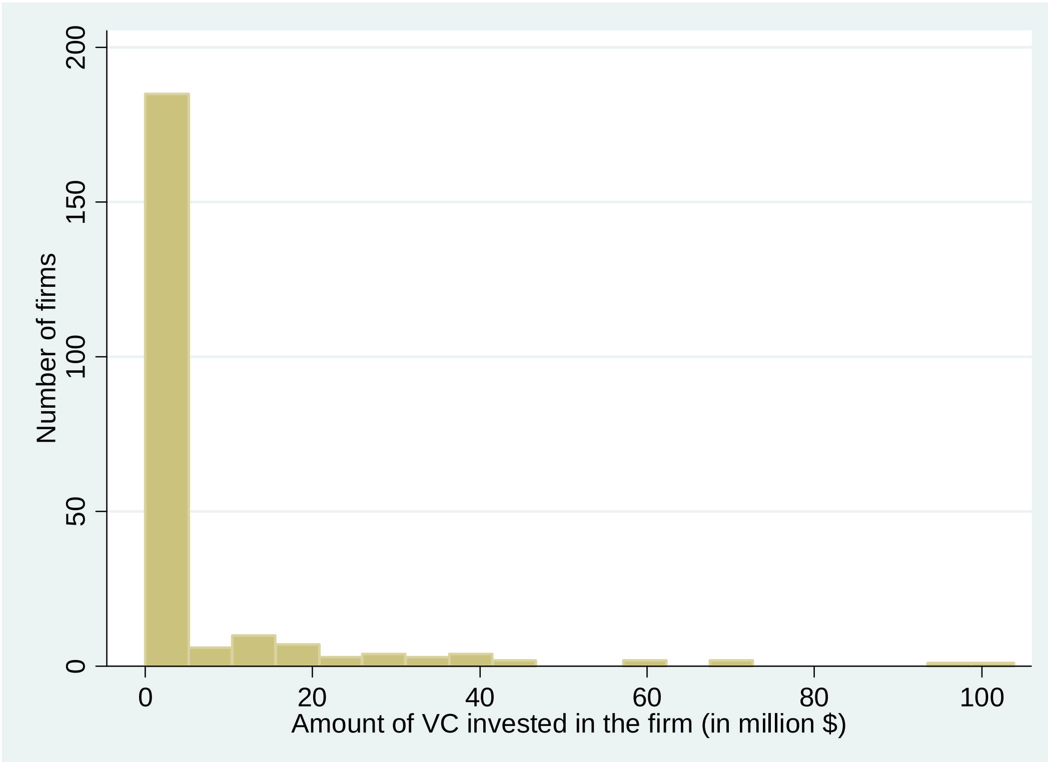

Figure 5.6 Frequency distribution of the value of venture capital

5.3 Tie between NNBFs and universities: co-authored publications

5.3.1 Data collection

Publication information is found in the nanotechnology publication database developed by the CNS-ASU Georgia Tech team. This database contains 105,068 publication records, from 1990 to 2006, retrieved from the SCI using a set of nanotechnology keywords. SCI is the most well-accepted international publication database, covering around 6,000 scientific journals and 170 scientific disciplines. It constitutes the core of international scientific journals with certain quality (Moed, Burger et al. 1985). However, the use of SCI as a source of publication data has its limitation since many journals in engineering sciences are not covered by SCI. Therefore, research activities revealed by SCI publications show biases towards basic sciences (Moed and van Leeuwen 1995). Nevertheless, it is the most extensive bibliometric database and until recently the only database that carries reference and citation information[6] (Bar-Ilan, Levene et al. 2007). Information provided by this database includes article titles, journal names, authors, affiliations, and so forth.

The search for co-publications of firms and university scientists began with a search for all the publications of a firm. As SCI does not present the full name of affiliations, variations in the abbreviation of the firm name were noted. As a result of this search, 114 of the 230 NNBFs were found to have published in 1996-2005, with a total number of publications of 620. The number of publications by each firm varied between 0 and 45, and 16 firms had at least 10 publications (Figure 5.7).

[6] Recently introduced Elsevier's Scopus and Google Scholar also provide citation information.

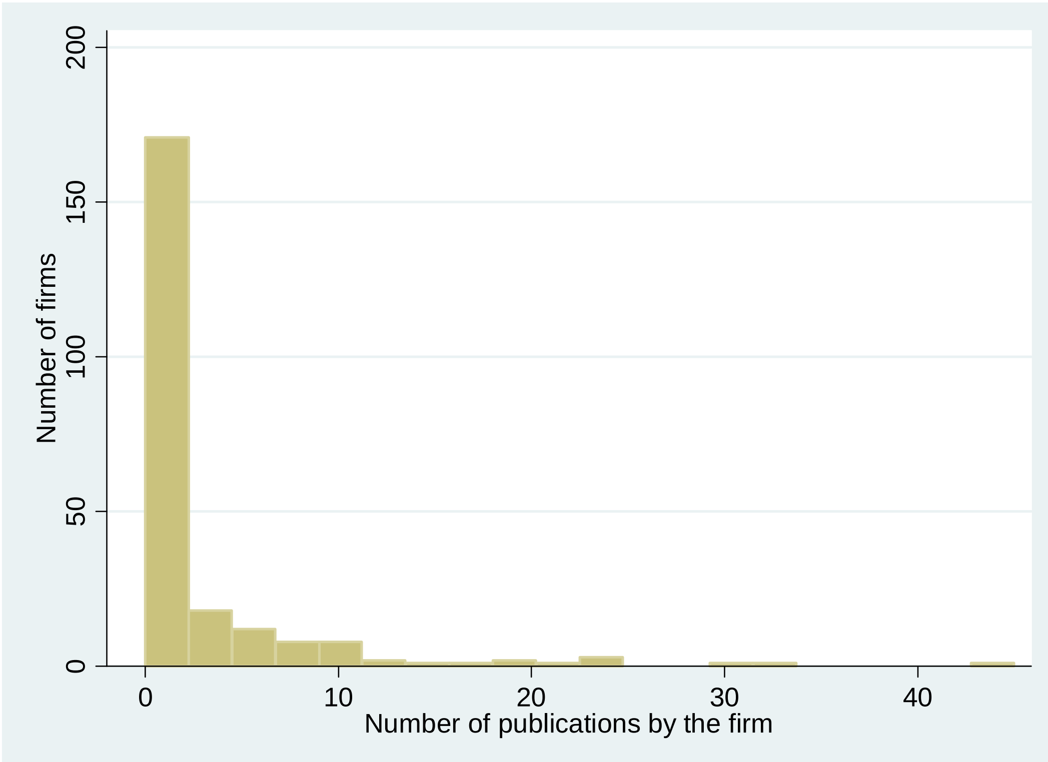

Figure 5.7 Frequency distribution of publications

The next step was to create a sub-set of publications that had co-authors from universities, which resulted in 334 publications from 85 firms. Scientists from approximately a hundred universities collaborated with the 85 NNBFs to co-author publications. The most active firm had 23 co-authored publications with university scientists and 22 publications without university scientists.

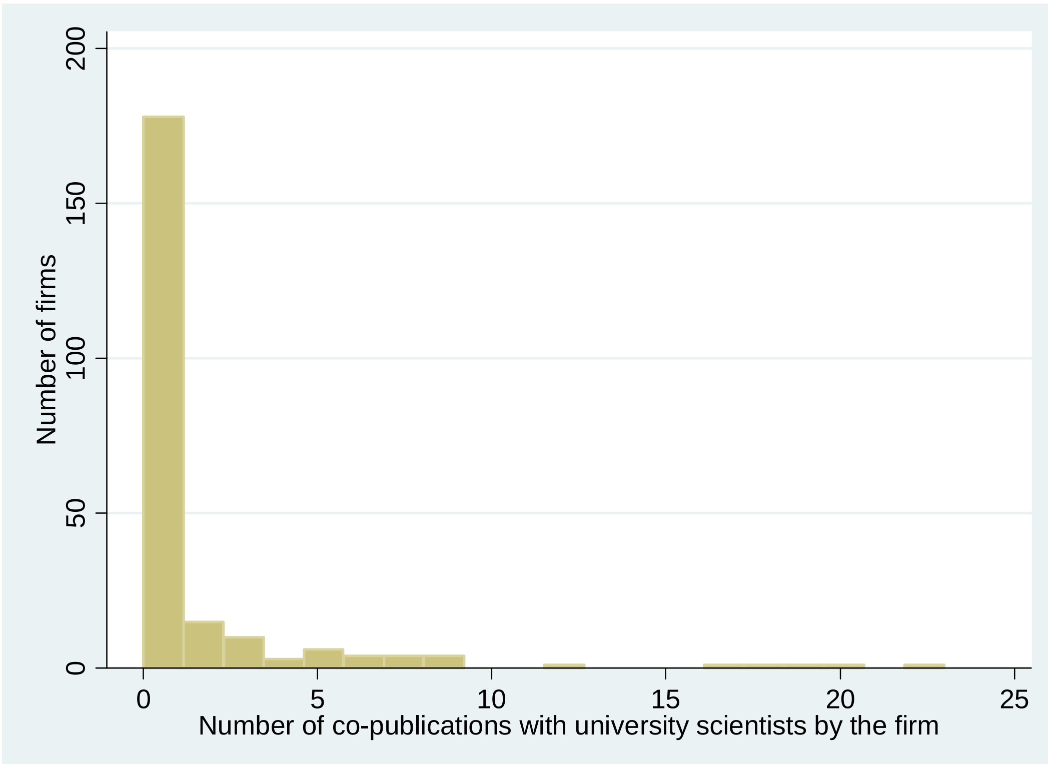

Figure 5.8 Frequency distribution of co-publications with university scientists

To measure the resources associated with university scientists that could produce spillover to NNBFs, the most critical step was to identify the university scientists and their affiliations. However, the names of publication authors could not be easily found since the SCI published only the last name and the initial of the first name of each author. Furthermore, in downloaded records, author names and affiliations were placed in two separate categories, with no one-to-one match between author names and affiliations, which caused problems for this study. In general, authors with the same last name, the same initials of the first and middle names (if there were any), and affiliations with the same institution, were regarded as the same person. However, since scientists frequently move from one institution to another, it was difficult to determine whether the same abbreviations of authors from different affiliations referred to the same person. In addition, names appearing in publications might vary because the initials of middle names are omitted in some publications while included in others.

The names were checked against the journal article to ensure accuracy. Journal articles were located using the citation information obtained from the publication database mentioned above. In most journal articles, the full names and affiliations of the authors are provided. However, a few journals print only the last name and initials. Nevertheless, each name is associated with an affiliation. In this case, the abbreviated name was matched with the full name if they were affiliated with the same institution. Otherwise, given the affiliation information, abbreviated names were searched in their affiliations to determine the full names.

In addition, people with the same full name but different affiliations were not treated as the same person by default. Instead, I visited the website hosting the author's information for verification. This study is targeting university scientists, most of whom have their CV, employment history, and publication records published online. Therefore, in the case of the same abbreviated names but different affiliations, they were treated as the same person only when affiliations matched the author's work experience. See Figure 5.9 for the flowchart of the data collection process and some basic statistics.

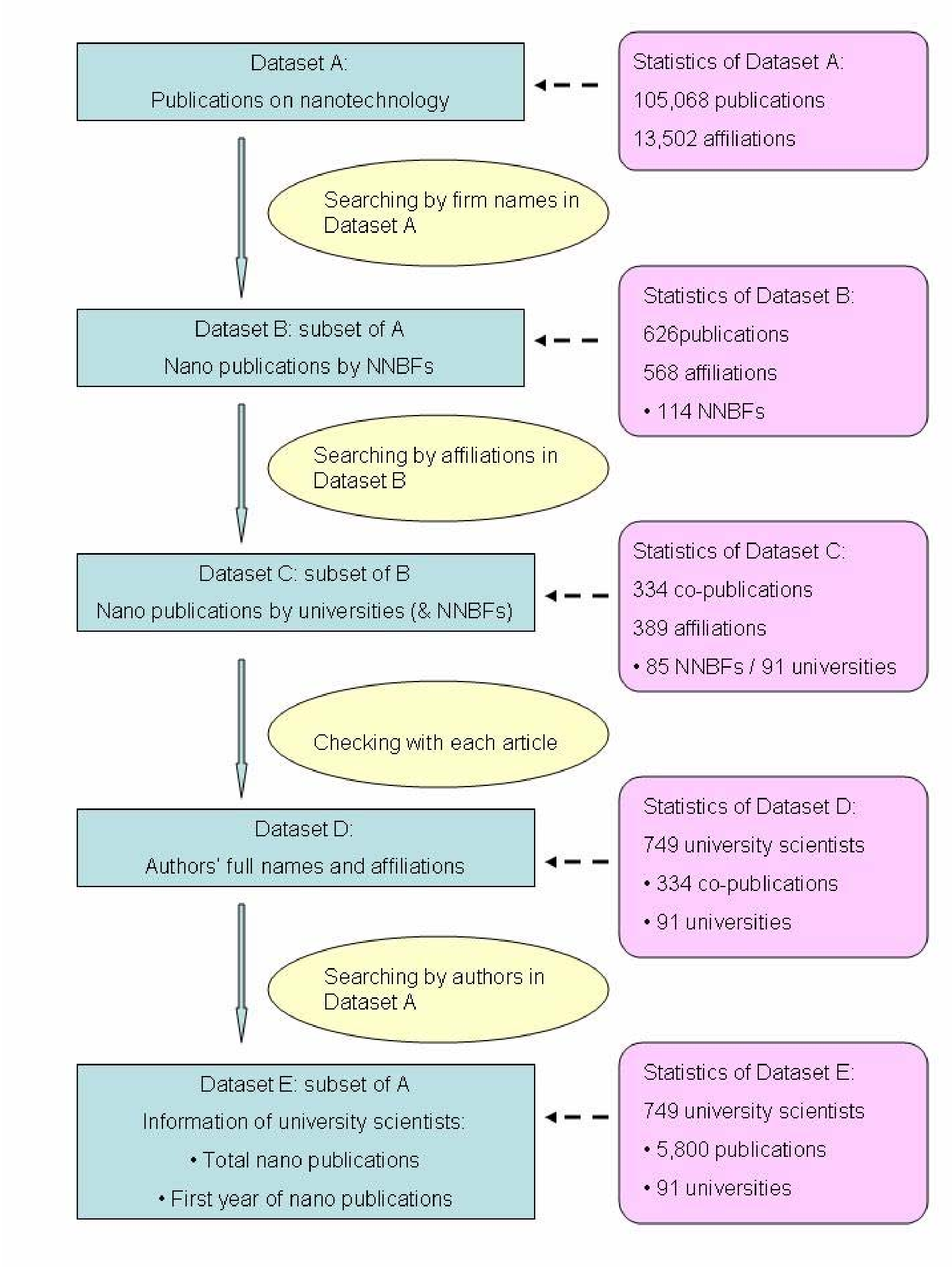

Figure 5.9 Flowchart of data collection process

5.3.2 Data description

With this method, 749 university scientists from over 90 universities were identified as having co-authored publications with NNBFs and 27 had co-authorship with more than one NNBF. Ten percent of university scientists were found to have multiple affiliations in this publication database. In particular, 54 university scientists were employed in both universities and NNBFs. Some of them were the founders of the NNBFs and either stayed at the universities after founding the NNBFs or left the universities to work full-time in the firms.

The 749 university scientists who had co-authored publications with NNBFs contributed a total of about 5,800 publications on nanotechnology. Fifteen of them had over 100 publications in the past fifteen years, but more than 60 percent had fewer than ten publications on nanotechnology (Figure 5.10). Half of those who had fewer than ten publications had entered the field only recently, with less than five years' publication history (Figure 5.11). As shown in Table 5.2, scientists who had more work experience in this field tended to have more publications. Among the 749 scientists, half were senior researchers with over eight years of work experience, while one-third of them were new comers, mostly graduate students who worked on projects together with their advisors and whose names appeared on these publications. However, their contribution is not as significant as that of the senior scientists.

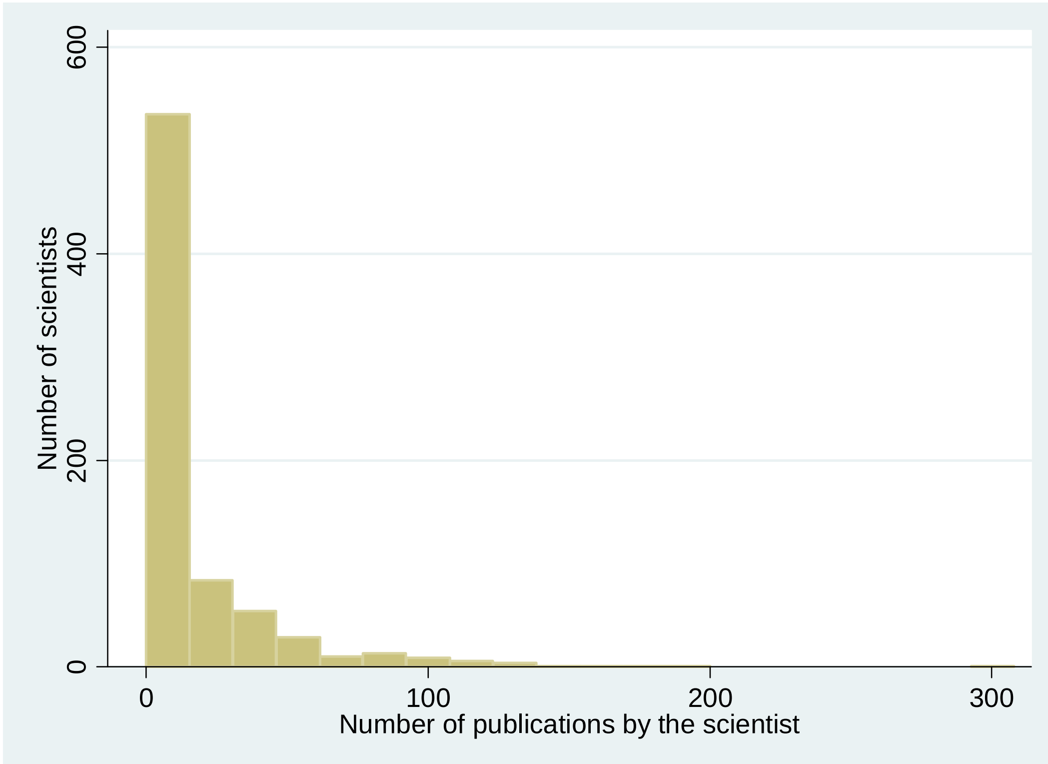

Figure 5.10 Frequency distribution of publications by university scientists

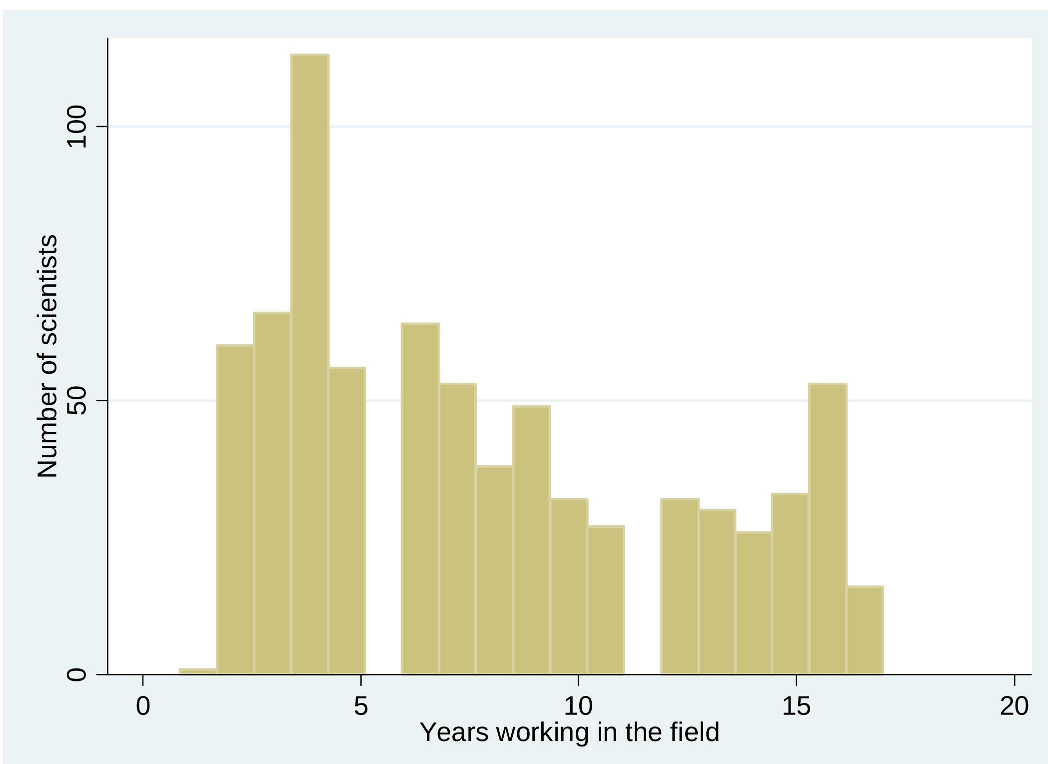

Figure 5.11 Frequency distribution of years of experience of university scientists

Table 5.2 Crosstable of publications and years of experience

Number of publications	Years of experience				Total
	1-4 (p25)	5-7 (p50)	8-12 (p75)	13-17	
1-2 (25th percentile)	155	42	17	0	214
3-6 (50th percentile)	61	60	34	6	161
7-20(75th percentile)	24	66	80	26	196
20-308	0	5	47	126	178
Total	240	173	178	158	749

5.4 Independent variables: research productivity, network size, and university reputation

5.4.1 Research productivity

Research productivity, as measured by the number of publications per year, varies largely among scientists, ranging from 0.1 to 18.12. On average, 331 scientists have less than one publication per year, 412 scientists have at least one publication but fewer than ten publications per year, and six scientists have at least ten publications per year (Figure 5.12).

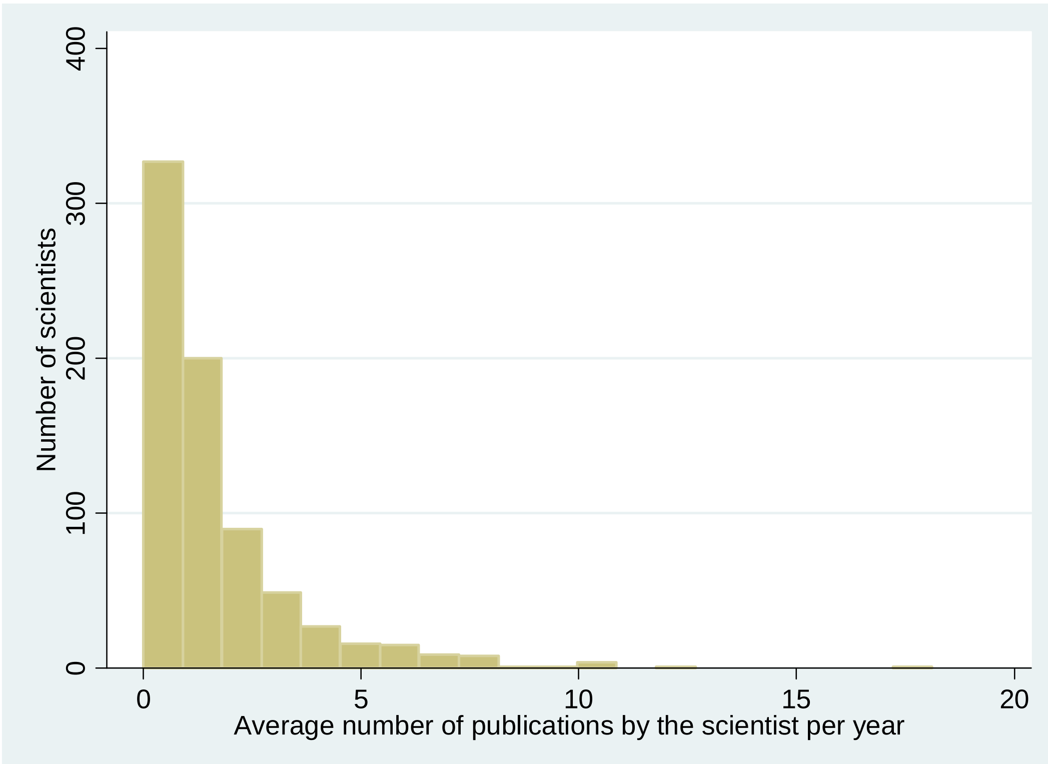

Figure 5.12 Frequency distribution of the research productivity of university scientists

5.4.2 Network size

Among the 749 university scientists in this sample, 363 have fewer than 20 collaborators with whom they publish (Figure 5.13), 57 scientists have at least 100 collaborators, and 17 scientists work and publish with more than 200 researchers. As in most cases of collaboration between NNBFs and universities, the university teams are led by a few senior scientists and joined by some junior scientists, mostly graduate students.

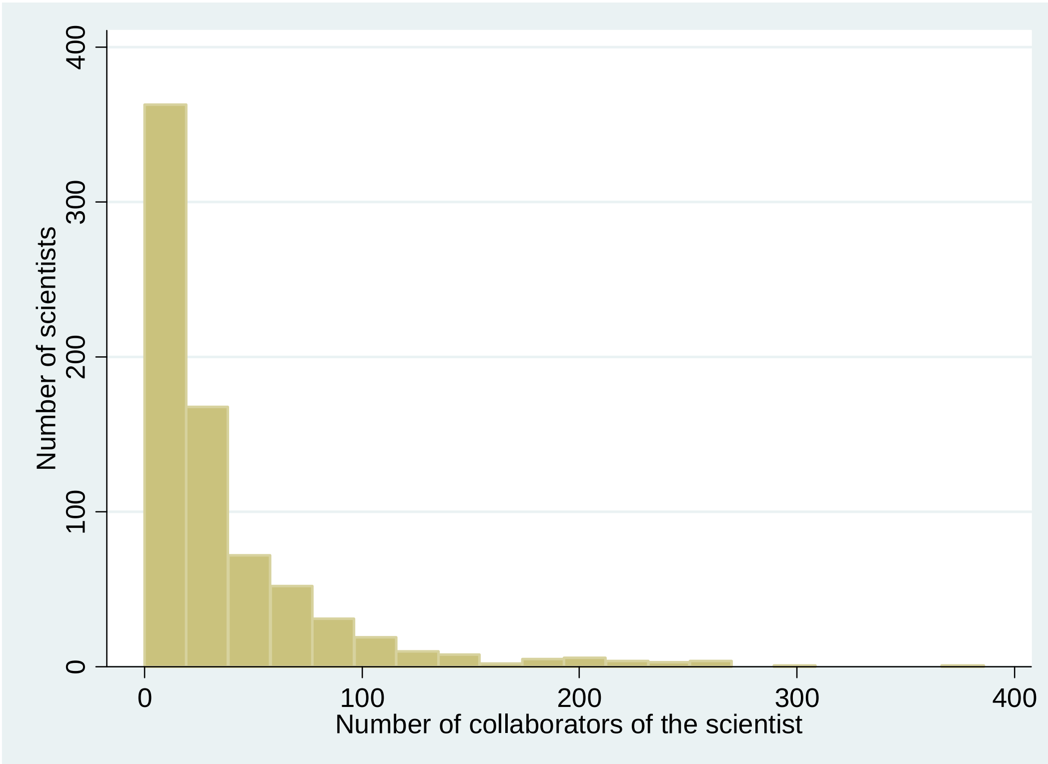

Figure 5.13 Frequency distribution of network size of university scientists

5.4.3 University reputation

Since the ranking of universities doesn't change significantly from year to year (Table 5.3), the year 2000, the median year in the time frame between 1996 and 2005, was chosen as the reference year. The complete lists of Tier 1 universities in 1996, 2000, and 2005 are presented in Appendix A1-3. Thirty-four Tier 1 universities were found to have collaborative activities with NNBFs between 1996 and 2005.

Table 5.3 Top ten Tier 1 universities in 2000 and their ranking in 1996 and 2005

Top 10 in 2000	Rank in 2000	Rank in 1996	Rank in 2005
Princeton University (NJ)	1	2	1
Harvard University (MA)	2	3	1
Yale University (CT)	2	1	3
California Institute of Technology (CA)	4	9	7
Massachusetts Inst. of Technology (MA)	5	5	7
Stanford University (CA)	6	6	5
University of Pennsylvania (PA)	6	13	4
Duke University (NC)	8	4	5
Dartmouth College (NH)	9	7	9
Columbia University (NY)	10	11	9
Cornell University (NY)	10	14	13
University of Chicago (IL)	10	12	15

Among the 797 scientists who collaborated with NNBFs, 318 came from universities listed as Tier 1 universities in *U.S. New and World Report* in 2000 (Figure 5.14). Rank zero in Figure 6.14 refers to all universities that are not in Tier 1. The most active collaborators with NNBFs were the following four universities, each with over 30 scientists: the University of Michigan (35), the Massachussets Institute of Technology (27), the University of New Mexico (27), and Rutgers University (24).

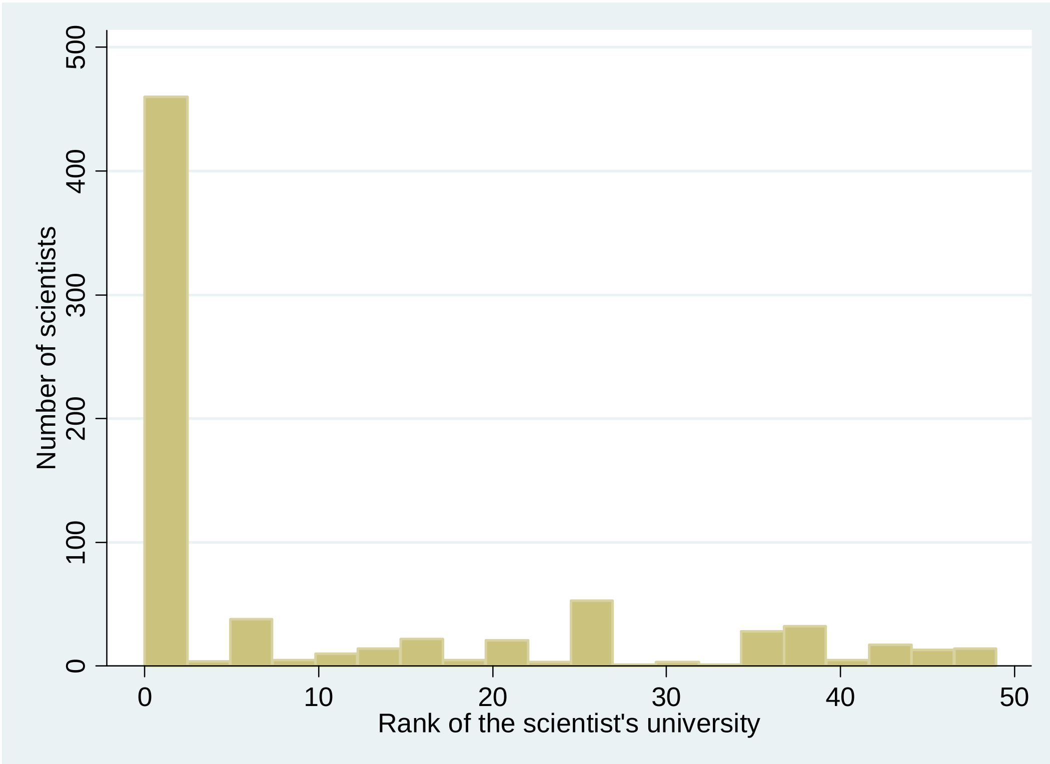

Figure 5.14 Frequency distribution of university ranking of university scientists

CHAPTER 6: VARIABLE OPERATIONALIZATION AND MODEL SPECIFICATION

This chapter describes the final dataset and explains the coding of variables. It continues by presenting the statistical distribution of variables and then proposes different econometric models. The assumption and applicability of each model in this dataset is discussed. The chapter ends by presenting the regression output of each model.

6.1 Variable coding and description

This study uses a longitudinal dataset [7] that contains information about 230 NNBFs between 1996 and 2005 – 2,300 observations. However, since many of the NNBFs were not founded until near the end of last century, values were reported as missing for years before the firm was founded, which resulted in unbalanced panel data with 1,539 observations. Table 6.1 describes the participation pattern of this panel dataset, which shows that 230 firms (n=230) are included in this dataset and distributed over ten years (t=10) 1996-2005. The participation pattern is shown on the right side of the table, where a "1" indicates one observation in that year and a dot (.) indicates no observation that year (STATA 2005). The largest fraction of the firms, 27.83 percent of the total, can

[7] A two-period model was considered for this study. Instead of using cross-sectional time series models, efforts have been made to construct the data into two time periods, such as 2000-2002/2003-2005. That is, only firms established in 2000-2002 (T1) are taken as the object of the study, and their activities such as patenting, SBIR/STTR awards, and VC investment in 2003-2005 (T2) are examined. Eighty-one firms were founded in T1. However, only 8 firms collaborated with universities in T1. A different set of T1 and T2 with 1998-2001/2002-2005 ended with 10 firms in T1 that collaborated with universities. Therefore, the variance in these data is not big enough to render the models significant.

be seen in all ten years, followed by 14.35 percent of the firms, which can be seen after 2000. Eight percent of the firms were observed only in 2004 and 2005. The statistical software STATA (version 9.2) was used for analysis throughout this chapter.

Table 6.1 Description of participation pattern of panel dataset

```
. xtdes, i(id) t(year)

      id:  6, 8, ..., 303                                      n =        230
    year:  1996, 1997, ..., 2005                               T =         10

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+------------
       64     27.83   27.83 |  1111111111
       33     14.35   42.17 |  ....111111
       31     13.48   55.65 |  .....11111
       19      8.26   63.91 |  ........11
       17      7.39   71.30 |  ......1111
       17      7.39   78.70 |  ...1111111
       16      6.96   85.65 |  .......111
       16      6.96   92.61 |  ..11111111
       16      6.96   99.57 |  .111111111
        1      0.43  100.00 | (other patterns)
 ---------------------------+------------
      230    100.00         |  XXXXXXXXXX
```

Table 6.2 presents the variables created for this model and their definitions. Variable $Patent_{i\,t}$ is the number of patents assigned to firm *i* (i = 1, …, 230) by the USPTO and applied in year *t* (t = 1990, …, 2005). If the firm was founded in 1998, the variable *Patent* was coded as a missing value in 1996-1997. The same rule applies to other firm level variables. Variables $SBIRfirst_{it}$ and $SBIRsecond_{it}$ are the number of SBIR/STTR awards in million dollar values assigned to firm *i* in year *t*, respectively. If the firm received more than one award in a particular year, the values of the awards were summed. Variable VC_{it} is the amount of venture capital in million dollar values invested in firm *i* in year *t*. Since 68 percent of observations (firm-year) have zero-value for *SBIRfirst*, 82 percent for *SBIRsecond*, and 90 percent for *VC*, these three variables are not put into a log format.

Table 6.2 Variable description

Variable	Type	Description
Patent $_{it}$	Count	The number of granted patents applied by firm *i* in year *t*
SBIRfirst $_{it}$	Interval	SBIR/STTR grants in Phase 1 assigned to firm *i* in year *t* (in million $)
SBIRsecond $_{it}$	Interval	SBIR/STTR grants in Phase 2 assigned to firm *i* in year *t* (in million $)
VC $_{it}$	Interval	Venture capital investment received by firm *i* in year *t* (in million $)
Collaboration $_{it}$	Count	The number of co-authored publications with university scientists by firm *i* by year *t*
Productivity $_{it}$	Count	The number of highly productive university scientists tied to firm *i* by year *t*
Network $_{it}$	Count	The number of highly collaborative university scientists tied to firm *i* by year *t*
Reputation $_{it}$	Count	The number of Tier 1 universities tied to firm *i* by year *t*

Table 6.2 continued

$Firmage_{it}$	Interval	Age of firm *i* in year *t*
$SBIRdummy_{i}$	Dummy	Whether firm *i* has received any SBIR/STTR awards: 1 for yes and 0 for no
$Ownership_{i}$	Dummy	Whether firm *i* is a private firm: 1 for yes and 0 for no
$Univspinoff_{i}$	Dummy	Whether firm *i* is a spin-off from a university: 1 for yes and 0 for no
$Nanomaterial_{i}$	Dummy	Whether firm *i* works in the field of nanomaterials: 1 for yes and 0 for no
$Nanobiotech_{i}$	Dummy	Whether firm *i* works in the field of nanobiotechnology: 1 for yes and 0 for no
$Nanoelectro_{i}$	Dummy	Whether firm *i* works in the field of nanoelectronics or nanoinstruments: 1 for yes and 0 for no
$Otherfield_{i}$	Dummy	Whether firm *i* works in other fields of nanotechnology: 1 for yes and 0 for no
CA_{i}	Dummy	Whether firm *i* is located in California: 1 for yes and 0 for no
MA_{i}	Dummy	Whether firm *i* is located in Massachusetts: 1 for yes and 0 for no

The connection between NNBFs and university scientists is assumed to begin with their first collaboration, or the first publication co-authored by both sides, and to continue in the following years, even if they do not co-author a publication. Although a co-publication clearly shows collaboration, lack of a co-publication does not necessarily indicate a lack of collaborative activity. Furthermore, as long as a network tie has been built between a firm and a university scientist, informal exchange or resource spillover takes place without formal research collaboration. Thus, the resources of a university scientist were added to those of the firm starting from the first year of their collaboration and then applied to the following years. This rule applies to three variables of university and university scientists: $Productivity_{it}$, $Network_{it}$, and $Reputation_{it}$.

Variable $Productivity_{it}$ was coded as the number of highly productive university scientists who had co-publications with firm *i* by year *t*. Research productivity of an individual scientist is the annual number of publications, calculated as the total number of publications divided by the length of his or her scientific career. Highly productive scientists are those above the 75th percentile. According to Table 6.3, scientists who have at least 2.06 publications every year are labeled as highly productive scientists in this study.

Table 6.3 Distribution of university scientists' attributes (N=749)

	Mean	Min	Max	p25	p50	p75
The number of publications per year	1.68	0.1	18.12	0.5	1	2.06
The number of collaborators	37.33	2	386	11	20	46

According to these criteria, 200 out of 749 scientists were highly productive. Sixty-five firms were found to have collaborated with these highly productive scientists (Table 6.4). While one firm worked with 20 highly productive scientists, most of the others (29 firms) worked with only one collaborator who was highly productive.

Similarly, variable $Network_{it}$ indicates the number of highly collaborative university scientists who had collaborated with firm *i* by year *t*. The variable is measured by the number of collaborators that the scientists had in their scientific community, identified by counting the co-authorships on their publications. Again, using the 75th percentile criteria, scientists who had at least 46 collaborators are considered highly collaborative scientists (Table 6.3), which comprises 26 percent of all university scientists in this sample. As shown in Table 6.4, 66 firms worked with these collaborative scientists. Among them, 27 firms (41 percent) were tied to only one highly collaborative scientist and three-quarters of the firms collaborated with three or fewer highly collaborative scientists.

Variable $Reputation_{it}$ is the number of Tier 1 universities that collaborated with firm *i* by year *t*. The list of Tier 1 universities was obtained from the *U.S. News and World Report* ranking of 2000, as described in Chapter 5. Thirty-four of the 51 Tier 1 universities had research connections with NNBFs between 1996 and 2005, and 53 of the 230 NNBFs worked with at least one Tier 1 university. One firm had a connection with eight Tier 1 universities (Table 6.4).

Table 6.4 Distribution of variables *Productivity*, *Network*, and *Reputation* (N=230)

	Mean	**Min**	**Max**
Productivity	0.813	0 (n=165)	20 (n=1)
Network	0.826	0 (n=164)	22 (n=1)
Reputation	0.378	0 (n=177)	8 (n=1)

Several variables were used to control other factors that might affect a firm's research performance and perceived potential. The control variable $Firmage_{it}$ measures the number of years that firm *i* had been running until year *t*. In general, firms with a longer history have more resources and experience that they can benefit from. The variable $Ownership_{i}$ shows whether firm *i* is public or private. Public firms have different financing behavior, so their funding sources are different from those of private firms. Variable $Univspinoff_{i}$ shows the origin of the firm. Firms that are spin-offs from universities have many more ties to the hosting universities and universities scientists than firms that are not. Such connections cannot be captured entirely by research collaboration that leads to co-authored publications. The variables $Nanomaterial_{i}$, $Nanobiotechnology_{i}$, $Nanoelectro_{i}$ and $Otherfield_{i}$ are four dummy variables that represent the field in which firm *i* works. These field dummy variables are used to control the effect of the differing patenting behavior of firms in the various technical fields, which might have different priorities when they make grant and investment decisions. Variable CA_{i} and variable MA_{i} are two dummy variables showing whether firm *i* is located in these strongly entrepreneurial regions.

Table 6.5 presents the descriptive statistics of these variables. All the variables have 1,539 observations for the 230 firms from 1996 to 2005. To illustrate them more clearly, Table 6.4 shows the statistics of the 230 firms for the entire ten-year period, while Table 6.5 presents the statistics for the 230 firms by year.

Table 6.5 Descriptive statistics of variables (obs = 1539)

Variable	Mean	Std. Dev.	Min	Max
Patent $_{it}$	0.804	2.931	0	51
SBIRfirst $_{it}$	0.095	0.231	0	2.6
SBIRsecond $_{it}$	0.219	0.715	0	11
VC $_{it}$	0.855	3.737	0	40
Collaboration $_{it}$	0.669	2.189	0	23
Productivity $_{it}$	0.415	1.389	0	20
Network $_{it}$	0.452	1.483	0	22
Reputation $_{it}$	0.177	0.696	0	8
Firmage $_{it}$	6.182	4.881	1	25
Ownership $_{i}$	0.945	0.227	0	1
Univspin $_{i}$	0.528	0.499	0	1
Nanomaterial $_{i}$	0.442	0.497	0	1
Nanobiotech $_{i}$	0.213	0.410	0	1
Nanoelectro $_{i}$	0.285	0.451	0	1
CA $_{i}$	0.181	0.385	0	1
MA $_{i}$	0.112	0.316	0	51

6.2 Dependent variables: distribution and comparison

Before examining the impact of the various resources of university scientists on NNBFs through collaboration, a statistical test is conducted to show any differences between the performance of firms that cooperate with university scientists and the performance of those that do not. That is, only when firms that collaborated with universities performed differently (i.e., better within the context of this study), from those that did not, was there a need to explore the factors that contributed to the difference. Although none of the dependent variables has normally distributed mean (Table 6.6 and Figures 6.1-6.4), given the fact that the test is done in a large sample, a t test still generates valid statistics in a comparison between the two groups.

Table 6.6 Test of normality [8]

```
. sktest patent SBIRfirst SBIRsecond vc

                   Skewness/Kurtosis tests for Normality
                                                 ------- joint ------
    Variable |  Pr(Skewness)   Pr(Kurtosis)  adj chi2(2)    Prob>chi2
-------------+-------------------------------------------------------
      patent |      0.000          0.000                .           .
   SBIRfirst |      0.000          0.000                .           .
  SBIRsecond |      0.000          0.000                .           .
          vc |      0.000          0.000                .
```

[8] The normality of these variables was tested based on their skewness and kurtosis. Skewness measures the deviation of the distribution from symmetry, and kurtosis measures the peakedness of the distribution compared with the normal distribution. For a standard normal distribution, skewness is zero and kurtosis is three. Table 6.6 presents the results of the normality test, where skewness and kurtosis both strongly reject the normality assumption. That is, none of these four variables have normal distribution of their means.

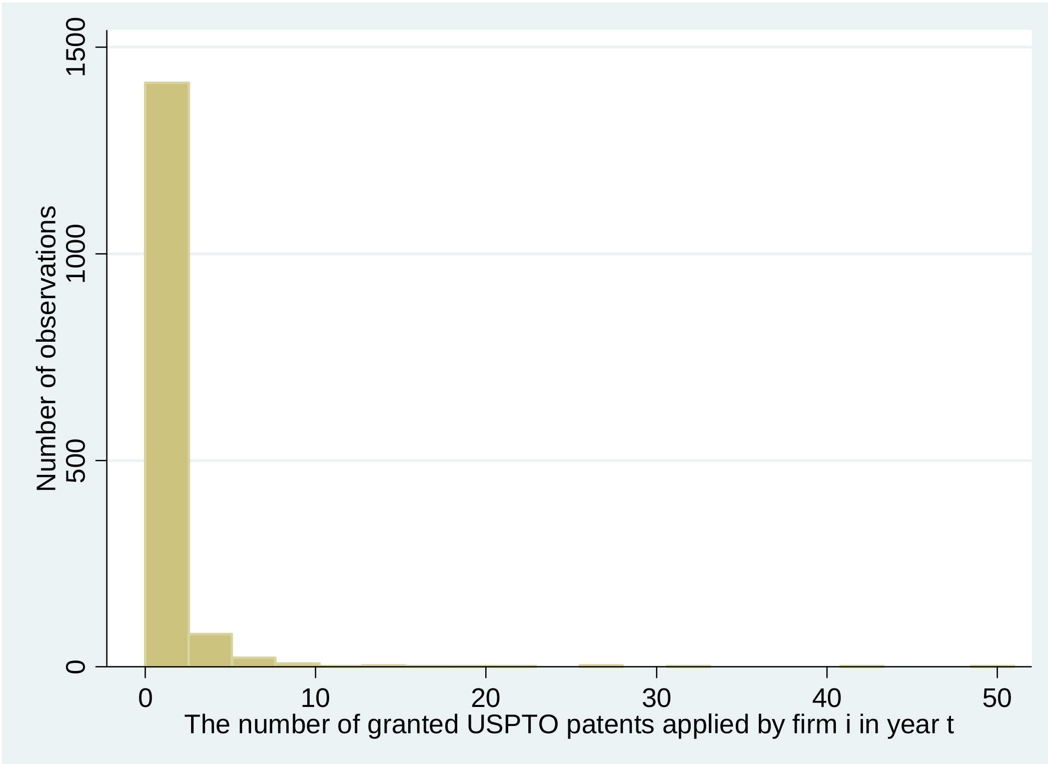

Figure 6.1 Frequency distribution of the variable *Patent*

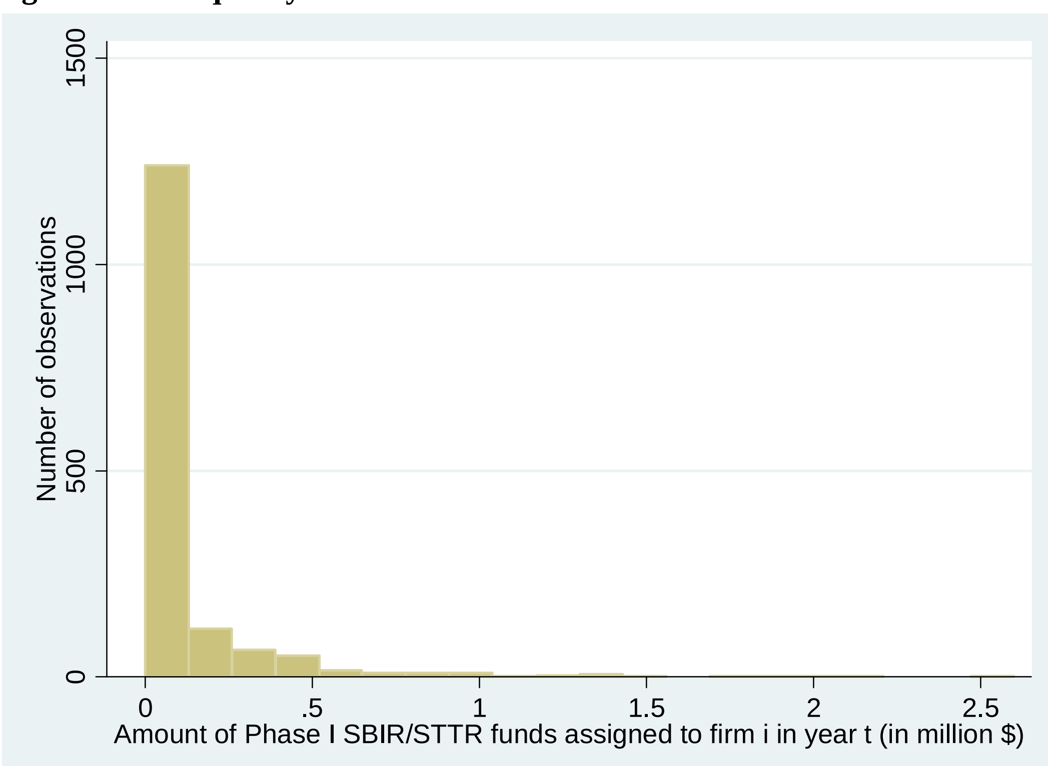

Figure 6.2 Frequency distribution of the variable *SBIRfirst*

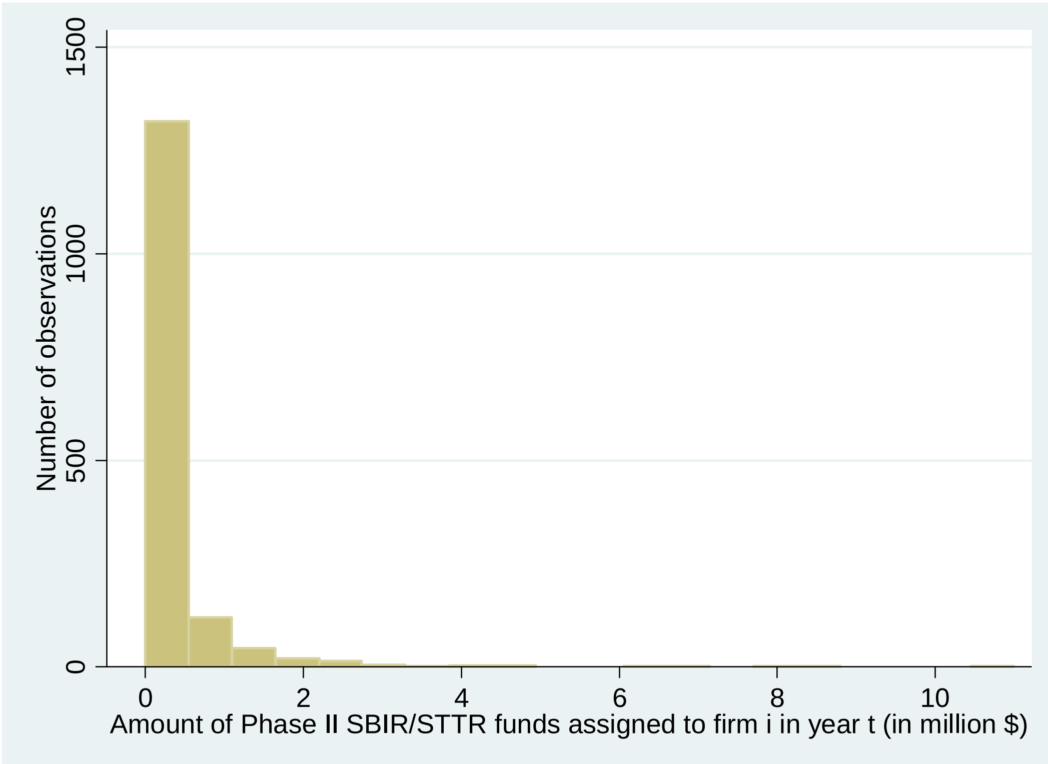

Figure 6.3 Frequency distribution of the variable *SBIRsecond*

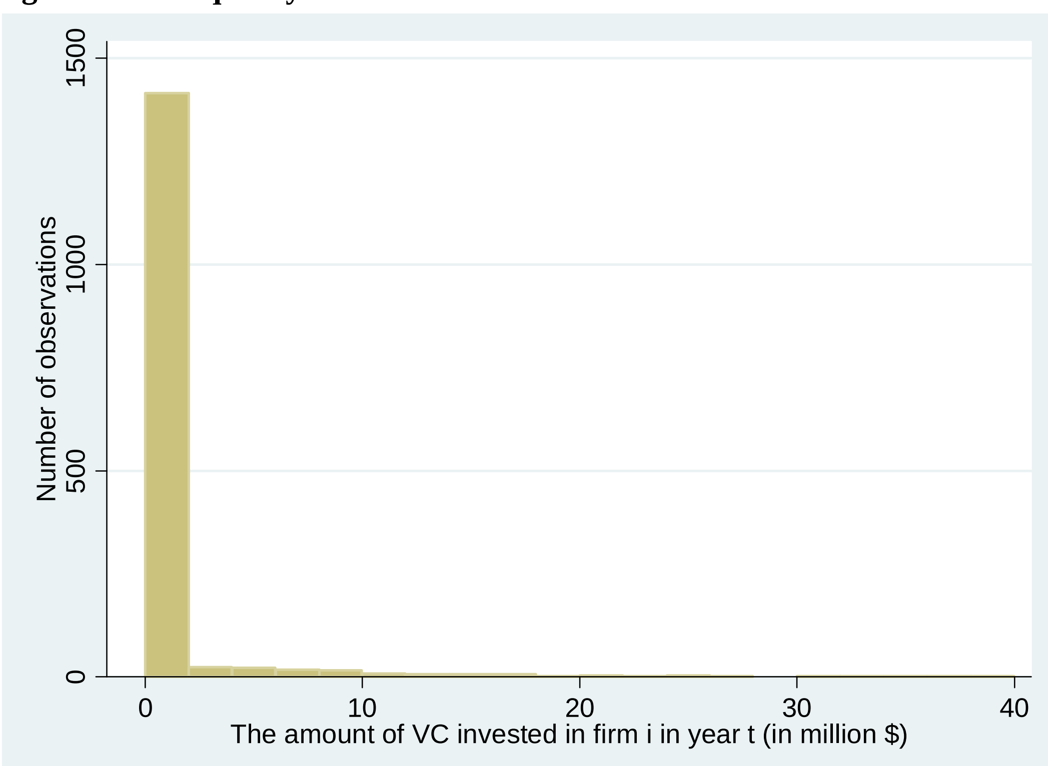

Figure 6.4 Frequency distribution of the variable *VC*

A dummy variable *Coopdummy* was created to differentiate two groups of firms. It was coded as 1 for firms that had collaborated with university scientists and as 0 for firms that had not collaborated with university scientists. In the sample, 85 firms had research collaboration with universities, while 145 firms did not. The results in Table 6.7 show the means of these two groups and the t-values of the test on the difference in the means.

Table 6.7 T-test on dependent variables (N=230)

	Coopdummy =0 N=145	**Coopdummy =1 N=85**	**T-test**
Patent	4.427 (0.850)	9.788 (2.944)	-2.136**
SBIRfirst	0.744 (0.131)	1.883 (0.369)	-3.458***
SBIRsecond	1.409 (0.311)	4.754 (1.271)	-3.175***
VC	3.501 (0.761)	9.603 (2.298)	-3.022***

a. The numbers in parentheses are standard errors.

b. ***indicates a significance level of 1%.

**indicates a significance level of 5%.

The t-test compares the means of the firms not collaborating with universities (the group on the left) with the means of firms collaborating with universities (the group on the right). The null hypothesis signifies no difference in the means between these two groups. This hypothesis is strongly rejected in testing the means of all four dependent variables: *Patent*, *SBIRfirst*, *SBIRsecond*, and *VC*. In addition, the t-value—the difference between the left group and the right group—is negative for all these four variables, indicating that the means of the left group is smaller than that of the right group. In other words, firms not collaborating with universities did not perform as well as those working with universities in the measures of patents, SBIR, and VC. However, the t-test doesn't suggest the casual-effect relationship between collaboration and firm performance. The positive correlation might also come from assortive selection, which is, firms performing well are more willing to collaborate with university scientists. More analysis is needed to differentiate between the causal interpretation and assortive selection.

In the remainder of this chapter, two sets of models are used to test the effects of having research collaborate with university scientists on firm performance: Model 1 uses the variable *Collaboration* to test the overall impact of collaboration with universities, and Model 2 uses three the variables *Productivity*, *Network*, and *Reputation* to test the special impact of the various attributes of university scientists.

6.3 Model specification

6.3.1 Models on the variable *Patent*

The variable *Patent* is a count variable with a large number of zero values. Both the Poisson model and the negative binomial model were specifically designed for count outcomes (Long and Freese 2001). The Poisson distribution is the basis for the Poisson regression model (Equation 6.1), where μ is the mean of the distribution.

$$\Pr(y|\mu) = \frac{e^{-\mu}\mu^{y}}{y!} \quad \text{for y = 0, 1, 2, …} \qquad \text{(Equation 6.1)}$$

As μ increases, the odds of zero counts decrease, and the Poisson distribution gets close to the normal distribution. The Poisson distribution is restricted by the assumption that the mean of the dependent variable equals the variance of the dependent variable: Var (y) = μ. By contrast, the negative binomial model is not restricted by Poisson distribution assumptions and provides unbiased estimates, even with overdispersion. The negative binomial model has the same mean structure as the Poisson model, but it adds an error term that is uncorrelated with the independent variables: $y_i \mid x_i, c_i \sim Po(c_i E(y_i \mid x_i))$ where $c_i \sim Gamma(1, \eta^2)$ and c_i independent of x_i. If overdispersion exists ($\eta^2 > 0$), compared with the negative binomial model, the standard errors in the Poisson model have larger z-values and smaller p-values (Long and Freeze 2001).

Therefore, the negative binomial model is preferred in this case, while the results of the OLS and Poisson models are also provided for the purpose of comparison. The fixed effects regression method is used to control the firm effects on the independent variables. In the case of OLS, the robust option is used to produce estimators that are robust to possible heteroskedasticity, or inconstant variance in the regression error term.

Table 6.8 Regression output on the variable *Patent$_t$* (1996-2005)

Number of observations = 2539
Number of groups = 230

	OLS FE		Poisson FE		NBRE FE	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Collaboration	0.026		0.027		0.001	
	(0.033)		(0.017)		(0.025)	
Productivity		-0.187		-0.298***		-0.236*
		(0.151)		(0.092)		(0.123)
Network		0.265		0.302***		0.284**
		(0.165)		(0.088)		(0.113)
Reputation		0.018		0.094		-0.045
		(0.103)		(0.086)		(0.129)
Univspin					-0.646**	-0.620**
	dropped	dropped	dropped	dropped	(0.273)	(0.277)
Ownership					-0.126	-0.139
	dropped	dropped	dropped	dropped	(0.373)	(0.377)
Firmage	-0.099***	-0.103***	-0.104***	-0.111***	-0.052***	-0.059***
	(0.027)	(0.024)	(0.012)	(0.012)	(0.017)	(0.016)
Nanomaterial					0.723*	0.767*
	dropped	dropped	dropped	dropped	(0.388)	(0.406)
Nanobiotech					0.799*	0.934**
	dropped	dropped	dropped	dropped	(0.415)	(0.428)

Table 6.8 continued

Nanoelectro					0.462	0.544
	dropped	dropped	dropped	dropped	(0.395)	(0.411)
CA					-0.213	-0.181
	dropped	dropped	dropped	dropped	(0.304)	(0.311)
MA					0.381	0.322
	dropped	dropped	dropped	dropped	(0.346)	(0.345)
F	6.90***	5.48***				
Wald chi2(9)			75.09***	92.50***	16.27*	24.83***

a. The numbers in parentheses are standard errors (robust standard errors for GLS).

b. ***indicates a significance level of 1%.

**indicates a significance level of 5%.

*indicates a significance level of 10%.

In Model 1, the variable *Collaboration* is found to have a positive impact on a firm's patenting activities (Table 6.8). Firms collaborating with universities tend to have more patents. However, this effect is not statistically significant, so no conclusions about the population could be generated from this sample.

The three attributes of university scientists in Model 2 exhibit different effects on their collaborating firms. The variable *Productivity* has a negative impact on the dependent variable *Patent*. The impact is not significant in the OLS regression, but significant in both the Poisson and NBRE regressions. This result shows that the research attitude toward publications and patents is different in that, scientists who are productive in publications tend to be less active in patenting. The variable *Network* has positive coefficients in all three regressions of OLS, Poisson, and NBRE, and the coefficients of the latter two regressions are significant. This finding provides evidence of the contribution of social capital of university scientists to firms through their collaboration. The coefficient of the variable *Reputation* is inconsistent across the three models and not significant.

Among the control variables that are statistically significant, the sign of the variable *Firmage* is consistently negative and significant, suggesting that firms are more likely to patent their inventions in early years. After all, many high tech firms are established based on an acquisition of IPRs, but as a firm progresses, emphasis is placed on the improvement and development of technology and products. In the NBRE model, the variables *Nanomaterial* and *Nanobiotech* are found to have positive and significant coefficients, suggesting that firms working in the fields of nanomaterials and nanobiotech have more patents than those working in other fields.

In addition to OLS, Poisson and NBRE, the variable *Patent* is also tested on the zero-inflated model since it has excess zeros. The zero-inflated model generates two separate models: a binary process and a count process, and then combines them together (Long and Freeze 2001). In the binary process, a logit model is generated to predict whether the observation (firm *i* in year *t*) belongs to the always zero (patent) group. In the count process, a Poisson or NBRE model is generated to predict the number of patents for observations that are not in the always zero group. However, currently there is no panel data command available to run the zero-inflated model in STATA. Therefore, the zero-inflated model is tried using regular command and year dummies are incorporated to control for trend effects. Since this is not the optimal approach, the results only represent the rough relationship between independent variables and the dependent variable.

Table 6.9 Zero-inflated models on variable *Patent$_t$* (1996-2005)

Number of observations = 1539
Nonzero observations = 396
Zero observations = 1143

	Model 1		**Model 2**	
	Poisson	**Logit**	**Poisson**	**Logit**
Collaboration	0.028	-0.093*		
	(0.020)	(0.048)		
Productivity			-0.239***	0.328
			(0.079)	(0.236)
Network			0.142**	-0.679***
			(0.067)	(0.228)
Reputation			0.308***	0.228
			(0.063)	(0.140)
Univspin	-0.182**	-0.085	-0.173**	-0.108
	(0.080)	(0.160)	(0.082)	(0.162)
Ownership	-0.893***	0.238	-0.951***	0.101
	(0.082)	(0.318)	(0.083)	(0.313)
Firmage	-0.051***	-0.159***	-0.050***	-0.152***
	(0.009)	(0.023)	(0.008)	(0.021)
Nanomaterial	-0.306***	0.758***	0.013	0.706**
	(0.116)	(0.290)	(0.133)	(0.317)
Nanobiotech	0.658***	1.215***	0.914***	1.093***
	(0.119)	(0.313)	(0.132)	(0.337)
Nanoelectro	-0.290**	0.811***	-0.044	0.730**
	(0.121)	(0.295)	(0.133)	(0.322)
CA	0.534***	-0.446**	0.566***	-0.460**
	(0.081)	(0.182)	(0.084)	(0.184)
MA	0.184*	-0.687***	0.273***	-0.598**
	(0.105)	(0.243)	(0.103)	(0.232)
Y1997	0.724***	1.194***	0.734***	1.178**
	(0.179)	(0.457)	(0.179)	(0.460)

Table 6.9 continued

Y1998	0.446**	0.889**	0.461**	0.903**
	(0.183)	(0.444)	(0.183)	(0.447)
Y1999	0.587***	0.961**	0.617***	0.991**
	(0.177)	(0.433)	(0.177)	(0.436)
Y2000	0.715***	1.008**	0.702***	1.005**
	(0.169)	(0.418)	(0.169)	(0.422)
Y2001	0.816***	0.973**	0.803***	0.953**
	(0.164)	(0.409)	(0.165)	(0.414)
Y2002	0.863***	1.274***	0.901***	1.313***
	(0.165)	(0.410)	(0.166)	(0.414)
Y2003	0.355*	1.204***	0.347*	1.206***
	(0.181)	(0.417)	(0.181)	(0.423)
Y2004	0.164	2.169***	0.093	2.111***
	(0.206)	(0.442)	(0.207)	(0.450)
Y2005	-0.787	3.533***	-0.517	3.881***
	(0.491)	(0.698)	(0.459)	(0.673)
LR Chi2	623.25***		654.02***	
Log likelihood	-1697.198		-1669.293	

a. The numbers in parentheses are standard errors (robust standard errors for OLS).

b. ***indicates a significance level of 1%.

**indicates a significance level of 5%.

*indicates a significance level of 10%.

Table 6.9 shows the results of both the count model (Poisson) and the binary model (logit) generated by the zero-inflated Poisson model. To be noted, many variables have opposite directions of coefficients in the count and binary models since the binary model is predicting the possibility of being in the always zero group. Among the variables that are statistically significant, the variable *Collaboration* has negative coefficient in the logit model in Model 1. It shows that firms having collaboration with university scientists are less likely to have zero patents. In Model 2, the variable *productivity* is negatively associated with the number of patents assigned to the firm. The variable network has a negative impact on the possibility of having no patents, and a positive impact on the number of patents. The variable *reputation* has positive coefficient on the number of patents. The results are consistent with those produced by panel data models (Table 6.8).

6.3.2 Models on the variables *SBIRfirst* and *SBIRsecond*

Both variables *SBIRfirst* and *SBIRsecond* are non-negative interval variables with zero for a nontrivial fraction (Figures 6.2 and 6.3), which is a typical corner solution response. The corner solution response occurs when a variable is continuously distributed over a large range of positive values but takes a certain value, usually zero, for a significant fraction of the population. In the case of corner solution responses, while a linear model still captures the expected values of estimators for x_i near the mean value, it leads to negative predictions for some observations (Wooldridge 2003).

By contrast, the Tobit model was specifically designed to model corner solution dependent variables (Ibid) and expresses an observed variable y with a latent variable y^*, which satisfies the classic linear model assumptions. The observed variable y equals the latent variable y^* when $y^* \geq 0$, and equals zero when $y^*<0$ (Equation 6.2). Thus, the observed variable y has a continuous distribution over positive values with a greater fraction on zero while the latent variable y^* is normally distributed.

$$\begin{cases} y = y^* \text{ if } y^* \geq 0 \\ y = 0 \text{ if } y^* < 0 , \end{cases} \qquad \text{Equation 6.2}$$

where $y^* = \beta_0 + x\beta + u, u \mid x \sim Normal(0, \sigma^2)$

No sufficient statistic allows a fixed-effects Tobit model, except in the case of an unconditional fixed-effects Tobit model with indicator variables for the panels, which generally provide biased estimators (STATA 2005). Hence, only the random-effects Tobit model was applied here. In addition to the Tobit model, the linear regression model was also applied to test the variables using the ordinary least squares (OLS) method even though OLS doesn't provide consistent estimators.

The regression outputs of both the Tobit model and the OLS model are presented in Tables 6.10 and 6.11, respectively. In both models on the variables *SBIRfirst* and *SBIRsecond*, the Tobit coefficient estimates of the independent variables have the same sign as the corresponding OLS estimates, and the statistical significance of the estimates is similar. The variable *Collaboration* in Model 1 has a significant and positive impact on *SBIRfirst* and *SBIRsecond* in both models. Thus, collaboration with universities is helping firms obtain more SBIR/STTR awards from the government.

In Model 2, the variable *Productivity* is significantly positive in both the OLS and Tobit regressions on the variables *SBIRfirst* and *SBIRsecond*, implying that the scientific merit of proposals is valued in SBIR/STTR awards. By contrast, the variable *Network* is negatively associated with both the *SBIRfirst* and *SBIRsecond* variables. The variable *Reputation* is positively associated with the variables *SBIRfirst/SBIRsecond*, but again the coefficient is not significant.

Among the control variables that passed the significance test, *Firmage* is positive on both dependent variables, suggesting that the older a firm is, the more likely it can secure awards because firms build their credibility over time. The variable *Univspin* is negative on the variable *SBIRsecond*, which shows that firms that spin off from universities are less likely to secure awards from federal agencies, as firms whose founders are full-time professors may not be eligible for awards from the SBIR program while many university spin-offs whose founders are still affiliated with universities remain eligible. The variable *Ownership* is positive on both dependent variables since public firms are generally not qualified for SBIR/STTR awards. The variable *MA* is positively correlated with the variable *SBIRsecond*, suggesting that firms in Massachusetts have some advantage when applying for SBIR/STTR awards. In addition, the variable *SBIRfirst* is significantly positively correlated with the variable *SBIRsecond*, suggesting that the value of SBIR/STTR awards in Phase 2 is positively dependent on the value in Phase 1.

Table 6.10 Regression output on the variable *SBIRfirst*$_t$ (1996-2005)

Number of observations = 2539
Number of groups = 230

	OLS FE		Tobit	
	Model 1	**Model 2**	**Model 1**	**Model 2**
Collaboration	0.014*** (0.004)		0.014*** (0.003)	
Productivity		0.052*** (0.015)		0.055*** (0.012)
Network		-0.042*** (0.014)		-0.044*** (0.012)
Reputation		0.009 (0.011)		0.003 (0.010)
Univspin	dropped	dropped	-0.022 (0.022)	-0.020 (0.022)
Ownership	dropped	dropped	0.095* (0.052)	0.095* (0.052)
Firmage	0.006*** (0.002)	0.008*** (0.002)	0.007*** (0.002)	0.008*** (0.002)
Nanomaterial	dropped	dropped	0.026 (0.043)	0.020 (0.043)
Nanobiotech	dropped	dropped	0.056 (0.045)	0.047 (0.046)
Nanoelectro	dropped	dropped	0.026 (0.044)	0.021 (0.044)
CA	dropped	dropped	-0.043 (0.027)	-0.045 (0.027)
MA	dropped	dropped	0.037 (0.033)	0.031 (0.033)
F	14.33***	7.91***		
Wald chi2			79.90***	80.28***

a. The numbers in parentheses are standard errors (robust standard errors for OLS).

b. ***indicates a significance level of 1%.

**indicates a significance level of 5%.

*indicates a significance level of 10%.

Table 6.11 Regression output on the variable *SBIRsecond$_t$* (1996-2005)

Number of observations = 2539
Number of groups = 230

	OLS FE		Tobit	
	Model 1	**Model 2**	**Model 1**	**Model 2**
SBIRfirst	0.874***	0.879***	1.290***	1.294***
	(0.187)	(0.186)	(0.078)	(0.078)
Collaboration	0.029**		0.026***	
	(0.011)		(0.007)	
Productivity		0.086*		0.085***
		(0.045)		(0.031)
Network		-0.081*		-0.071**
		(0.046)		(0.031)
Reputation		0.025		0.005
		(0.036)		(0.028)
Univspin	dropped	dropped	-0.086*	-0.081*
			(0.046)	(0.046)
Ownership	dropped	dropped	0.161	0.161
			(0.108)	(0.109)
Firmage	0.022***	0.026***	0.018***	0.021***
	(0.006)	(0.006)	(0.004)	(0.004)
Nanomaterial	dropped	dropped	0.119	0.105
			(0.091)	(0.092)
Nanobiotech	dropped	dropped	0.071	0.048
			(0.097)	(0.098)
Nanoelectro	dropped	dropped	0.049	0.036
			(0.093)	(0.094)
CA	dropped	dropped	-0.030	-0.034
			(0.058)	(0.058)
MA	dropped	dropped	0.172**	0.160**
			(0.070)	(0.070)
F	17.44***	11.03***		
Wald chi2			426.93***	423.25***

a. The numbers in parentheses are standard errors (robust standard errors for OLS).

b. ***indicates a significance level of 1%.

**indicates a significance level of 5%.

*indicates a significance level of 10%.

6.3.3 Models on the variable *VC*

Similar to the variables SBIRfirst and SBIRsecond, the variable VC is tested in both OLS and Tobit regressions. The OLS and Tobit regression outputs are reported in Table 6.12. The variable *Collaboration* in Model 1 is positive but not significantly correlated with the dependent variable *VC*.

In Model 2, the variable *Productivity* has a negative impact on the dependent variable while the variable *Network* is positively associated with the dependent variable. Both effects are statistically significant, indicating that the social capital of university scientists contributes to a firm's attractiveness to venture capital. In contrast, the research productivity of scientists is less attractive in this aspect since venture capitalists place more value on the commercial and marketing capability of a firm in their investment decisions. Again, the variable *Reputation* has no significant impact on the dependent variable.

In terms of the control variables, *Univspin* is consistently positive and significant across all the models. It seems that firms that spin off from universities are more likely to be trusted by venture capitalists. The field variable *Nanoelectro* is negatively associated with the dependent variable and is significant in both models, suggesting that firms in the field of nanoelectronics are less favored by venture capitalists than those in other fields. Variable *CA* and variable *MA* are significantly positive in both models. That is, the location of a firm in California or Massachussets helps it to procure more venture capital investment since most VC companies are also located in these areas and find it easier to manage their investments in nearby firms. All the other control variables exhibit mixed and insignificant effects.

Table 6.12 Regression output on the variable VC_t (1996-2005)

Number of observations = 2539
Number of groups = 230

	OLS FE		Tobit	
	Model 1	**Model 2**	**Model 1**	**Model 2**
Collaboration	0.019 (0.029)		0.044 (0.051)	
Productivity		-0.526** (0.237)		-0.603** (0.213)
Network		0.514* (0.272)		0.608** (0.215)
Reputation		0.030 (0.172)		0.158 (0.195)
Univspin	dropped	dropped	0.881*** (0.325)	0.890* (0.321)
Ownership	dropped	dropped	0.251 (0.768)	0.308 (0.758)
Firmage	0.079** (0.037)	0.086** (0.036)	0.027 (0.029)	0.025 (0.028)
Nanomaterial	dropped	dropped	-1.213* (0.647)	-1.053 (0.643)
Nanobiotech	dropped	dropped	-1.239* (0.687)	-1.088 (0.683)
Nanoelectro	dropped	dropped	-1.315** (0.660)	-1.170* (0.655)
CA	dropped	dropped	1.277*** (0.408)	1.303*** (0.403)
MA	dropped	dropped	0.917* (0.495)	0.928* (0.488)
F	3.90**	2.14*		
Wald chi2			23.11***	33.55***

a. The numbers in parentheses are standard errors (robust standard errors for OLS).

b. ***indicates a significance level of 1%.

**indicates a significance level of 5%.

*indicates a significance level of 10%.

CHAPTER 7: DISCUSSION AND CONCLUSIONS

This chapter reviews the structure of this thesis and summarizes its methodology and main findings. The hypotheses proposed in Chapter 4 are evaluated using the regression results presented in Chapter 6. It is followed by the discussion of the implications of this study for theory and policy. In the end, the chapter addresses the limitations of the study and presents recommendations for future study.

7.1 Summary of the main findings

This thesis reviews the development of nanotechnology and the nanotechnology industry, specifically with regard to NNBFs in the United States. It describes R&D activities in different sectors in the field of nanotechnology, in which university research shows its dominance, as it does in other knowledge-intensive industries. As universities move from Mode 1 to Mode 2, which is, from doing interest-driven research to problem-driven research, the transition is not homogenous across fields. For example, research in fields of natural sciences such as mathematics, theoretical physics and astronomy is still largely in Mode 1. The advances in applied sciences including nanotechnology and others such as information and computer technology and biotechnology in fact propel the transition of the function of universities. Technological breakthroughs in these fields are of value to enterprises and can be applied to industrial products, which promotes the growth of high-tech industries. The development of high-tech enterprises creates a market for knowledge generated in universities. Therefore, the involvement of university research in these high-tech industries is more active and visible.

This thesis continues with an exploration of the impact of university research on NNBFs by examining resource spillover from universities to NNBFs via their collaboration. The relationship under investigation in this study is mainly research collaboration between NNBFs and universities as reflected in co-authored publications. This connection shows a mixed, but positive effect on a firm's research capability and development potential.

As nanotechnology is still in its early stages of development, it has neither matured nor exhibited any clear applications for industry. The bulk of research is still carried out in universities. As shown in Figures 3.5 and 3.6, 80 percent of overall nano- publications and half of industry publications between 1990 and 2005 were contributed by university scientists. When firms collaborate with academic scientists, it facilitates the diffusion of knowledge from universities to the firms, which enjoy an advantageous position in the marketplace, as they enjoy access to state-of-art knowledge and translate it into their own research capability; and if they continue to work closely with these scientists who generate this knowledge, they continue to benefit.

In addition to increased research output, research collaboration is found to improve the likelihood of procuring funds from both public and private sources. Establishing research collaboration with university scientists conveys to skeptics that a firm has research capability at the benchmark level with universities, which offsets any uncertainty about the nanotechnology of the firm or the firm itself. Hence, the fact that the firm is collaborating with universities improves firms' perceived technology potential and increases its investment opportunities.

These three types of effects are visible in the data collected for this study. Table 6.7 provides evidence that firms working with universities have a distinct advantage in obtaining patenting, government funding and external investment. In all measurements, firms collaborating with universities show better performance than those that do not, and the difference is statistically significant. Backing up this finding, this study further investigates resources owned by each university scientist as a collaborator and breaks down these resources into human capital, social capital, and positional capital.

This investigation found that approximately 750 university scientists have collaborated with NNBFs since 1996 and their resources vary in the three dimensions. The number of publications produced by these scientists ranges between 1 and 308 (Figure 5.10) and the mean value of publications per year ranges from 0.1 to 18 (Figure 5.12). Each scientist has an average of 17 publications, or 1.68 publications per year. Slightly over 100 university scientists have worked in the field of nanotechnology for over 15 years, while a similar number of scientists are newcomers with fewer than three years of experience (Figure 5.11). Some scientists are relatively more collaborative than others. The network size of each university scientist varies from 2 to 386 (Figure 5.13). In addition, these 750 scientists are affiliated with 90 universities, which are ranked differently and have diverse reputations (Figure 5.14). Hence, questions arise as to whether scientists from high-ranked universities bring different benefits to a firm through collaboration than other universities and to what extent and how these benefits differ.

Three variables on different dimensions of resources were constructed to examine their impact on a firm's innovative capability, perceived technology and investment potential. In particular, the number of publications per year is used to measure research productivity; the number of collaborators is used to indicate network size; and the national rank of each university is used as a proxy for university reputation. Regression results of econometric models provide a clear picture of the relationship among the variables of university scientists' resources and firm performance (Tables 6.8-6.11).

7.2 A review of the hypotheses

7.2.1 Hypotheses 1-3: Research productivity

The first three hypotheses show that firms collaborating with more productive university scientists tend to have more innovation output and more government funding and external investment opportunities. Only hypothesis 2 is supported. Measured by the average number of publications each year, research productivity of university scientists is found to help firms procure funding from the government. The scientific quality and significance are important criteria when funding agencies evaluate proposals. The scientific knowledge of university scientists contributes by diffusing this knowledge to collaborators and by conveying a sense of the research quality of collaborators. Therefore, firms working with highly productive scientists are more likely to have higher research capability, which leads to a higher probability of getting funded.

By contrast, hypothesis 1 is rejected by the regression results. Working with highly productive scientists is found to be negatively associated with a firm's research output. This finding can be explained by the construction of these two variables. A scientist's productivity is measured by publications while a firm's research output is measured by patents. These two research activities have different research priorities. In fact, they are substitutes for each other to some extent. In order to apply for patents, a large part of the research cannot be published. Thus, many scientists who are more interested in holding patents restrain themselves from publishing. Hence, the fact that a university scientist's publication activities are negatively associated with a firm's patent activities is not inconsistent with the contribution of university scientists' intellectual capital. It simply shows that publications and patents each represent a distinct focus.

Hypothesis 3 is also rejected. The research productivity of university scientists does not increase the likelihood of venture capital investment in a firm. Venture capitalists care about a firm's technology and innovation capabilities, which are important for a firm's competitiveness in the high tech field. Thus, they place more attention on a firm's patents, new technologies, and products that can be applied to the market and less on its publications, which involve more fundamental and exploratory research. As mentioned above, patents and other forms of innovation output come at the cost of publications, which explains why firms working with scientists doing more fundamental research are less favored by venture capitalists.

7.2.2 Hypotheses 4-6: Network size

Hypotheses 4 through 6 suggest that the network size of a university scientist has a positive impact on the performance of a collaborating firm. Hypotheses 4 and 6, in which a university scientist's social capital is found to be positively associated with a firm's patents and venture capital investment, are supported. By working with university scientists, firms also have access to the networks of these scientists and the resources embedded in the network. The network, mostly composed of weak ties, provides channels through which firms are exposed to state-of-the-art knowledge and information. Therefore, these firms are more likely to be on the right track and have more technology breakthroughs. In addition, scientists with more connections and experience work more active in transferring knowledge and are more likely to enhance research and development in firms, which reduces any uncertainty about their capability and conveys the development potential of the firms to investors. Thus, the social capital of university scientists, which is the indirect social capital of the firm, is valuable to venture capitalists.

Interestingly, Hypothesis 5, which states that the social capital of university scientists does not help firms get more SBIR/STTR awards, is rejected. Instead, firms working with university scientists with less social capital, that is, those with a smaller network size, have an advantage when they apply for SBIR/STTR funds. This finding can be attributed to the design of the SBIR/STTR programs, whose roles are to help small firms develop in their early stages. As most qualifying firms are small and young, in the initial phase of their development, they are more likely to be connected with junior or medium-level scientists, who generally have less social capital than senior scientists. Hence, the network size of university scientists who collaborate with a firm is negatively correlated with its enrollment in the SBIR/STTR programs.

7.2.3 Hypotheses 7-9: University reputation

This set of hypotheses proposes that the reputation of a university has a positive impact on the amount of research output of a partner firm and the number of awarded funds and VC investments to the firm. Based on the regression results, these hypotheses are neither supported nor rejected. According to the reported statistics, university reputation produces positive but insignificant coefficients on all four dependent variables, suggesting that firms working with Tier 1 universities in the sample have better performance. However, the difference between Tier 1 universities and other universities is not significant enough to produce an accurate estimate. That is, from the sample, no conclusions can be generalized to the population.

7.2.4 Discussions

These empirical results show the mix effects of university scientists' resources on firm performance. These results are not completely consistent with findings reported in other similar studies. For example, university scientists' intellectual capital is found to have positive impact on partner firms' performance in terms of granted patents (Zucker and Darby 1998) and on investors' expectation of firms' value (Darby, Liu et al. 1999), while in this thesis, intellectual capital of university scientists is not contributing to firms' performance in any of these two measurements. The difference can be attributed to following reasons.

Firstly, in those studies, the level of intellectual capital refers to the ties with star scientists and star scientists are identified according to their gene sequence discoveries (Zucker, Darby et al. 1994), which represent technological breakthroughs in biotechnology. In this thesis, the level of intellectual capital is measured by ties with highly productive scientists who are identified based on their publication activities. Compared with technological breakthroughs, publications are more distant from industrial application. As explained in Section 7.2.1, publications and patents represent different research orientation, while technological breakthroughs can directly lead to patents. Therefore, it is not surprising to find scientists with more technological breakthroughs are more able to help their collaborators get more patents.

Secondly, the measurement of intellectual capital is different. In those studies, star scientists are defined as those who have at least 41 sequence discoveries, which is a cumulative measurement. This measurement inevitably brings in the effect of other attributes of scientists. Although not reported in those studies, senior scientists who have worked in the field for a long period are more likely to have more discoveries compared with new comers. Working experience is in general positively correlated with network size. Senior scientists with more discoveries tend to have more contacts in the community and have more information channels, which is also valued by investors. In addition, it is possible that star scientists are affiliated with prestigious universities and are more likely to be trusted by investors. Therefore, intellectual capital is not the only contributing factor to firms' performance. Instead, the concept of intellectual capital in Zucker and Darby's series of studies is in fact a mixture with the effect of social capital and position capital. By contrast, this study tries to separate different types of capital and test the impact of each capital individually, which makes the study a good complement to prior studies.

That being said, a caveat in interpreting the results should be mentioned here. Using different measurements, these studies report almost opposite findings, which shows the sensitivity of the results to variable constructions. Therefore, it is suggested to avoid over-generalization of these results. For example, the negative coefficient of scientists' intellectual capital on firms' patents and VC investment does not imply an overall negative consequence of scientists' R&D capabilities. It is important to bear in mind that intellectual capital in this context is indicated by scientists' SCI publications, which has rather basic research orientation.

7.3 Significance and implications

7.3.1 Theoretical implications

Among the numerous studies on the university-industry relationship, this study is the first to apply social capital theory to determine the beneficial effects of this relationship. The concept of network ties is used to show that the university-firm connection and the social capital that firms can mobilize through networks can benefit firms. Meanwhile, the idea of unequal resource distribution is applied to explain the motivation of selecting different research collaboration partners. By employing these concepts, this thesis is able to integrate the research on university-industry partnership into the broader picture of social capital and social network studies.

In addition, unlike other studies that consider the human capital of university scientists as the sole contributing factor to the university-firm relationship, this study categorizes the resources of university scientists into three dimensions: human capital, social capital, and positional capital. Each form of capital and its impact on collaborating firms is examined separately. This study found that while the human capital of university scientists indeed contributes to the performance of firms, their social capital is equally important. Furthermore, the study suggests that an increase in research capability with the help of university scientists is not the only consequence that firms enjoy in research collaboration. More recognition in the scientific community and a strengthening of perceived technology and investment potential are among the benefits for firms collaborating with university scientists. Therefore, this study expands the scope of the analyses of the university-industry relationship from a single dimension of resources, intellectual capital, and a single dimension of benefits, technology transfer, or knowledge spillover, to multiple dimensions of resources and benefits.

7.3.2 Methodological challenges

This study is faced with several methodological challenges. First of all, as an emerging technology, the term "nanotechnology" has no clear definition, nor do the terms "nanotechnology firms" or "nanotechnology industry." In fact, the concepts of nanotechnology firms and nanotechnology industry have been the focus of debate in several studies (Luxresearch 2006). The lack of consensus on a definition for nanotechnology firms added to the difficulties with sample selection for this study. Each firm needed to be checked and verified before being selected as an NNBF. In order to reduce the selection bias and identify as many firms as possible, the selection started with a large number of candidate firms (around 4,000). Thus, not only was the process of selection time-consuming and tedious, but it also required considerable knowledge of technical terms in the review of a firm's technology and product descriptions.

The second challenge comes from the large publication dataset. Because the records of SCI publications obtained from the Web of Science do not reveal authors' full names or their corresponding affiliations, a manual check has to be performed before data analysis. To find the full names and affiliations, the author had to locate the original journal article. However, through this effort, this study assured the accuracy of the name of each author and the co-publication tie between each firm and university.

7.3.3 Policy implications

The finding that collaboration with universities helps firms enhance their research capability and development potential supports the widely acknowledged positive role of academia in the development of industry. Research partnerships between universities and firms not only increase efficiency in knowledge sharing but also provide access to complementary resources. It is especially beneficial to small and young firms since they can be supported by university scientists, which certifies their research capabilities. Hence, NNBFs can gain from the knowledge that university scientists encouraged to work with industry partners will benefit their economic development. Of course, the benefit is mutual, as university scientists who collaborate with firms can explore potential applications of their research and avoid being "the last to recognize what inventions are useful to the general public" (Crow and Tucker 2001). Therefore, it is advisable for both firm scientists and university scientists to actively participate in research collaboration.

In particular, this study proves the importance of the intellectual and social capital of university scientists. These resources contribute to a firm's performance in different ways. In other words, depending on the aim—to hold more patents or to secure government funding or venture capital investment—a firm may have different preference in choosing partners. Therefore, a match in strength and interests is critical in research collaboration. Some firms may be interested in partnerships with academicians, but they may not know which university or scientist best fits their needs, as they may have limited knowledge about the university, the scientists, and their research. Since it is unrealistic for firms to maintain up-to-date on such matters, research partnership programs that provide relevant and easily accessible information are needed to help firms identify the appropriate research partners.

Serving this function, research partnership programs or intermediary organizations could publicize government policies regarding small businesses and assist firms with securing funding and investment. More importantly, they could facilitate information exchange between academia and industry. Firms could learn about current research trends in academia and the research interests of university scientists. They could also pose research questions and technical problems that academicians might work on. University scientists could also access such programs for interesting research topics and learn about market trends. By pooling information from both academia and industry, research partnership programs could reduce transaction costs for both sides when they are seeking partners.

In addition to the advantage of firms working with certain university scientists in firm performance, this study also notes the advantage of firms in certain regions in obtaining investment. For example, NNBFs located in California and Massachusetts are found to be more favored by venture capitalists due to their proximity to many venture capital firms. This poses a challenge for regions without significant venture capital. In order to encourage and maintain entrepreneurial activities, these regions need to provide incentives to compensate the disadvantage of lacking venture capital. Hence, it is even more important for these regions to promote active research partnerships to attract firms.

Shared research infrastructure could be one of the options. Due to interdisciplinary and complicated nature of nanotech experience, setting up necessary equipments is rather expensive to many NNBFs. Providing NNBFs with access to research facilities at a low cost or even free will largely alleviate firms' need for capital in the beginning stages. Furthermore, it brings in scientists from different sectors, which naturally creates a network opportunity for them. On the other hand, these regions can provide additional government funding to NNBFs. This fund can be provided either by state government solely or by federal agencies and state government jointly. While SBIR/STTR funds support R&D activities in the stage of early development for NNBFs, this fund could serve the need to support commercialization and marketing technologies developed in the firms, a substitute to venture capital. With the availability of R&D infrastructure and additional funding opportunities, firms in these regions are not at a too disadvantageous position compared with firms in regions with more entrepreneurial resources.

7.4 Limitations and future studies

Similar to other research, this study is not immune to limitations and weaknesses. For practical reasons, the measurement of certain variables suffers from validity issues. The lack of some data limits the scope of this study. Given these problems, its results should be taken more as suggestive rather than definitive.

7.4.1 Measurement validity

Several measurement limitations of this study need to be recognized. First, the number of co-authored publications is used to measure research collaboration between firm scientists and university scientists, and research collaboration is used as an indicator for network ties between the two. While publications are an important output of scientific research, they are not the sole determinants of output. Among other research output are patents, new products, and technological improvements. Research collaboration that resulted in these forms could not be captured by the measurement of co-authored publications.

Meanwhile, research collaboration is only one of the ways that firms may be connected to universities. Other connections may include the flow of researchers from one entity to another, the training or internships of students, the membership of university scientists on boards of director or scientific advisory boards, and so forth. These connections might play similar or different roles in linking firms with university scientists, but are not included in this investigation.

Another concern is with the measurement of the social capital of university scientists, which is relatively abstract and difficult to quantify. This study uses the number of collaborators as a proxy of social capital, but it fails to measure the amount of resources that could be mobilized through the network and to distinguish active ties from distant ones. In addition, the number of collaborators, as measured by co-authors in publications, did not capture the number of contacts with colleagues and outsiders who may have collaborated or exchanged information in other formats.

7.4.2 Data limitation

This study is restrained by the limitation on data availability. The majority of the sample is represented by small private companies whose information is generally not publicly available. Therefore, some firm-level information is missing. For example, R&D expenditures indicate a firm's interest and investment in research, which directly affects its R&D performance.

Meanwhile, the number of new products, market share, and sales are stable performance measures that firms are more interested in and concerned about. Exploring the impact of collaboration on these measures of their performance may provide a more direct and convincing picture for firms. However, these data are not available in this study.

7.4.3 Future studies

Future studies need to address the above limitations and improve the model validity. In particular, the scope of research could be expanded to consider different types of network ties and their density. In addition, more types of firm performance measurements could be taken into account.

In addition, this study could be largely complemented by a qualitative approach. Case studies and in-depth interviews with firm employees and university scientists could reveal motivations for collaboration and patterns of collaborative interaction, which would further the understanding of networking between firms and universities.

It is also worth mentioning that firms are not the only beneficiaries of university-industry partnerships. University scientists, free to apply their research in product development, are closer to the market and thus the first to learn about the problems of applications and actual technology needs, which they can turned into new research topics. Thus, a similar study that explores how university scientists benefit from university-industry collaboration and from the firms' resources could be conducted. In the meantime, while this study focuses on the nanotechnology industry, the model and analysis could also be applied to other emerging knowledge-intensive industries.

APPENDIX A: BEST NATIONAL UNIVERSITIES (TIER 1)

Table A.1 Best national universities in 1996

Rank	University
1	Yale University
2	Princeton University
3	Harvard University
4	Duke University
5	Massachusetts Institute of Technology
6	Stanford University
7	Dartmouth College
8	Brown University
9	California Institute of Technology
9	Northwestern University
11	Columbia University
12	University of Chicago
13	University of Pennsylvania
14	Cornell University
15	Johns Hopkins University
16	Rice University
17	University of Notre Dame
17	Washington University
19	Emory University
20	Vanderbilt University
21	University of Virginia
22	Tufts University
23	Georgetown University
24	University of Michigan--Ann Arbor
25	U. of North Carolina--Chapel Hill
25	Wake Forest University
27	University of California--Berkeley
28	Carnegie Mellon University

Table A.1 continued

29	Brandeis University
30	University of Rochester
31	University of California--Los Angeles
32	Lehigh University
33	College of William and Mary
34	University of California--San Diego
35	New York University
36	Tulane University
37	University of California--Irvine
38	Boston College
38	Case Western Reserve Univ.
40	University of California--Davis
41	University of Wisconsin--Madison
42	University of Washington
43	University of Southern California
44	Syracuse University
45	Yeshiva University
46	George Washington University
46	University of California--Santa Barbara
48	Georgia Institute of Technology
48	Texas A&M University--College Station
50	University of Illinois--Urbana-Champaign

Source: *U.S. News & World Report* (1996), Vol. 121 Issue 11, p110.

Table A.2 Best national universities in 2000

Rank	University
1	Princeton University
2	Harvard University
2	Yale University
4	California Institute of Technology
5	Massachusetts Institute of Technology
6	Stanford University
6	University of Pennsylvania
8	Duke University
9	Dartmouth College
10	Columbia University
10	Cornell University
10	University of Chicago
13	Northwestern University
13	Rice University
15	Brown University
15	Johns Hopkins University
15	Washington University in St. Louis
18	Emory University
19	University of Notre Dame
20	University of California-Berkeley
20	University of Virginia
22	Vanderbilt University
23	Carnegie Mellon University
23	Georgetown University
25	University of North Carolina-Chapel Hill
25	University of California-Los Angeles
25	University of Michigan-Ann Arbor
28	Wake Forest University
29	Tufts University
30	College of William and Mary

Table A.2 continued

31	Brandeis University
31	University of California-San Diego
33	New York University
33	University of Rochester
35	Georgia Institute of Technology
35	University of Southern California
35	University of Wisconsin-Madison
38	Boston College
38	Case Western Reserve University
38	Lehigh University
41	University of Illinois-Urbana-Champaign
41	University of California-Davis
41	University of California-Irvine
44	Pennsylvania State University-University Park
45	Tulane University
45	University of California-Santa Barbara
45	University of Washington
45	Yeshiva University
49	Pepperdine University
49	Rensselaer Polytechnic Inst.
49	University of Texas-Austin

Source: *U.S. News & World Report* (2000), Vol. 129 Issue 10, p106.

Table A.3 Best national universities in 2005

Rank	University
1	Harvard University
1	Princeton University
3	Yale University
4	University of Pennsylvania
5	Duke University
5	Stanford University
7	Massachusetts Institute of Technology
7	California Institute of Technology
9	Dartmouth College
9	Columbia University
11	Washington University in St Louis
12	Northwestern University
13	Cornell University
13	Johns Hopkins University
15	Brown University
15	University of Chicago
17	Rice University
18	University of Notre Dame
19	Vanderbilt University
20	University of California-Berkeley
20	Emory University
22	Carnegie Mellon University
23	University of Virginia
23	Georgetown University
25	University of Michigan-Ann Arbor
25	University of California-Los Angeles
27	University of North Carolina-Chapel Hill
27	Wake Forest University
27	Tufts University
30	University of Southern California

Table A.3 continued

31	College of William and Mary
32	University of California-San Diego
32	Lehigh University
34	University of Wisconsin-Madison
34	University of Rochester
34	Brandeis University
37	Case Western Reserve University
38	Georgia Institute of Technology
38	New York University
40	University of California-Irvine
40	Boston College
42	University of Illinois-Urbana-Champaign
43	Rensselaer Polytechnic Institute
43	Tulane University
45	University of Washington
45	University of California-Santa Barbara
45	Yeshiva University
48	University of California-Davis
48	Pennsylvania State University
50	University of Florida
50	Syracuse University

Source: *U.S. News & World Report* (2005), Vol. 139, No. 7, Pg. 80.

APPENDIX B: STATA OUTPUTS: DESCRIPTIVE STATISTICS

Table B.1 Descriptive statistics at the firm level (N=230)

	All firms (N=230)			Firms collaborating with universities (N=85)			Firms not collaborating with universities (N=145)		
Variable	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Patent $_i$	6.409 (18.517)	0	232	9.788 (27.144)	0	232	4.428 (10.237)	0	76
SBIRfirst $_i$	1.165 (2.469)	0	22	1.883 (3.399)	0	22	0.744 (1.572)	0	14
SBIRsecond $_i$	2.645 (7.864)	0	93	4.754 (11.720)	0	93	1.409 (3.750)	0	34
VC $_i$	5.756 (15.041)	0	104	9.603 (21.192)	0	104	3.501 (9.163)	0	68
Co-publication $_i$	1.452 (3.393)	0	23	3.929 (4.641)	1	23	0.000 (0.000)	0	0
productivity $_i$	0.813 (2.044)	0	20	2.165 (2.890)	0	20	0.021 (0.249)	0	3
network $_i$	0.826 (2.101)	0	22	2.188 (2.978)	0	22	0.028 (0.332)	0	4
reputation $_i$	0.378 (0.989)	0	8	0.906 (1.259)	0	8	0.069 (0.608)	0	7

Note: numbers in parentheses are standard deviation.

Table B.2 Correlation matrix at the firm level (N=230)

	patent	SBIR1	SBIR2	VC	Co-publication	productivity	network	reputation
patent	1							
SBIR1	0.016	1						
SBIR2	0.031	0.900	1					
VC	0.316	-0.062	-0.031	1				
Co-publication	0.069	0.236	0.225	0.000	1			
productivity	0.081	0.149	0.140	0.003	0.788	1		
network	0.092	0.074	0.083	0.056	0.739	0.930	1	
reputation	0.164	0.039	0.060	0.098	0.582	0.640	0.673	1

Table B.3 Descriptive statistics at the observation level (N=1539)

	All observations (N=1539)			Observations collaborating with universities (N=325)			Observations not collaborating with universities (N=1214)		
Variable	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
$patent_{i\,t}$	0.804 (2.932)	0	51	0.757 (1.803)	0	16	0.817 (3.167)	0	51
$SBIRfirst_{i\,t}$	0.095 (0.231)	0	2.6	0.175 (0.344)	0	2.6	0.074 (0.185)	0	2.1
$SBIRsecond_{i\,t}$	0.219 (0.716)	0	11	0.484 (1.238)	0	11	0.148 (0.465)	0	4.7
$VC_{i\,t}$	0.855 (3.737)	0	40	1.606 (5.720)	0	40	0.654 (2.963)	0	38
$productivity_{i\,t}$	0.415 (1.390)	0	20	1.935 (2.481)	0	20	0.007 (0.138)	0	3
$network_{i\,t}$	0.452 (1.483)	0	22	2.083 (2.630)	0	22	0.015 (0.190)	0	4
$reputation_{i\,t}$	0.177 (0.696)	0	8	0.723 (1.185)	0	8	0.030 (0.372)	0	7
$univspin_{i\,t}$	0.528 (0.499)	0	1	0.526 (0.500)	0	1	0.528 (0.499)	0	1
$ownership_{i\,t}$	0.945 (0.227)	0	1	0.935 (0.246)	0	1	0.948 (0.222)	0	1
$firmage_{i\,t}$	6.182 (4.881)	1	25	8.345 (4.966)	1	24	5.603 (4.694)	1	25
$nanomaterial_{i\,t}$	0.442 (0.497)	0	1	0.437 (0.497)	0	1	0.444 (0.497)	0	1
$nanobiotech_{i\,t}$	0.213 (0.410)	0	1	0.191 (0.394)	0	1	0.219 (0.414)	0	1
$nanoelectro_{i\,t}$	0.285 (0.451)	0	1	0.295 (0.457)	0	1	0.282 (0.450)	0	1
$CA_{i\,t}$	0.181 (0.385)	0	1	0.142 (0.349)	0	1	0.191 (0.393)	0	1
$MA_{i\,t}$	0.112 (0.316)	0	1	0.086 (0.281)	0	1	0.119 (0.324)	0	1

Note: numbers in parentheses are standard deviation.

Table B.4 Correlation matrix at the observation level (N=1539)

	patent	SBIR 1	SBIR 2	vc	coop	Pro-duc tivity	net-work	repu-tation	univs pin	own-er-ship	fir-mage	nano ma-terial	nano bio-tech	nano elec-tro	CA	MA
patent	1															
SBIR1	0.002	1														
SBIR2	0.004	0.649	1													
vc	0.182	-0.029	-0.003	1												
collaboration	0.003	0.178	0.196	0.007	1											
productivity	0.024	0.110	0.116	0.010	0.743	1										
network	0.046	0.058	0.067	0.041	0.684	0.935	1									
reputation	0.048	0.021	0.029	0.066	0.504	0.622	0.653	1								
univspin	-0.096	-0.094	-0.137	0.108	-0.053	-0.051	-0.064	-0.031	1							
ownership	-0.237	0.047	0.029	0.006	-0.055	-0.040	-0.054	-0.116	0.151	1						
firmage	0.048	0.197	0.236	-0.056	0.217	0.144	0.160	0.169	-0.329	-0.248	1					
nanomaterial	-0.068	0.030	0.082	-0.045	0.040	0.013	0.005	-0.044	-0.085	0.099	0.031	1				
nanobiotech	0.103	0.049	0.020	0.010	-0.080	-0.088	-0.092	-0.055	0.013	-0.015	0.142	-0.464	1			
nanoelectro	-0.047	-0.038	-0.069	-0.013	0.003	-0.002	-0.004	-0.003	0.083	-0.026	-0.119	-0.562	-0.328	1		
CA	0.115	-0.105	-0.091	0.096	-0.056	-0.049	-0.058	-0.025	-0.134	0.039	-0.113	-0.082	0.003	0.063	1	
MA	0.018	0.051	0.119	0.053	-0.038	-0.031	-0.032	0.004	-0.009	-0.096	0.107	0.060	-0.070	-0.001	-0.167	1

APPENDIX C: STATA OUTPUTS: REGRESSIONS

Model C.1 The fixed effects OLS model on patents with the variable *Cooperation*

```
. xtreg patent collaboration univspin ownership firmage nanomaterial nanobio-
tech
nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.0116                         Obs per group: min =         1
       between = 0.0269                                        avg =       6.7
       overall = 0.0024                                        max =        10

                                                F(2,1307)          =      6.90
corr(u_i, Xb)  = -0.2778                        Prob > F           =    0.0010

------------------------------------------------------------------------------
             |               Robust
      patent |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 collaboration |    .0258509    .0325604     0.79   0.427     -
.0380254    .0897272
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |  -.0987107   .0273196    -3.61   0.000    -.1523057   -.0451157
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |   1.397357   .1715473     8.15   0.000     1.060819    1.733895
-------------+----------------------------------------------------------------
     sigma_u |  1.9589888
     sigma_e |  2.1783686
         rho |  .44712452   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.2 The fixed effects OLS model on patents with variables *Productivity*, *Network* and *Reputation*

```
. xtreg patent productivity network reputation univspin ownership firmage
nanomaterial nanobiotech nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.0142                         Obs per group: min =         1
       between = 0.0160                                        avg =       6.7
       overall = 0.0005                                        max =        10

                                                F(4,1305)          =      5.48
corr(u_i, Xb)  = -0.2594                        Prob > F           =    0.0002

------------------------------------------------------------------------------
             |               Robust
      patent |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
productivity |  -.1874726   .1508032    -1.24   0.214    -.4833159    .1083707
     network |   .2647878   .1652491     1.60   0.109    -.0593951    .5889707
  reputation |   .0177573   .1028435     0.17   0.863    -.1839993     .219514
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |  -.1025203   .0246732    -4.16   0.000    -.1509238   -.0541169
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |   1.393196    .162489     8.57   0.000     1.074428    1.711964
-------------+----------------------------------------------------------------
     sigma_u |  1.9532774
     sigma_e |   2.177171
         rho |  .44595317   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.3 The fixed effects Poisson model on patents with the variable *Collaboration*

```
. xtpoisson patent collaboration univspin ownership firmage nanomaterial nano-
biotech nanoelectro CA MA, fe
note: 1 group (1 obs) dropped because of only one obs per group
note: 114 groups (577 obs) dropped due to all zero outcomes
note: univspin omitted because it is constant within group
note: ownership omitted because it is constant within group
note: nanomaterial omitted because it is constant within group
note: nanobiotech omitted because it is constant within group
note: nanoelectro omitted because it is constant within group
note: CA omitted because it is constant within group
note: MA omitted because it is constant within group

Iteration 0:   log likelihood =  -1172.783
Iteration 1:   log likelihood = -1134.5139
Iteration 2:   log likelihood = -1134.5098
Iteration 3:   log likelihood = -1134.5098

Conditional fixed-effects Poisson regression    Number of obs      =       961
Group variable (i): ID                          Number of groups   =       115

                                                Obs per group: min =         3
                                                               avg =       8.4
                                                               max =        10

                                                Wald chi2(2)       =     75.09
Log likelihood  = -1134.5098                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
      patent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 collaboration |    .0269658    .0167894     1.61   0.108     -
.0059408    .0598724
     firmage |  -.1043528   .0123541    -8.45   0.000    -.1285663   -.0801393
------------------------------------------------------------------------------
```

Model C.4 The fixed effects Poisson model on patents with variables *Productivity*, *Network* and *Reputation*

```
. xtpoisson patent productivity network reputation univspin ownership firmage
nanomaterial nanobiotech nanoelectro CA MA, fe
note: 1 group (1 obs) dropped because of only one obs per group
note: 114 groups (577 obs) dropped due to all zero outcomes
note: univspin omitted because it is constant within group
note: ownership omitted because it is constant within group
note: nanomaterial omitted because it is constant within group
note: nanobiotech omitted because it is constant within group
note: nanoelectro omitted because it is constant within group
note: CA omitted because it is constant within group
note: MA omitted because it is constant within group

Iteration 0:   log likelihood =  -1172.783
Iteration 1:   log likelihood = -1124.7133
Iteration 2:   log likelihood = -1124.5125
Iteration 3:   log likelihood = -1124.5125

Conditional fixed-effects Poisson regression    Number of obs      =       961
Group variable (i): ID                          Number of groups   =       115

                                                Obs per group: min =         3
                                                               avg =       8.4
                                                               max =        10

                                                Wald chi2(4)       =     92.50
Log likelihood  = -1124.5125                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
      patent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
productivity |  -.2989772    .092203    -3.24   0.001    -.4796918   -.1182625
     network |   .3020516   .0876813     3.44   0.001     .1301993    .4739039
  reputation |   .0941275   .0861351     1.09   0.274    -.0746942    .2629492
     firmage |  -.1112437   .0123306    -9.02   0.000    -.1354111   -.0870762
------------------------------------------------------------------------------
```

Model C.5 The fixed effects negative binomial model on patents with the variable *Collaboration*

```
. xtnbreg patent collaboration univspin ownership firmage nanomaterial nano-
biotec
> h nanoelectro CA MA, fe
note: 1 group (1 obs) dropped because of only one obs per group
note: 114 groups (577 obs) dropped due to all zero outcomes

Iteration 0:   log likelihood = -928.56765
Iteration 1:   log likelihood = -909.24719
Iteration 2:   log likelihood = -902.90283
Iteration 3:   log likelihood = -902.83549
Iteration 4:   log likelihood = -902.83548

Conditional FE negative binomial regression     Number of obs      =       961
Group variable (i): ID                          Number of groups   =       115

                                                Obs per group: min =         3
                                                               avg =       8.4
                                                               max =        10

                                                Wald chi2(9)       =     16.27
Log likelihood  = -902.83548                    Prob > chi2        =    0.0615

------------------------------------------------------------------------------
      patent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 collaboration |   .0012146    .024597     0.05   0.961    -
.0469947    .0494238
    univspin |  -.6461938   .2730086    -2.37   0.018    -1.181281   -.1111068
   ownership |  -.1264386   .3725311    -0.34   0.734    -.8565861    .6037089
     firmage |  -.0523604   .0166711    -3.14   0.002     -.085035   -.0196857
nanomaterial |   .7225901   .3882791     1.86   0.063     -.038423    1.483603
 nanobiotech |   .7994722   .4147545     1.93   0.054    -.0134316    1.612376
 nanoelectro |   .4624155   .3945798     1.17   0.241    -.3109466    1.235778
          CA |  -.2133345   .3036253    -0.70   0.482    -.8084292    .3817602
          MA |    .380503   .3459834     1.10   0.271     -.297612    1.058618
       _cons |   .0282448   .4191576     0.07   0.946    -.7932889    .8497785
------------------------------------------------------------------------------
```

Model C.6 The fixed effects negative binomial model on patents with variables *Productivity*, *Network* and *Reputation*

```
. xtnbreg patent productivity network reputation univspin ownership firmage
nan
> omaterial nanobiotech nanoelectro CA MA, fe
note: 1 group (1 obs) dropped because of only one obs per group
note: 114 groups (577 obs) dropped due to all zero outcomes

Iteration 0:   log likelihood =  -923.9769
Iteration 1:   log likelihood = -905.24891
Iteration 2:   log likelihood = -898.65039
Iteration 3:   log likelihood = -898.58062
Iteration 4:   log likelihood = -898.58061

Conditional FE negative binomial regression     Number of obs      =       961
Group variable (i): ID                          Number of groups   =       115

                                                Obs per group: min =         3
                                                               avg =       8.4
                                                               max =        10

                                                Wald chi2(11)      =     24.83
Log likelihood  = -898.58061                    Prob > chi2        =    0.0097

------------------------------------------------------------------------------
      patent |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
productivity |  -.2363398   .1233787    -1.92   0.055    -.4781575     .005478
     network |   .2839773   .1130466     2.51   0.012     .0624101    .5055445
  reputation |  -.0453216   .1290409    -0.35   0.725    -.2982371    .2075938
    univspin |  -.6202927   .2768834    -2.24   0.025    -1.162974   -.0776111
   ownership |  -.1390341   .3772901    -0.37   0.712    -.8785091    .6004409
     firmage |  -.0588051   .0161427    -3.64   0.000    -.0904442   -.0271659
nanomaterial |   .7670627   .4055921     1.89   0.059    -.0278833    1.562009
 nanobiotech |   .9342101   .4277202     2.18   0.029     .0958938    1.772526
 nanoelectro |   .5436486   .4110001     1.32   0.186    -.2618968    1.349194
          CA |  -.1806518   .3113805    -0.58   0.562    -.7909464    .4296428
          MA |   .3223334   .3449752     0.93   0.350    -.3538055    .9984724
       _cons |  -.0365786   .4323843    -0.08   0.933    -.8840362    .8108791
------------------------------------------------------------------------------
```

Model C.7 The zero-inflated Poisson model on patents with the variable *Collaboration*

```
. zip patent collaboration univspin ownership firmage nanomaterial nanobiotech
nanoelectro CA MA y1997 y1998 y1999 y2000 y2001 y2002 y2003 y2004 y2005, in-
flate(collaboration univspin ownership firmage nanomaterial nanobiotech nanoe-
lectro CA MA  y1997 y1998 y1999 y2000 y2001 y2002 y2003 y2004 y2005) vuong

Fitting constant-only model:

Iteration 0:   log likelihood = -2684.2788
Iteration 1:   log likelihood = -2092.839
Iteration 2:   log likelihood = -2015.1051
Iteration 3:   log likelihood = -2008.8937
Iteration 4:   log likelihood = -2008.8235
Iteration 5:   log likelihood = -2008.8234

Fitting full model:

Iteration 0:   log likelihood = -2008.8234
Iteration 1:   log likelihood = -1741.1764
Iteration 2:   log likelihood = -1698.8848
Iteration 3:   log likelihood = -1697.2196
Iteration 4:   log likelihood = -1697.1975
Iteration 5:   log likelihood = -1697.1975

Zero-inflated Poisson regression                  Number of obs   =       1539
                                                  Nonzero obs     =        396
                                                  Zero obs        =       1143

Inflation model = logit                           LR chi2(18)     =     623.25
Log likelihood  = -1697.198                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
patent       |
 collaboration |   .0275595   .0198053     1.39   0.164    -
.0112582    .0663773
    univspin |  -.1819302   .0802717    -2.27   0.023    -.3392598   -.0246006
   ownership |  -.8934932   .0819201   -10.91   0.000    -1.054054   -.7329327
     firmage |  -.0510143   .0088035    -5.79   0.000    -.0682687   -.0337598
nanomaterial |  -.3059538   .1164784    -2.63   0.009    -.5342473   -.0776603
 nanobiotech |   .6581282   .1188192     5.54   0.000     .4252468    .8910095
 nanoelectro |   -.289899   .1207605    -2.40   0.016    -.5265852   -.0532128
          CA |   .5344035   .0814115     6.56   0.000     .3748399    .6939671
          MA |    .184448   .1047843     1.76   0.078    -.0209254    .3898214
       y1997 |   .7236744   .1792187     4.04   0.000     .3724121    1.074937
       y1998 |   .4456325   .1834646     2.43   0.015     .0860485    .8052164
       y1999 |   .5866728   .1768688     3.32   0.001     .2400164    .9333292
       y2000 |   .7151383   .1691857     4.23   0.000     .3835405    1.046736
       y2001 |   .8159191   .1642851     4.97   0.000     .4939263    1.137912
       y2002 |   .8631587   .1654221     5.22   0.000     .5389373     1.18738
       y2003 |   .3547916   .1806509     1.96   0.050     .0007224    .7088607
       y2004 |   .1643393   .2063321     0.80   0.426    -.2400641    .5687427
       y2005 |  -.7873672   .4911807    -1.60   0.109    -1.750064    .1753292
       _cons |   1.443697   .1852479     7.79   0.000     1.080618    1.806776
-------------+----------------------------------------------------------------
inflate      |
 collaboration |  -.0928096   .0475848    -1.95   0.051    -
.1860741    .0004549
    univspin |  -.0852025   .1595072    -0.53   0.593    -.3978308    .2274258
   ownership |   .2383186   .3181286     0.75   0.454    -.3852021    .8618393
```

Model C.7 continued

firmage	-.1593689	.0227371	-7.01	0.000	-.2039329	-.1148049
nanomaterial	.7581703	.2900759	2.61	0.009	.1896319	1.326709
nanobiotech	1.215096	.3128127	3.88	0.000	.6019942	1.828197
nanoelectro	.8113335	.2953276	2.75	0.006	.2325019	1.390165
CA	-.4459959	.1815543	-2.46	0.014	-.8018357	-.0901561
MA	-.6866877	.24259	-2.83	0.005	-1.162155	-.2112201
y1997	1.1936	.4570602	2.61	0.009	.2977783	2.089421
y1998	.8891141	.4436988	2.00	0.045	.0194805	1.758748
y1999	.9611674	.4327944	2.22	0.026	.1129059	1.809429
y2000	1.007909	.4182936	2.41	0.016	.1880685	1.827749
y2001	.9730518	.4091903	2.38	0.017	.1710535	1.77505
y2002	1.274293	.4095427	3.11	0.002	.4716037	2.076981
y2003	1.204359	.4172869	2.89	0.004	.3864922	2.022227
y2004	2.168859	.4416639	4.91	0.000	1.303214	3.034504
y2005	3.533004	.6976458	5.06	0.000	2.165643	4.900365
_cons	-.3826371	.5142725	-0.74	0.457	-1.390593	.6253185

Vuong test of zip vs. standard Poisson: z = 7.12 Pr>z = 0.0000

Model C.8 The zero-inflated Poisson model on patents with variables *Productivity*, *Network* and *Reputation*

```
. zip patent productivity network reputation univspin ownership firmage nano-
material nanobiotech nanoelectro CA MA  y1997 y1998 y1999 y2000 y2001 y2002
y2003 y2004 y2005, inflate(productivity network reputation univspin ownership
firmage nanomaterial nanobiotech nanoelectro CA MA  y1997 y1998 y1999 y2000
y2001 y2002 y2003 y2004 y2005) vuong

Fitting constant-only model:

Iteration 0:   log likelihood = -2684.2788
Iteration 1:   log likelihood = -2090.6288
Iteration 2:   log likelihood = -2018.3875
Iteration 3:   log likelihood = -1997.1009
Iteration 4:   log likelihood = -1996.3082
Iteration 5:   log likelihood = -1996.3052
Iteration 6:   log likelihood = -1996.3052

Fitting full model:

Iteration 0:   log likelihood = -1996.3052
Iteration 1:   log likelihood = -1722.0486
Iteration 2:   log likelihood = -1671.1303
Iteration 3:   log likelihood = -1669.3057
Iteration 4:   log likelihood = -1669.2933
Iteration 5:   log likelihood = -1669.2933

Zero-inflated Poisson regression                  Number of obs   =       1539
                                                  Nonzero obs     =        396
                                                  Zero obs        =       1143

Inflation model = logit                           LR chi2(20)     =     654.02
Log likelihood  = -1669.293                       Prob > chi2     =     0.0000

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
patent       |
productivity |  -.2393871   .0788995    -3.03   0.002    -.3940273    -.084747
     network |   .1424327   .0672738     2.12   0.034     .0105785    .2742869
  reputation |   .3076942   .0627432     4.90   0.000     .1847197    .4306687
    univspin |  -.1733031   .0817216    -2.12   0.034    -.3334745   -.0131317
   ownership |  -.9511395   .0825713   -11.52   0.000    -1.112976   -.7893027
     firmage |  -.0500747   .0082217    -6.09   0.000     -.066189   -.0339604
nanomaterial |   .0130978   .1328996     0.10   0.921    -.2473806    .2735763
 nanobiotech |   .9144061   .1316659     6.94   0.000     .6563457    1.172466
 nanoelectro |  -.0440383   .1328925    -0.33   0.740    -.3045028    .2164262
          CA |   .5657853   .0835934     6.77   0.000     .4019453    .7296253
          MA |   .2733941   .1031539     2.65   0.008     .0712162     .475572
       y1997 |   .7338957   .1789842     4.10   0.000      .383093    1.084698
       y1998 |   .4607993   .1831989     2.52   0.012      .101736    .8198625
       y1999 |   .6172417   .1766876     3.49   0.000     .2709404    .9635429
       y2000 |   .7022291   .1692492     4.15   0.000     .3705067    1.033952
       y2001 |   .8027634   .1646968     4.87   0.000     .4799636    1.125563
       y2002 |   .9011274   .1655274     5.44   0.000     .5766996    1.225555
       y2003 |   .3474891    .180503     1.93   0.054    -.0062903    .7012685
       y2004 |   .0927922   .2068221     0.45   0.654    -.3125717    .4981561
       y2005 |  -.5171231   .4587178    -1.13   0.260    -1.416193    .3819473
       _cons |    1.17143   .1960999     5.97   0.000     .7870816    1.555779
-------------+----------------------------------------------------------------
inflate      |
productivity |   .3278215   .2363042     1.39   0.165    -.1353263    .7909693
     network |  -.6792876   .2284801    -2.97   0.003      -1.1271   -.2314748
  reputation |   .2284186   .1398933     1.63   0.103    -.0457673    .5026045
```

Model C.8 continued

univspin	-.1084389	.1622716	-0.67	0.504	-.4264855	.2096077
ownership	.1014068	.3126391	0.32	0.746	-.5113545	.7141681
firmage	-.1519404	.0210215	-7.23	0.000	-.1931417	-.1107391
nanomaterial	.7056585	.3169175	2.23	0.026	.0845117	1.326805
nanobiotech	1.092649	.3365094	3.25	0.001	.4331026	1.752195
nanoelectro	.7298644	.3217065	2.27	0.023	.0993313	1.360397
CA	-.4603532	.1844262	-2.50	0.013	-.821822	-.0988844
MA	-.5982356	.2317321	-2.58	0.010	-1.052422	-.144049
y1997	1.178033	.4600554	2.56	0.010	.2763412	2.079725
y1998	.9033897	.4473674	2.02	0.043	.0265657	1.780214
y1999	.9905878	.4357942	2.27	0.023	.136447	1.844729
y2000	1.005153	.4223963	2.38	0.017	.1772714	1.833034
y2001	.9533491	.4136774	2.30	0.021	.1425564	1.764142
y2002	1.313144	.4140636	3.17	0.002	.5015946	2.124694
y2003	1.205542	.4226005	2.85	0.004	.3772607	2.033824
y2004	2.11061	.4504887	4.69	0.000	1.227668	2.993551
y2005	3.880729	.6730825	5.77	0.000	2.561512	5.199946
_cons	-.1804494	.5337804	-0.34	0.735	-1.22664	.865741

Vuong test of zip vs. standard Poisson: z = 7.19 Pr>z = 0.0000

Model C.9 The fixed effects OLS model on SBIRfirst with the variable *Collaboration*

```
. xtreg SBIRfirst collaboration univspin ownership firmage nanomaterial nano-
biotech nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.0379                         Obs per group: min =         1
       between = 0.0802                                        avg =       6.7
       overall = 0.0578                                        max =        10

                                                F(2,1307)          =     14.33
corr(u_i, Xb)  = 0.0502                         Prob > F           =    0.0000

------------------------------------------------------------------------------
             |               Robust
   SBIRfirst |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 collaboration |    .0136458   .0041339     3.30
0.001      .005536    .0217556
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |   .0062813   .0022276     2.82   0.005     .0019112    .0106513
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |   .0470275   .0133309     3.53   0.000     .0208752    .0731799
-------------+----------------------------------------------------------------
     sigma_u |  .14913129
     sigma_e |  .16303676
         rho |  .45554339   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.10 The fixed effects OLS model on SBIRfirst with variables *Productivity*, *Network* and *Reputation*

```
. xtreg SBIRfirst productivity network reputation univspin ownership firmage
nanomaterial nanobiotech nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.0381                         Obs per group: min =         1
       between = 0.0793                                        avg =       6.7
       overall = 0.0608                                        max =        10

                                                F(4,1305)          =      7.91
corr(u_i, Xb)  = 0.0540                         Prob > F           =    0.0000

------------------------------------------------------------------------------
             |               Robust
   SBIRfirst |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
productivity |   .0515023   .0153402     3.36   0.001     .0214082    .0815965
     network |  -.0422471   .0138926    -3.04   0.002    -.0695014   -.0149927
  reputation |    .009135   .0112385     0.81   0.416    -.0129124    .0311825
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |   .0078265   .0021411     3.66   0.000     .0036261     .012027
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |    .042712   .0131542     3.25   0.001     .0169062    .0685178
-------------+----------------------------------------------------------------
     sigma_u |  .14909799
     sigma_e |   .1631393
         rho |  .45512076   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.11 The Tobit model on SBIRfirst with the variable *Collaboration*

```
. xttobit SBIRfirst collaboration univspin ownership firmage nanomaterial
nanobiotech nanoelectro CA MA

Obtaining starting values for full model:

Iteration 0:   log likelihood =  419.40731
Iteration 1:   log likelihood =   421.3398
Iteration 2:   log likelihood =  421.42413
Iteration 3:   log likelihood =  421.42426

Fitting full model:

Iteration 0:   log likelihood =  421.42426
Iteration 1:   log likelihood =  421.42426

Random-effects tobit regression                 Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       6.7
                                                               max =        10

                                                Wald chi2(9)       =     79.90
Log likelihood  =  421.42426                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
   SBIRfirst |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 collaboration |    .013992   .0027411     5.10
0.000     .0086196    .0193644
    univspin |  -.0224432   .0215609    -1.04   0.298    -.0647018    .0198153
   ownership |    .095094   .0523219     1.82   0.069    -.0074551     .197643
     firmage |   .0067418   .0016212     4.16   0.000     .0035643    .0099192
nanomaterial |     .02576   .0428015     0.60   0.547    -.0581293    .1096493
 nanobiotech |   .0558255   .0453942     1.23   0.219    -.0331456    .1447965
 nanoelectro |   .0264526   .0437278     0.60   0.545    -.0592524    .1121576
          CA |   -.042763    .027268    -1.57   0.117    -.0962074    .0106814
          MA |   .0367395   .0331224     1.11   0.267    -.0281792    .1016582
       _cons |  -.0637682   .0616418    -1.03   0.301    -.1845839    .0570474
-------------+----------------------------------------------------------------
    /sigma_u |    .137776    .007599    18.13   0.000     .1228823    .1526697
    /sigma_e |   .1621101   .0031398    51.63   0.000     .1559562     .168264
-------------+----------------------------------------------------------------
         rho |   .4193863   .0288377                      .3638813    .4765461
------------------------------------------------------------------------------

  Observation summary:         0  left-censored observations
                            1539     uncensored observations
                               0 right-censored observations
```

Model C.12 The Tobit model on SBIRfirst with variables *Productivity*, *Network* and *Reputation*

```
. xttobit SBIRfirst productivity network reputation univspin ownership firmage
nanomaterial nanobiotech nanoelectro CA MA

Obtaining starting values for full model:

Iteration 0:   log likelihood =  417.24107
Iteration 1:   log likelihood =  421.48427
Iteration 2:   log likelihood =  421.58447
Iteration 3:   log likelihood =  421.58461

Fitting full model:

Iteration 0:   log likelihood =  421.58461
Iteration 1:   log likelihood =  421.58461

Random-effects tobit regression                 Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       6.7
                                                               max =        10

                                                Wald chi2(11)      =     80.28
Log likelihood  =  421.58461                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
   SBIRfirst |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
productivity |   .0550824   .0115137     4.78   0.000      .032516    .0776488
     network |  -.0441913   .0116661    -3.79   0.000    -.0670564   -.0213263
  reputation |   .0033897   .0103497     0.33   0.743    -.0168952    .0236747
    univspin |  -.0202122   .0215451    -0.94   0.348    -.0624398    .0220154
   ownership |   .0946341   .0522914     1.81   0.070    -.0078551    .1971233
     firmage |   .0083562   .0015897     5.26   0.000     .0052406    .0114719
nanomaterial |   .0197942   .0429323     0.46   0.645    -.0643515      .10394
 nanobiotech |   .0465438   .0455319     1.02   0.307    -.0426971    .1357848
 nanoelectro |   .0212634   .0438262     0.49   0.628    -.0646343    .1071612
          CA |   -.044623    .027258    -1.64   0.102    -.0980478    .0088017
          MA |   .0314678   .0330816     0.95   0.341    -.0333709    .0963066
       _cons |  -.0615676   .0616663    -1.00   0.318    -.1824312    .0592961
-------------+----------------------------------------------------------------
    /sigma_u |   .1376125   .0076084    18.09   0.000     .1227003    .1525247
    /sigma_e |   .1621171   .0031409    51.62   0.000     .1559612    .1682731
-------------+----------------------------------------------------------------
         rho |    .418787   .0289028                      .3631658    .4760834
------------------------------------------------------------------------------

  Observation summary:         0  left-censored observations
                            1539     uncensored observations
                               0 right-censored observations
```

Model C.13 The fixed effects OLS model on SBIRsecond with the variable *Collaboration*

```
. xtreg SBIRsecond SBIRfirst collaboration univspin ownership firmage nanoma-
terial nanobiotech nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.1310                         Obs per group: min =         1
       between = 0.6336                                        avg =       6.7
       overall = 0.3964                                        max =        10

                                                F(3,1306)          =     17.44
corr(u_i, Xb)  = 0.4609                         Prob > F           =    0.0000

------------------------------------------------------------------------------
             |               Robust
  SBIRsecond |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   SBIRfirst |   .8743527   .1870884     4.67   0.000     .5073261    1.241379
 collaboration |   .0257833   .0107814     2.39
0.017     .0046326     .046934
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |   .0221112   .0057593     3.84   0.000     .0108128    .0334097
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |  -.0178638   .0368045    -0.49   0.627    -.0900662    .0543387
-------------+----------------------------------------------------------------
     sigma_u |   .3425567
     sigma_e |  .46513597
         rho |  .35165209   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.14 The fixed effects OLS model on SBIRsecond with variables *Productivity*, *Network* and *Reputation*

```
. xtreg SBIRsecond SBIRfirst productivity network reputation univspin owner-
ship firmage nanomaterial nanobiotech nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.1295                         Obs per group: min =         1
       between = 0.6136                                        avg =       6.7
       overall = 0.3895                                        max =        10

                                                F(5,1304)          =     11.03
corr(u_i, Xb)  = 0.4418                         Prob > F           =    0.0000

------------------------------------------------------------------------------
             |               Robust
  SBIRsecond |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   SBIRfirst |   .8790729   .1860962     4.72   0.000     .5139921    1.244154
productivity |   .0861252    .044868     1.92   0.055    -.0018961    .1741466
     network |  -.0812655   .0459147    -1.77   0.077    -.1713402    .0088093
  reputation |   .0249885   .0358702     0.70   0.486    -.0453811    .0953581
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |    .026227   .0059587     4.40   0.000     .0145374    .0379166
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |  -.0299376   .0367746    -0.81   0.416    -.1020815    .0422063
-------------+----------------------------------------------------------------
     sigma_u |  .34355805
     sigma_e |  .46590542
         rho |  .35222959   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.15   The Tobit model on SBIRsecond with the variable *Collaboration*

```
. xttobit SBIRsecond SBIRfirst collaboration univspin ownership firmage nano-
material nanobiotech nanoelectro CA MA

Obtaining starting values for full model:

Iteration 0:   log likelihood = -1159.3184
Iteration 1:   log likelihood = -1131.9661
Iteration 2:   log likelihood = -1130.9306
Iteration 3:   log likelihood = -1130.9265

Fitting full model:

Iteration 0:   log likelihood = -1130.9265
Iteration 1:   log likelihood = -1130.9265

Random-effects tobit regression                 Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       6.7
                                                               max =        10

                                                Wald chi2(10)      =    426.93
Log likelihood  = -1130.9265                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
  SBIRsecond |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   SBIRfirst |    1.28985   .0782799    16.48   0.000     1.136424    1.443275
 collaboration |   .0258536   .0074025     3.49
0.000     .0113449    .0403623
    univspin |   -.085559   .0459269    -1.86   0.062    -.1755741     .004456
   ownership |   .1606443   .1084666     1.48   0.139    -.0519463     .373235
     firmage |   .0175345   .0041684     4.21   0.000     .0093645    .0257045
nanomaterial |   .1194614   .0914884     1.31   0.192    -.0598526    .2987754
 nanobiotech |   .0709415   .0972823     0.73   0.466    -.1197283    .2616113
 nanoelectro |   .0487604   .0933555     0.52   0.601     -.134213    .2317339
          CA |  -.0299759   .0577792    -0.52   0.604     -.143221    .0832692
          MA |   .1717178   .0699084     2.46   0.014     .0346999    .3087357
       _cons |  -.2342322   .1305532    -1.79   0.073    -.4901118    .0216473
-------------+----------------------------------------------------------------
    /sigma_u |   .2619851   .0190863    13.73   0.000     .2245767    .2993936
    /sigma_e |   .4648608   .0090907    51.14   0.000     .4470433    .4826784
-------------+----------------------------------------------------------------
         rho |   .2410556   .0286033                      .1886678    .3004851
------------------------------------------------------------------------------

  Observation summary:         0  left-censored observations
                            1539     uncensored observations
                               0 right-censored observations
```

Model C.16 The Tobit model on SBIRsecond with variables *Productivity*, *Network* and *Reputation*

```
. xttobit SBIRsecond SBIRfirst productivity network reputation univspin owner-
ship firmage nanomaterial nanobiotech nanoelectro CA MA

Obtaining starting values for full model:

Iteration 0:   log likelihood = -1161.4414
Iteration 1:   log likelihood = -1134.0325
Iteration 2:   log likelihood = -1132.9837
Iteration 3:   log likelihood = -1132.9796

Fitting full model:

Iteration 0:   log likelihood = -1132.9796
Iteration 1:   log likelihood = -1132.9796

Random-effects tobit regression                 Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       6.7
                                                               max =        10

                                                Wald chi2(12)      =    423.25
Log likelihood  = -1132.9796                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
  SBIRsecond |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   SBIRfirst |   1.294451   .0783681    16.52   0.000     1.140852     1.44805
productivity |   .0854368    .031209     2.74   0.006     .0242683    .1466053
     network |  -.0713061   .0312684    -2.28   0.023     -.132591   -.0100213
  reputation |   .0050285   .0282652     0.18   0.859    -.0503704    .0604273
    univspin |  -.0808805   .0460556    -1.76   0.079    -.1711479    .0093869
   ownership |   .1609769   .1088606     1.48   0.139    -.0523859    .3743398
     firmage |   .0208706   .0041308     5.05   0.000     .0127743    .0289669
nanomaterial |   .1052386    .092375     1.14   0.255    -.0758132    .2862903
 nanobiotech |   .0475881   .0981929     0.48   0.628    -.1448665    .2400427
 nanoelectro |   .0359598   .0941242     0.38   0.702    -.1485203    .2204399
          CA |  -.0338905   .0579868    -0.58   0.559    -.1475425    .0797614
          MA |   .1601591   .0700454     2.29   0.022     .0228727    .2974455
       _cons |  -.2277649   .1313366    -1.73   0.083    -.4851799    .0296501
-------------+----------------------------------------------------------------
    /sigma_u |   .2628491    .019167    13.71   0.000     .2252824    .3004158
    /sigma_e |   .4653833   .0091045    51.12   0.000     .4475388    .4832278
-------------+----------------------------------------------------------------
         rho |   .2418502   .0287003                       .189279    .3014723
------------------------------------------------------------------------------

  Observation summary:         0  left-censored observations
                            1539     uncensored observations
                               0 right-censored observations
```

Model C.17 The fixed effects OLS model on VC with the variable *Collaboration*

```
. xtreg vc collaboration univspin ownership firmage nanomaterial nanobiotech
nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.0045                         Obs per group: min =         1
       between = 0.0126                                        avg =       6.7
       overall = 0.0029                                        max =        10

                                                F(2,1307)          =      3.90
corr(u_i, Xb)  = -0.2537                        Prob > F           =    0.0204

------------------------------------------------------------------------------
             |               Robust
          vc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 collaboration |   .0191174   .0294171     0.65   0.516    -
.0385925    .0768274
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |   .0793467   .0365521     2.17   0.030     .0076394    .1510539
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |   .3521066   .2152718     1.64   0.102    -.0702094    .7744226
-------------+----------------------------------------------------------------
     sigma_u |  2.4929748
     sigma_e |   3.197349
         rho |  .37808353   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.18 The fixed effects OLS model on VC with variables *Productivity*, *Network* and *Reputation*

```
. xtreg vc productivity network reputation univspin ownership firmage nanoma-
terial nanobiotech nanoelectro CA MA, fe robust

Fixed-effects (within) regression               Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

R-sq:  within  = 0.0080                         Obs per group: min =         1
       between = 0.0002                                        avg =       6.7
       overall = 0.0000                                        max =        10

                                                F(4,1305)          =      2.14
corr(u_i, Xb)  = -0.2176                        Prob > F           =    0.0732

------------------------------------------------------------------------------
             |               Robust
          vc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
productivity |  -.5258599   .2371129    -2.22   0.027     -.991024   -.0606958
     network |   .5142811   .2716977     1.89   0.059     -.018731    1.047293
  reputation |   .0300926   .1715084     0.18   0.861    -.3063696    .3665549
    univspin |  (dropped)
   ownership |  (dropped)
     firmage |   .0864867    .035721     2.42   0.016     .0164097    .1565636
nanomaterial |  (dropped)
 nanobiotech |  (dropped)
 nanoelectro |  (dropped)
          CA |  (dropped)
          MA |  (dropped)
       _cons |    .301184   .2126781     1.42   0.157    -.1160444    .7184123
-------------+----------------------------------------------------------------
     sigma_u |  2.4771937
     sigma_e |  3.1941971
         rho |  .37556426   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Model C.19 The Tobit model on VC with the variable *Collaboration*

```
. xttobit vc collaboration univspin ownership firmage nanomaterial nanobiotech
nanoelectro CA MA

Obtaining starting values for full model:

Iteration 0:   log likelihood = -4108.3419
Iteration 1:   log likelihood =  -4106.717
Iteration 2:   log likelihood = -4106.7086
Iteration 3:   log likelihood = -4106.7086

Fitting full model:

Iteration 0:   log likelihood = -4106.7148
Iteration 1:   log likelihood = -4106.7148

Random-effects tobit regression                 Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       6.7
                                                               max =        10

                                                Wald chi2(9)       =     23.11
Log likelihood  = -4106.7148                    Prob > chi2        =    0.0060

------------------------------------------------------------------------------
          vc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 collaboration |   .0441125   .0509175     0.87   0.386    -
.0556839    .1439089
    univspin |    .880833   .3245607     2.71   0.007     .2447056     1.51696
   ownership |   .2514161   .7678568     0.33   0.743    -1.253556    1.756388
     firmage |   .0269381   .0289453     0.93   0.352    -.0297937      .08367
nanomaterial |  -1.212668   .6466896    -1.88   0.061    -2.480157    .0548199
 nanobiotech |  -1.238568   .6867684    -1.80   0.071    -2.584609    .1074733
 nanoelectro |  -1.315295   .6599274    -1.99   0.046    -2.608729   -.0218608
          CA |   1.276891   .4082312     3.13   0.002     .4767729     2.07701
          MA |     .91663   .4945164     1.85   0.064    -.0526044    1.885864
       _cons |   .8420844     .92432     0.91   0.362    -.9695495    2.653718
-------------+----------------------------------------------------------------
    /sigma_u |    1.87866   .1359599    13.82   0.000     1.612183    2.145136
    /sigma_e |   3.201277   .0628267    50.95   0.000     3.078139    3.324415
-------------+----------------------------------------------------------------
         rho |   .2561678   .0296752                      .2016049     .317569
------------------------------------------------------------------------------

  Observation summary:         0  left-censored observations
                            1539     uncensored observations
                               0 right-censored observations
```

Model C.20 The Tobit model on VC with variables *Productivity*, *Network* and *Reputation*

```
. xttobit vc productivity network reputation univspin ownership firmage nano-
material nanobiotech nanoelectro CA MA

Obtaining starting values for full model:

Iteration 0:   log likelihood = -4103.7658
Iteration 1:   log likelihood = -4101.8166
Iteration 2:   log likelihood = -4101.8071
Iteration 3:   log likelihood = -4101.8071

Fitting full model:

Iteration 0:   log likelihood = -4101.8126
Iteration 1:   log likelihood = -4101.8126

Random-effects tobit regression                 Number of obs      =      1539
Group variable (i): ID                          Number of groups   =       230

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       6.7
                                                               max =        10

                                                Wald chi2(11)      =     33.55
Log likelihood  = -4101.8126                    Prob > chi2        =    0.0004

------------------------------------------------------------------------------
          vc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
productivity |   -.602959   .2134389    -2.82   0.005    -1.021292   -.1846265
     network |   .6083808   .2145461     2.84   0.005     .1878782    1.028883
  reputation |    .157904   .1947204     0.81   0.417    -.2237408    .5395489
    univspin |   .8897504   .3205087     2.78   0.006     .2615648    1.517936
   ownership |   .3084648   .7575837     0.41   0.684    -1.176372    1.793302
     firmage |    .025416   .0283518     0.90   0.370    -.0301525    .0809844
nanomaterial |  -1.053066   .6428406    -1.64   0.101    -2.313011    .2068781
 nanobiotech |  -1.087552   .6828564    -1.59   0.111    -2.425926    .2508217
 nanoelectro |  -1.170365   .6550633    -1.79   0.074    -2.454266     .113535
          CA |    1.30346   .4032412     3.23   0.001     .5131213    2.093798
          MA |   .9275346   .4877608     1.90   0.057     -.028459    1.883528
       _cons |   .6198674   .9148864     0.68   0.498    -1.173277    2.413012
-------------+----------------------------------------------------------------
    /sigma_u |   1.843684   .1351165    13.65   0.000      1.57886    2.108507
    /sigma_e |   3.196592   .0627461    50.94   0.000     3.073612    3.319572
-------------+----------------------------------------------------------------
         rho |   .2496201   .0295281                      .1954588    .3108589
------------------------------------------------------------------------------

  Observation summary:         0  left-censored observations
                            1539     uncensored observations
                               0 right-censored observations
```

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