Scientist Entrepreneurs and University Commercialization

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Outline

Chapter 1: Acknowledgements and Publications

1.1 Acknowledgements

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1.2 Publications

This book draws heavily from papers that have been published or which are forthcoming. Chapter three draws heavily from a paper published in an edited book volume with *Cambridge Press*, an accepted forthcoming paper to be published in *Research Policy*, and a paper to be submitted to *Nature*. Chapter four is currently in the process of improvement with the ambition of being submitted to *Management Science* by the end of 2009. Chapter five, draws on an accepted forthcoming publication in *Annals of Regional Science*. Chapter six draws on an accepted forthcoming publication in *International Small Business Journal*.

The content of these chapters has also been featured, among others, in *Nature* "U.S. Cancer Funding Creates Business as Well as Science", *New York Times* "U.S. Research Funds Often Lead to Startups", and *Max Planck Forschung* "Geschäftsideen aus dem Labor"

Chapter 2: Introduction and Overview

2.1 Introduction

It is often said that Silicon Valley is the cradle of Biotechnology. If however, the Bay Area is the cradle, then the parents of such high growth and innovation can only be academic scientists. Indeed, academic entrepreneurship in the United States has provided incredible amounts of highly innovative and successful enterprises. While Silicon Valley may be the most dazzling example of successful scientist entrepreneurship, many other regions and universities have also had highly academic entrepreneurship. Some of these examples are: Genentech, Google, Gatorade, Digital, Medtronic, Amgen, Biogen and Cellomics. In fact, over 50 scientist founded companies have graced the Fortune 500 club. Yet, as regions and policy makers turn to find new ways of growth and innovation, the notion of individual scientist entrepreneurs as pistons of economic growth, have never truly been entered into either the policy discussions or into economic literature.

These discussions have remained relatively obscure and enigmatic for several reasons. First, there is a clear lack of systematic data. Following scientist startups are incredibly costly for third parties. Part of the problem why there is little understanding of scientist startups is largely associated on a reliance on Technology Transfer Offices (TTOs). While the TTOs serve as the commercial mechanism for university knowledge to transform into commercial success, there is an underlying problem in their mission. These TTOs serves as financial arms for the university to

maximize licensing income, while substituting optimal commercialization whether through scientist entrepreneurship or other means.

The second problem is the TTOs are viewed as the primary meausre of university commercialization. Currently, the United States issues 40 billion dollars a year in federal grants, roughly 30 percent of total research and development (R&D) dollars spent in the United States per year. This public investment has left scholars and policy makers asking the question of what the rate of return is on this investment. Indeed, the rate is somewhere around 2.5% per year on public R&D. Yet, given this incredible investment, how can one justify such a low rate of return? The devil is in the details. By using almost exclusively TTO data, scientist startups, if indeed occurring, go unreported and therefore not included in the rate of return.

The third important problem relates to how academic knowledge spillovers into a mechanism for commercialization. Economic literature has relied heavily on the Solow and Romer growth models. These models have suggested that where there are high investments in knowledge, there will be higher rates of growth. But understanding exactly how these knowledge investments manifests themselves into growth have remained largely unclear for policy makers. Specifically, while knowledge generation is incredibly important, the path from knowledge creation to economic growth is not entirely clear. Many countries for example, have turned to high investments in knowledge but have had little success actually transforming knowledge into economic growth. This book will help to demonstrate that one path for knowledge to directly transform itself into growth are academic scientist startups. These startups inject high quality knowledge into the market and led to high economic growth.

2.2 Contribution to the Literature

There are three key areas of contribution. The first subject is quantifying and following scientist startup activity. As mentioned above, traditional mechanisms of measurement have relied on TTO data. This book offers an insight into scientist startup data using a unique dataset of scientist startups from 1998 to 2004. The contribution helps explain that there is indeed, much more commercialization occurring than previously thought. Secondly, it explains the route of commercialization. These routes are defined by whether a scientist startups up a company with TTO permission, whether the scientist startups a company that is not registered with the TTO and finally, licensing the technology through to TTO.

The second contribution is demonstrating that the only significant variables for scientists starting up are how heterogeneous her knowledge stock may be. Classifying the scientists registered patents using their forward and backward patent citations, the book offers a first look into how scientist startups actually occur. The book offers a clear suggestion that startups occur when a scientist has either a patent which has either a broad set of patent citations or a very narrow set of patent citations. The degree to which these patent citations are measured is used by applying Generality and Originality Herfindahl index.

The third contribution to the literature is demonstrating that there is indeed a substitution affect between starting up and licensing a patent. There is an open question as to what sort of commercialization occurs when scientist have a knowledge stock. The book will show that substation affects between starting up a company and licensing. This finding may have important affects for optimizing growth for the university, region and country.

2.3 Overview

The book will offer four scholarly chapters. Chapter three will offer several contributions. The chapter will first review the Romer and Solow model of economic growth and then offer the

Audretsch's "Knowledge Spillover of Economic Growth." The chapter will then proceed to offer a dataset which can qualitatively address the knowledge spillover of growth by using scientist data. The chapter then explains why academic commercialization may not be fully reported as previously thought. The chapter has offers three important conclusions. First the chapter finds that over 25 percent of scientists startup, second that there is a substitution affect between starting up and licensing, third that scientist have started up off of patents which are not registered with the TTO.

Chapter four offers a theoretical and empirical model as to why scientists startup firms. Controlling for a broad lists of usual suspects variables, the chapter attempts to categorize the scientist's knowledge stock. The chapter applies the Henderson *et al* (1998) model of patent classification. The model categorizes the knowledge stock of a patent in two ways. First it uses the patent's backward citation. These citations are where the patent cites its previous knowledge stock of off which it is built. This measure is defined by how *Original* the patent may be. For example, the patent may have very few backward citations drawing from different patent classification fields. The patent would therefore have a high originality score. The second measure is how often a patent is cited from future patents. If, for example, a patent is heavily cited from future issued patents, it would have a high *Generality* score. The paper then applies this metric to show that the only significant variables for starting a company are how heterogeneous her knowledge stock may be.

Chapter five explains geographic knowledge generation in scientists. Using the theory of knowledge spillover, the chapter explains how and where scientists generate their knowledge stock. The paper categorizes knowledge creation through where the scientist generates patents and what variables are important for a region to generate knowledge. The chapter finds that

several key variables are important for generating a high quality knowledge stock in a region. This knowledge stock for regions therefore becomes quite important to manifest itself into economic growth.

Chapter six taxonomizes the radical and incremental innovation literature. This paper offers a broad lens of understanding where the literature is with radical and incremental innovation. There is a broad understanding how radical and incremental literature has developed in scholarship. The chapter then attempts of find an *ex ante* approach to identifying radical innovation in patents. The conclusion finds the Dahlin Behrens method of identifying radical innovative patents may be the best method for scholars trying to identify radical innovations *ex ante*.

Chapter 3: The Knowledge Filter and Routes of Scientist Commercialization

3.1 Introduction

The enormous investment in physical plant and equipment propelled the United States to unprecedented post World War II prosperity. In the new era of globalization, both scholars and policy makers have been looking towards the country's unrivaled investment in research and knowledge to generate economic growth, employment and competitiveness in internationally linked markets for continued prosperity. However, it has been long recognized that investment in scientific knowledge and research alone will not automatically generate growth and prosperity. Rather, these new knowledge investments must penete what Audretsch et al. (2006) Acs and Armington (2006) and Acs et al. (2004) term "*the knowledge filter*" in order to contribute to innovation, competitiveness and ultimately economic growth. In fact, the knowledge filter impeding the commercialization

of investments in research and knowledge can be formidable. As Senator Birch Bayh warned, "A wealth of scientific talent at American colleges and universities — talent responsible for the development of numerous innovative scientific breakthroughs each year — is going to waste as a result of bureaucratic red tape and illogical government regulations…"[1] It is the knowledge filter that stands between investment in research on the one hand, and its commercialization through innovation, leading ultimately to economic growth, on the other.

Seen through the eyes of Senator Bayh, the magnitude of the knowledge filter is daunting, "What sense does it make to spend billions of dollars each year on government-supported research and then prevent new developments from benefiting the American people because of dumb bureaucratic red tape?"[2]

In an effort to penetrate such a formidable knowledge filter, the Congress enacted the Bayh-Dole Act in 1980 to spur the transfer of technology from university research to commercialization.[3] The goal of the Bayh-Dole Act was to facilitate the commercialization of university science. Assessments about the impact of the Bayh-Dole Act on penetrating the knowledge filter and facilitating the commercialization of university research have bordered on the euphoric:[4]

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[1] Introductory statement of Birch Bayh, September 13, 1978, cited from the Association of University Technology Managers Report (AUTM) (2004, p. 5).
[2] Statement by Birch Bayh, April 13, 1980, on the approval of S. 414 (Bayh-Dole) by the U.S. Senate on a 91-4 vote, cited from (AUTM) (2004, p. 16).
[3] Public Law 98-620
[4] Mowery (2005, p. 40-41) argues that such a positive assessment of the impact on Bayh-Dole is exaggerated, "Although it seems clear that the criticism of high-technology startups that was widespread during the period of pessimism over U.S. competitiveness was overstated, the recent focus on patenting and licensing as the essential ingredient in university-industry collaboration and knowledge transfer may be no less exaggerated. The emphasis on the Bayh-Dole Act as a catalyst to these interactions also seems somewhat misplaced."

> Possibly the most inspired piece of legislation to be enacted in America over the past half-century was the Bayh-Dole Act of 1980. Together with amendments in 1984 and augmentation in 1986, this unlocked all the inventions and discoveries that had been made in laboratories through the United States with the help of taxpayers' money. More than anything, this single policy measure helped to reverse America's precipitous slide into industrial irrelevance. Before Bayh-Dole, the fruits of research supported by government agencies had gone strictly to the federal government. Nobody could exploit such research without tedious negotiations with a federal agency concerned. Worse, companies found it nearly impossible to acquire exclusive rights to a government owned patent. And without that, few firms were willing to invest millions more of their own money to turn a basic research idea into a marketable product.[5]

An even more enthusiastic assessment suggested that:

> The Bayh-Dole Act turned out to be the Viagra for campus innovation. Universities that would previously have let their intellectual property lie fallow began filing for – and getting patents at unprecedented rates. Coupled with other legal, economic and political developments that also spurred patenting and licensing, the results seems nothing less than a major boom to national economic growth.[6]

The mechanism or instrument attributed to facilitating the commercialization of university scientist research has been the university Technology Transfer Office (TTO). While the TTO was not an invention of the Bayh-Dole Act, its prevalence exploded following passage of the Act in 1980. Not only does the TTO typically engage in painstaking collection of the intellectual property disclosed by scientists to the university but also the extent of commercialization emanating from the TTO. The Association of University Technology Managers (AUTM) collects and reports a number of measures reflecting the intellectual property and commercialization of its member universities. A voluminous and growing body of research has emerged documenting the impact of TTOs on the commercialization of university research. Most of these studies focus on various measures of output associated with university TTOs (Shane, 2004, Siegel and Phan, 2005; Mowery, 2005.) By most accounts, the impact on facilitating the commercialization of university science research has been impressive. For example, as Figure 1 shows, the number of patents registered by universities exploded subsequent to passage of Bayh-Dole.

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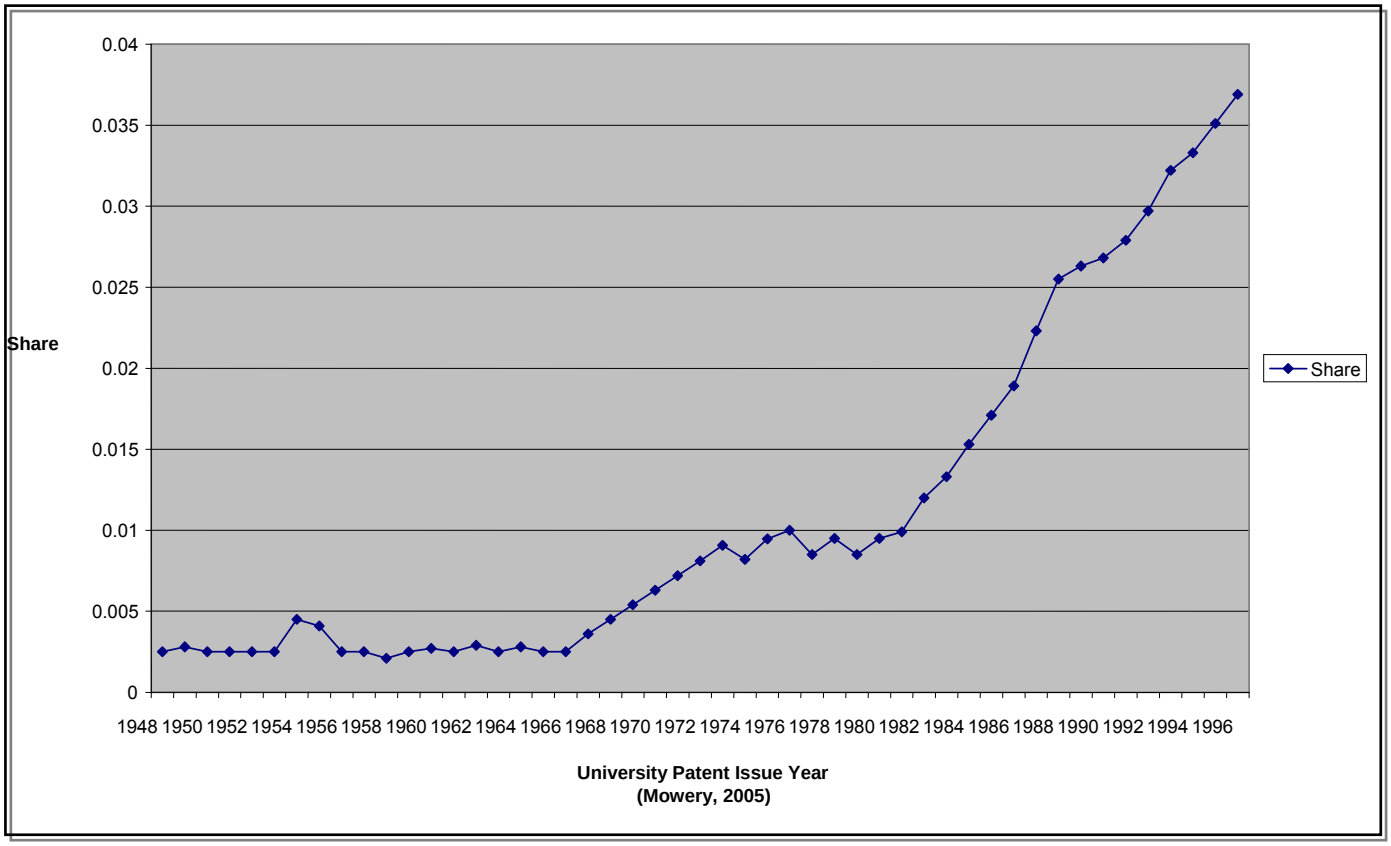
[5] "Innovation's Golden Goose," *The Economist*, 12 December, 2002.
[6] Cited in Mowery (2005, p. 64)

Figure 3.1.1: University Patents as a Share of All Patents with Domestic Assignees



However, there are compelling reasons to suspect that measuring and analyzing the commercialization of university research by relying solely upon the intellectual property disclosed to and registered by the TTOs *may lead to a systematic underestimation of commercialization and innovation emanating from university research*. The mandate of the TTO is not to measure and document all of the intellectual property created by university research along with the subsequent commercialization. Rather, what is measured and documented is the intellectual property and commercialization activities with which the TTO is involved. This involvement is typically a subset of the broader and more pervasive intellectual property being generated by university research and its commercialization which may or may not involve the TTO office (Thursby and Thursby, 2005). For example, in his exhaustive study on academic spinoffs, Scott Shane (2004, p. 4) warns:

> Sometimes patents, copyrights and other legal mechanisms are used to protect the intellectual property that leads to spinoffs, while at other times the intellectual property that leads to a spinoff company formation takes the form of know how or trade secrets. Moreover, sometimes entrepreneurs create university spinoffs by licensing university inventions, while at other times the spinoffs are created without the intellectual property being formally licensed from the institution in which it was created. These distinctions are important for two reasons. First it is harder for researchers to measure the formation of spinoff companies created to exploit intellectual property that is not protected by legal mechanisms or that has not been disclosed by inventors to university administrators. As a result, this book likely underestimates the spin-off activity that occurs to exploit inventions that are neither patented nor protected by copyrights. This book also underestimates the spin-off activity that occurs "through the back door", that is companies founded to exploit technologies that investors fail to disclose to university administrators.

There is little empirical evidence supporting Shane's admonition that relying solely upon the data registered with and collected by the TTO will result in a systematic underestimation of commercialization of university research. Such an underestimation of commercialization of university research may lead to an underestimation of the impact that spillovers of investment in university research have on innovation and ultimately economic growth.

If the spillover of knowledge generated by university research is viewed as essential for economic growth, employment creation, and international competitiveness in global markets, the systematic underreporting of university spillovers resulting from the commercialization of scientist research concomitantly may lead to severe policy distortions. Thus, rather than relying on commercialization reported by the TTO to measure and analyze the commercialization of university research, this chapter instead develops alternative measures based on the commercialization activities reported by scientists. In particular, the purpose of this chapter is to provide a measure of scientist commercialization of university research and identify which factors are conducive to scientist commercialization and which factors inhibit scientist commercialization. We do this by developing a new database measuring the propensity of scientists funded by grants from the National Cancer Institute (NCI) to commercialize their research as well as the mode of commercialization. We then subject this new university scientist-based data set to empirical scrutiny to ascertain which factors influence both the propensity and mode of scientist commercialization of university research.

As the second section of this chapter makes clear, there is no singular mode for scientist commercialization of research. Thus, in the third section, four distinct measures of scientist commercialization of research are introduced and explained: patents, SBIR awards, new firm startups and licenses. The main factors influencing the decision scientists make in choosing to commercialize their research are introduced in the fourth section. The four modes of commercialization are used to empirically identify the main determinants of scientist commercialization of research in the fifth section. Finally, in the last section, a summary and conclusion are provided. In particular, the results of this chapter suggest that

exclusive reliance upon measures of commercialization of university research published by the TTOs may systematically underestimate the contribution university research makes to commercialization, innovation and ultimately economic growth. University scientists appear to be more vigorously involved in entrepreneurial activity, in the form of starting new science-based firms, than had been perceived by relying solely upon the more easily accessible databases offered by the TTOs. In particular, over one-quarter of the scientists who were awarded a patent report that they have also started their own business, which is an astonishingly high rate of entrepreneurship based on comparable measures for other sub-groups of the population. Scientist entrepreneurship appears to be the sleeping giant of the commercialization of university research.

The modes of research commercialization used by NCI funded scientists are quite heterogeneous with respect to both prevalence and determinants. Reliance on publicly accessible databases, such as patents and SBIR, represent, at best, the tip of the iceberg of commercialization activities by NCI scientists. Other important commercialization modes, such as new-firm startups, can only be measured and analyzed by creating new systematic and comprehensive sources of data. In addition, both the prevalence and mode of commercialization vary considerably across scientists. Not all scientists are equally helped by the TTOs. Those that do report being helped by the TTO have a higher propensity to license their intellectual property to an existing firm but a lower propensity to start a new firm. By contrast, scientists reporting not being helped by the TTO have a lower propensity to license their intellectual property to existing firms but a higher propensity to start their own firm.

Scientists assigning their patents to the TTO, or those commercializing through the *TTO route*, exhibit a higher propensity to commercialize their research by licensing but not by starting a new firm. By contrast, those scientists choosing what we term as the *entrepreneurial route* to commercialize their research, in that they do not assign all of their patents to the TTO, exhibit a higher propensity to start a new firm but a lower likelihood of licensing their intellectual property.

Social capital and networks, as measured by the extent to which a scientist engages in industry co-publication, co-patenting with other NCI scientists, and serving on a company board of directors or scientific advisory board (SAB) clearly promote the likelihood of commercialization, particularly for the mode of entrepreneurship. The impact of social capital on entrepreneurial activity is more pronounced for scientists not helped by the TTO, suggesting that social networks may be an additional mechanism to the TTO in facilitating the commercialization of university research.

3.2 Scientist Commercialization of University Research

Why and how will scientists decide to commercialize their scientific research? One answer to the question of why was provided by Stephan and Levin (1992), who suggest that a scientist will choose to commercialize research if this furthers her life goals. But how should a scientist best appropriate the value of her human capital? That is, what mode of commercialization is most appropriate for a given scientist with a stock of knowledge and scientific human capital? Alternatives abound, such as working full time or part time with an incumbent firm, licensing the knowledge to an incumbent firm, starting a new firm, or joining an existing firm.

Previous studies have identified several major modes of scientist commercialization. Ownership of intellectual property, in the form of patented inventions, is an important step in the commercialization process. Jaffe and Lerner (2001), Henderson, Jaffe and Trajtenberg (1998) and Jaffe, Trajtenberg and Henderson (1993) all identify patents as an important mode by which scientists commercialize their research.

Thursby and Jensen (2005), Thursby, Jensen and Thursby (2001) and Jensen and Thursby (2001) identify both patents and the licensing of patents as important modes of scientist commercialization. In particular, Thursby and Jensen (2004, p. 4) employ a principal-agent framework in which the university administration is the principal and the faculty scientist is the agent, and identify that the "whether or not the researcher remains in the university, and if so her choice of the amount of time to spend on basic and applied research, is complicated by the fact that she earns license income and prestige both inside and outside the university."

Several studies have identified the important role that the Small Business Innovation Research (SBIR) program can play as a mode of scientist commercialization (Lerner, 1999; Audretsch, Link and Scott, 2002). Toole and Czarnitzki (2005) find that only eight percent of the unique Principle Investigators (PIs) were awarded an SBIR grant from the U.S. Department of Health and Human Services between 1983 and 1996, which suggests that the SBIR may perhaps be an important instrument of public policy, but not a prevalent mechanism for commercializing university scientist research.

A different mode of commercialization involves academic entrepreneurship, where the scientist starts a new firm to bring her research to the market. Louis, Blumenthal,

Gluck and Sioto (1989) identify the role of individual characteristics and attitudes, along with the norms of scientific peer groups as important factors in influencing the scientists' decision to commercialize their research in the form of a new-firm startup. Similarly, Shane (2004), Lockett, Siegel, Wright and Ensley (2005), Zucker, Darby and Brewer (1997), O'Shea, Allen, Chevalier and Roche (2005) and Audretsch and Stephan (1996 and 1999) focus on the role that new-firm startups play as a conduit for commercializing scientific research. Thus, research has pointed to four principle modes of scientist commercialization: patents, SBIR, licenses, and new-firm startups.

3.3 Measurement Issues

The commercialization activity of university scientists was measured by starting with those scientists awarded a research grant by the National Cancer Institute between 1998 and 2002. Of those research grant awards, the largest twenty percent, which corresponded to 1,693 scientist awardees, were taken to form the database used in this chapter. The National Cancer Institute (NCI) awarded a total of $5,350,977,742 to the 1,693 highest funded quintile of United States-based scientists from 1998 to 2002.

Since the focus of this chapter is on the propensity for scientists to commercialize their research, commercialization must be operationalized and measured. Based on the literature identified in the previous section, five main measures of scientist commercialization are used, which reflect five different modes by which scientists can and do commercialize their research. These are (1) patenting inventions, (2) issuing licenses, (3) receiving an SBIR grant to obtain funding for an innovative small business, (4) starting a new firm, and (5) selling a patent. In fact, there certainly are additional modes of commercialization remaining unexplored by this chapter. Examples include non-patenting

scientists who start a new firm, the mobility of students or faculty from the university to the private sector, consulting contracts, and informal interactions. The absence of these types of modes of commercialization of university research by scientists from this chapter does not suggest that they are unimportant, but rather that they are difficult to measure.

Based on these five different measures reflecting distinct modes of scientist commercialization of research, an NCI awardee database was created to answer the question, "Why do some scientists commercialize while others do not?"

3.3.1 Patents

The first measure of commercialization of research by an NCI award scientist is inventions which are patented. The propensity for NCI award scientists to patent was analyzed by obtaining patent data from the United States Patent and Trademark Office (USPTO).[7] The patent database spans 1975 to 2004 and contains over three million patents.

To match the patent records with the 1,692 NCI recipient scientists, Structured Query Language (SQL) and Python programming languages were written to extract and manipulate data. A match between the patentee and NCI awardee databases was considered to be positive if all four of the following necessary conditions were met:

(1) A positive match was made with the first, middle, and last name. If, for example, the scientist did not have a middle name listed on either the NCI award database

[7] On July 25th, 2005, Jim Hirabashi of the Office of Electronic Information Products at the patent Technology Monitoring Division was sent a request order for the "U.S. Patent CDs" from 1975 to 2004.

or the patent database, but did have a positive first and last name, this first condition was considered to be fulfilled.

(2) The second criterion involved matching the relevant time periods between the two databases. Observations from both databases were matched over the time period 1998-2004, which corresponds to the initial year in which observations were available from the NCI database (1998-2002) and the final year in which patents were recorded in the patent database (1975-2004). Because applications of patents may take anywhere from three months to two years to be issued, the 2003 and 2004 USPTO patent records were included in our query. Issued patents from 1998 to 2004 by NCI scientists fulfilled the second criterion.

(3) The third criterion was based on location. If the patentee resided within an approximate radius of 60 miles from the geographic location of the university, the third condition was fulfilled.

(4) The fourth criterion was based on USPTO patent classification. Using the USPTO patent classification code, all patents were separated into respective coding groups. Patents which did not fall under the traditional categories of biotechnology were identified. All non biotech patents were evaluated and patents such as “Bread Alfalfa Enhancer” were rejected as an NCI scientist patent (see Appendix A for a distribution of patent categories).

Based on these four match criteria, a subset of 398 distinctly issued patentees were identified between 1998 and 2004 with a total of 1,204 patents.

3.3.2 Survey Implementation

After identifying the full set of NCI patentees, a survey instrument was designed with two main criteria:

(1) To maximize information without overly burdening the nation's top medical scientists. Reducing the time and input burden imposed on the scientist was considered to have a favorable impact on the response rate; and

(2) To maximize information revealing the creation of intellectual property and its subsequent commercialization through licensing and entrepreneurial activity, while at the same time respecting the need for scientist confidentiality and not confronting the scientist with information requests that might compromise such confidentiality.

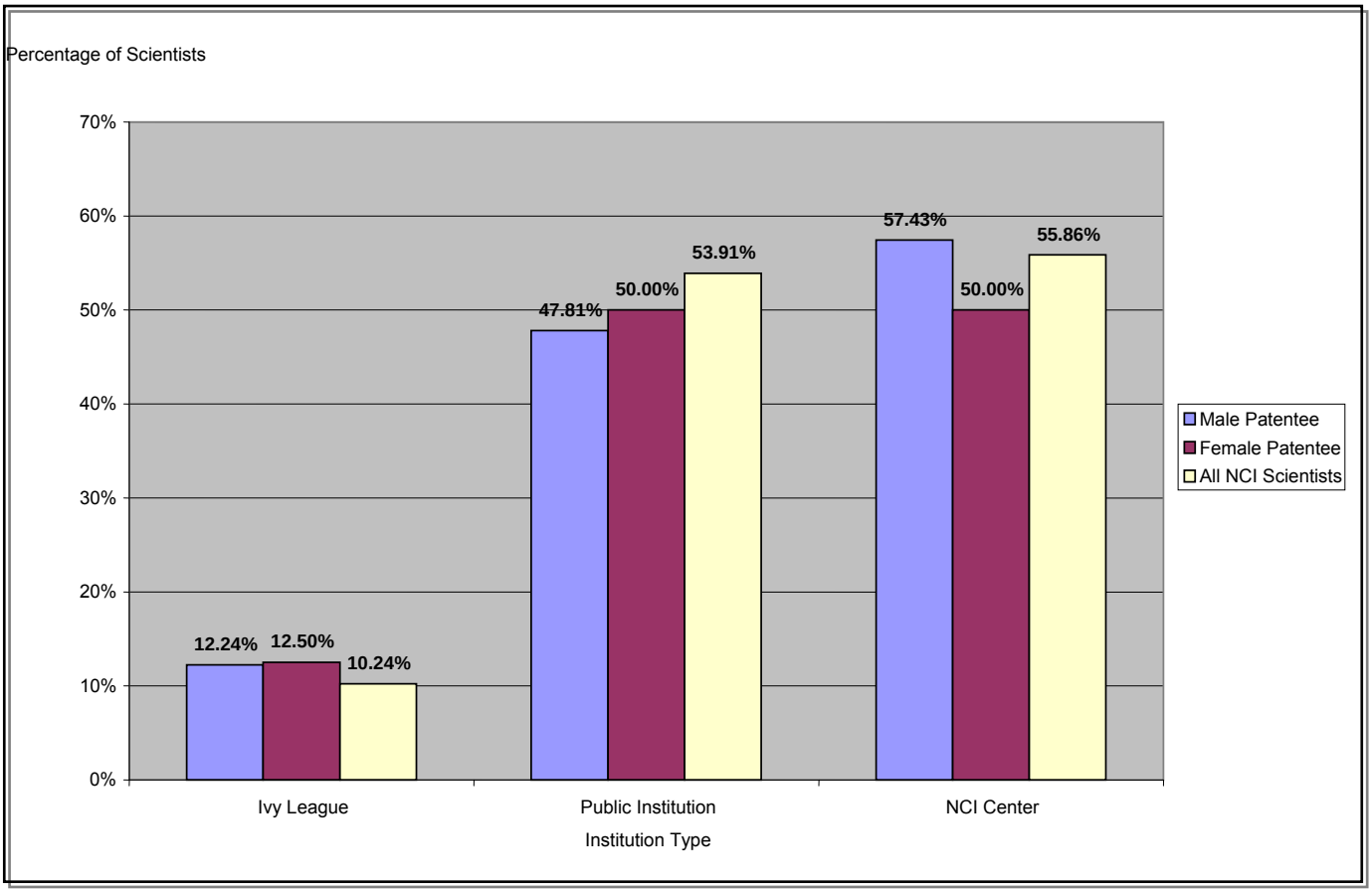
Based on these two criteria, an interview instrument was designed probing four subgroups of issues: licensing, entrepreneurship, social capital and the role of the TTO.

The question in the licensing section asked if the scientist has licensed. The question contained in the entrepreneurship section identified whether the scientist started a new firm. The questions concerning social capital asked the scientist if she sat on any industry science advisory boards (SAB) or board of directors, the extent to which the NCI grant award facilitated commercialization, along with other sources of major funding received from a governmental agency. The questions concerning the influence of the TTO asked whether the university's TTO "directly helped you to commercialize your research between 1998 to 2004".

The 398 patenting scientists were “Googled” to obtain their e-mail and telephone information. The records could, generally, be found by typing their full name, university and the word “oncology”. The ensuing patentee e-mail accounts and telephone numbers were then collected and registered in the scientist database. Of those 398 scientists identified in the database, 146 responded. Six respondents indicated that they had not patented the ascribed patents, therefore reducing the number of patentees to 392. The number of respondent, therefore, reflects a response rate of 36 percent. NCI awarded scientists commercializing through patents varied from those not commercializing in several important ways.

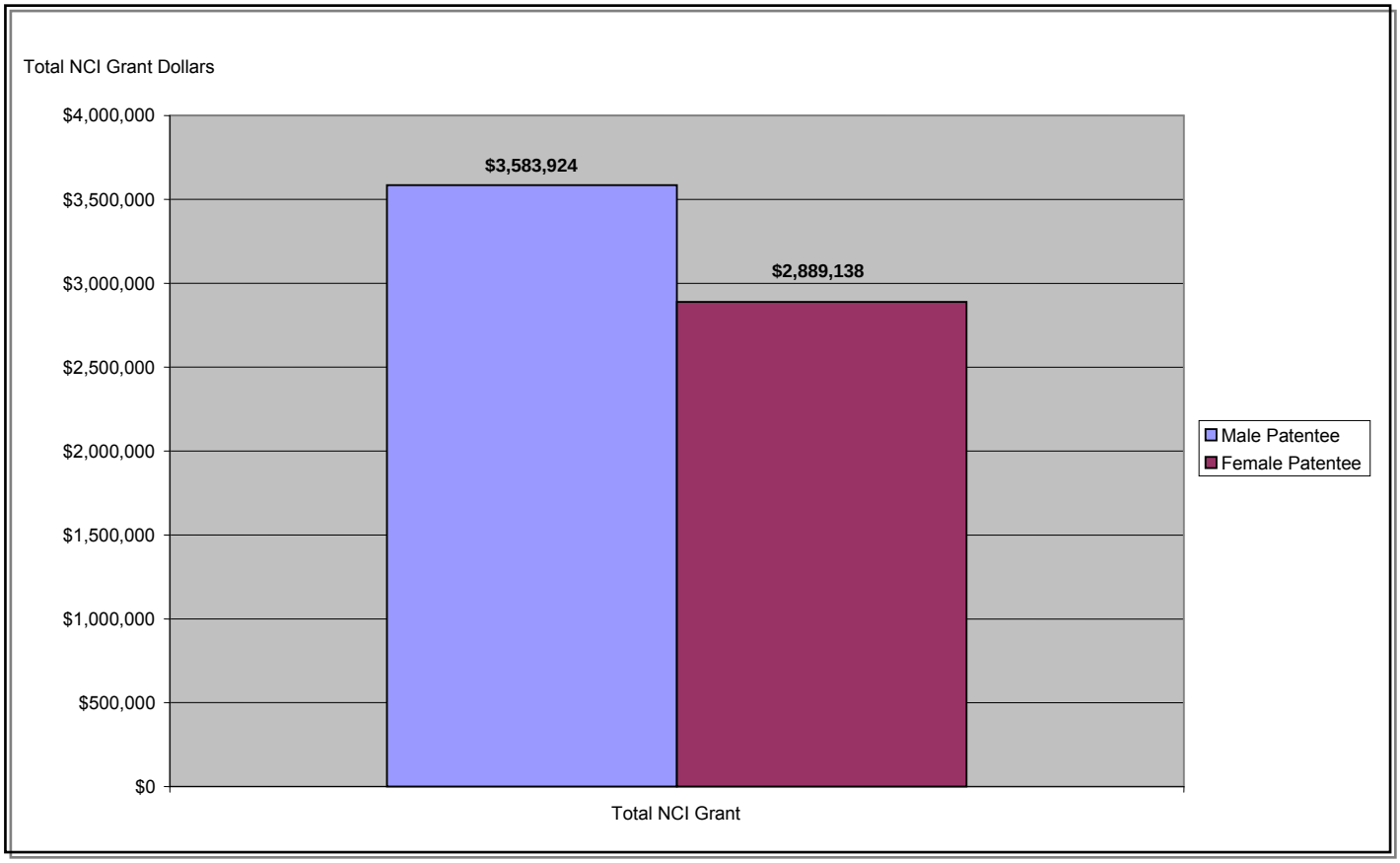
Figure 2 shows that the distribution of patentees varied both across institutions as well as by gender. In Ivy League and public institutions, the propensity for females to patent exceeded that of their male colleagues. Male scientists at universities with an NCI Center, however, had a greater propensity to patent.

Figure 3.2: Patents by Institution and Gender



Gender also clearly played a role in a number of other dimensions. For example, Figure 3 shows that the mean amount of the NCI grant was considerably greater for male scientists who patented than for their female counterparts.

Figure 3.3: NCI Grant Award by Gender for Patenting Scientists



3.3.4 Small Business Innovation Research (SBIR)

The second measure of scientist commercialization involves scientists awarded SBIR grants to finance innovative small businesses. Enactment of the SBIR program in the early 1980s was a response to the loss of American competitiveness in global markets. Congress mandated each federal agency with allocating around four percent of its annual budget to funding innovative small firms as a mechanism for restoring American

international competitiveness (Wessner, 2000). SBIR provides a mandate to the major R&D agencies in the United States to allocate a share of the research budget to innovative small firms. In 2001 the SBIR program amounted to around $1.4 billion. The SBIR consists of three phases. Phase I is oriented towards determining the scientific and technical merit along with the feasibility of a proposed research idea. A Phase I Award provides an opportunity for a small business to establish the feasibility and technical merit of a proposed innovation. The duration of the award is six months and cannot exceed $70,000. Phase II extends the technological idea and emphasizes commercialization. A Phase II Award is granted to only the most promising of the Phase I projects based on scientific/technical merit, the expected value to the funding agency, company capability and commercial potential. The duration of the award is a maximum of 24 months and generally does not exceed $600,000. Approximately 40 percent of the Phase I Awards continue on to Phase II. Phase III involves additional private funding for the commercial application of a technology. A Phase III Award is for the infusion of a product into the commercial market. Private sector investment, in various forms, is typically present in Phase III. Under the Small Business Research and Development Enhancement Act of 1992, funding in Phase I was increased to $100,000 and in Phase II to $750,000.

The SBIR represents about 60 percent of all public entrepreneurial finance programs (Lerner, 1999). Taken together, the public small-business finance is about two-thirds as large as private venture capital. In 1995, the sum of equity financing provided through and guaranteed by public programs financing Small and Medium Enterprises was $2.4 billion, which amounted to more than 60 percent of the total funding disbursed by traditional venture funds in that year (Lerner, 1999). Equally as important, the emphasis on

SBIR and most public funds is on early stage finance, which is generally ignored by private venture capital. Some of the most innovative American companies received early stage finance from SBIR, including Apple Computer, Chiron, Compaq and Intel.

There is compelling evidence that the SBIR program has had a positive impact on economic performance in the U.S. (Wessner, 2000; Audretsch, 2003; Audretsch, Weigand and Weigand, 2002; and Lerner, 1999). The relevant agency awarding SBIR grants to scientists for commercialization of science involving cancer research is the National Institutes of Health. This does not preclude the possibility that SBIR awards could be made to scientists engaged in cancer research from other agencies. The SBIR award data from the NIH between 1998 and 2002 is listed on the NIH home webpage at http://grants.nih.gov/grants/funding/award_data.htm.[8] The information provided in each SBIR record in the NIH database includes the phase type of the award, fiscal year, state, formal organizational name, award, application type, grant number, principle investigator (PI), project title, contact name, contact e-mail, organization line, address, research partner, and whether the SBIR award was a new grant.

Between 1998 and 2002, 6,461 SBIR awards were granted to 3,230 distinct scientists from the NIH. The Principle Investigator (PI) of each SBIR award was then matched to the 1,693 NCI scientists using an SQL program. Those scientists included in both the SBIR database as a PI and an NCI award recipient, and that were matched by last and first names, were considered for this chapter. The resulting 34 matches were then subjected to a location criterion: the address of the PI listed in the SBIR grant was matched

[8] The acting director of the Office of Extramural Research at NIH, Joanne Goodnight, and the "general help e-mail address" were twice e-mailed and called to confirm the veracity of the website's content. Neither the director nor any staff responded to confirmation requests.

to the NCI scientists using a 75 mile radius to the respective university. If the location was outside of a 75 mile radius, the match was not considered to be valid. For example, there are four PI scientists with the name David Johnson listed in the NIH SBIR database. Their addresses are given as Hamilton, Montana; Lawrence, Kansas; San Diego, California and Seattle, Washington. None of these addresses matched the two NCI recipients named David Johnson from Houston, Texas and Nashville, Tennessee. The geography criterion reduced the number of confirmed SBIR-NCI recipients to eight. Thus, one of the most striking insights to emerge in this chapter is that use of the SBIR is not a prevalent or even common mode of commercialization by scientists receiving NCI awards.

The most striking feature of the (small) group of SBIR scientists is that they tend to be highly accomplished in terms of research output and reputation. As Table 3 shows, their citations were about three times as great as the overall group of NCI scientists. Most of the SBIR scientists are employed at NCI Centers.

Interestingly, the mean value of their NCI award was relatively low. Thus, there are considerable reasons to view those scientists funded by the NCI who also obtain an SBIR grant as being outliers.

3.4 Determinants of Scientist Commercialization

3.4.1 Main Factors

A number of theories and hypotheses have posited why some scientists choose to commercialize research while others do not, and some compelling insights have been garnered through previous empirical studies. These include the gender, age, experience and also reputation of the scientist, as well the role of scientific human capital and resources, and the regional and university contexts, which highlight the role of geographically bounded spillovers and institutional incentives.

In addition to these control variables, which have already been probed in a number of studies examining factors that influence the propensity for a scientist to engage in commercialization activities, we also include a number of factors that can only be measured with the type of scientist-based data set constructed and described in the previous section. These additional factors include not just scientific human capital, but social capital as well, along with the role of the TTO, and the commercialization route selected by the scientist.

3.4.2 Social Capital

Social capital refers to meaningful interactions and linkages the scientist has with others. While *physical capital* refers to the importance of machines and tools as a factor of production (Solow, 1956), the endogenous growth theory (Romer 1986, 1990; Lucas 1988) puts the emphasis on the process of knowledge accumulation, and hence the creation of *knowledge capital*. The concept of *social capital* (Putnam, 1993 and Coleman, 1988) can

be considered a further extension because it adds a social component to those factors shaping economic growth and prosperity. According to Putnam (2000, p.19):

> Whereas physical capital refers to physical objects and human capital refers to the properties of individuals, social capital refers to connections among individuals – social networks. By analogy with notions of physical capital and human capital – tools and training that enhance individual productivity – social capital refers to features of social organization, such as networks that facilitate coordination and cooperation for mutual benefits.

A large and robust literature has emerged attempting to link social capital to entrepreneurship (Aldrich and Martinez, 2003; Aldrich, 2005; and Thorton and Flynn, 2003). According to this literature, entrepreneurial activity should be enhanced where investments in social capital are greater. Interactions and linkages, such as working together with industry, are posited as conduits not just of knowledge spillovers but also for the demonstration effect providing a flow of information across scientists about how scientific research can be commercialized (Thursby and Thursby, 2004). Thus, the social capital of a scientist is posited to be conducive to the commercialization of research.

3.4.3 Scientist Commercialization Route

Scientists choose to commercialize their research through two different routes. They can assign their patents to the university's TTO, which we refer to as the *TTO route*. Alternatively, they can choose what we term the *entrepreneurial route* of commercialization. The *entrepreneurial route* to scientist commercialization refers to those scientists who do not assign all of their patents to the university's TTO. Of the NCI patenting scientists, 70 percent assigned all of their patents to their university TTO and 30 percent chose the *entrepreneurial route* to commercialize their research.

Whether or not the particular commercialization route influences the commercialization mode is an empirical question best left for the data analysis to answer.

3.4.4 Technology Transfer Office

The TTO has a mandate to facilitate and promote the commercialization of university science. As the President of the Association of American Universities observed:

> Before Bayh-Dole, the federal government had accumulated 30,000 patents, of which only 5% had been licensed and even fewer had found their way into commercial products. Today under Bayh-Dole more than 200 universities are engaged in technology transfer, adding more than $21 billion each year to the economy[9]

The Commission of the U.S. Patent and Trademark Office claimed:

> In the 1970s, the government discovered that inventions that resulted from public funding were not reaching the marketplace because no one could make the additional investment to turn basic research into marketable products. That finding resulted in the Bayh-Dole Act, passed in 1980. It enabled universities, small companies, and nonprofit organizations to commercialize the results of federally funded research. The results of Bayh-Dole have been significant. Before 1981, fewer than 250 patents were issued to universities each year. A decade later universities were averaging approximately 1,000 patents a year.[10]

This, presumably, would suggest that the TTO is expected to have a positive impact on scientist commercialization of university research.

On the other hand, there are reasons to suspect that *involvement of the TTO might not have the same impact across all modes of commercialization*. For example, one response from the in-depth scientist interviews conducted in this chapter revealed:

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[9] Cited in Mowery (2005, p. 65)
[10] Cited in Mowery (2005, p. 65)

> I refuse to work with the TTO. They have destroyed any of my commercial work. I have given up on any sort of commercial enterprises with my TTO. I don't think any of my colleagues have attempted to commercialize anything here for the past six years.[11]

Similarly, a different scientist shared that "My commercial spirit stops at the TTO door."[12]

However, it is important to emphasize that such views are not reflective of all scientists. For example, a different scientist responded that "Our university technology transfer office does ok. They occasionally have some problems with some technical issues, but over all, they have served me for the better."[13]

Thus, the actual impact of the TTO on scientist commercialization in general and on the specific commercialization modes of entrepreneurship and licensing is a question best left to empirical scrutiny.

3.4.5 Scientific Human Capital

An implication of the knowledge production function is that those scientists with greater research and scientific prowess have the capacity for generating greater scientific output. But how does scientific capability translate into observable characteristics that can promote or impede commercialization efforts? Because the commercialization of scientific research is particularly risky and uncertain (Audretsch and Stephan, 2000), a strong scientific reputation, as evidenced through citations, provides a greatly valued signal of scientific credibility and capability to any anticipated commercialized venture or project. This suggests a hypothesis linking measures of the quality of the scientist, or her scientific reputation as measured by citations, to commercialization.

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[11] NCI scientist quote taken on January 25th, 2005
[12] NCI scientist quote taken January 15th, 2005
[13] NCI scientist quote taken on October 12th, 2005

3.4.6 Scientific Resources

The question of why some contexts generate more innovative activity than others has been the subject of considerable research in economics. While the conventional approach to analyzing innovative output at the microeconomic level has been at the level of the firm, it conceivably can apply to the unit of analysis of the individual knowledge worker, such as a scientist. The fundamental questions addressed in this literature are: *"What do firms do to generate innovative output?"* and "*Why are some firms more innovative than others?"* For the unit of observation of the individual scientist, this question translates into: "*What do scientists do to generate innovative output?*" and "*Why are some scientists more engaged in commercialization of scientific activity than others?*"

In what Zvi Griliches (1979) formalized as the *model of the knowledge production function*, knowledge generating inputs are linked to innovative outputs. Griliches, in fact, suggested that it was investments in knowledge inputs that would generate the greatest yield in terms of innovative output.

This might suggest a hypothesis that the propensity for a scientist to engage in commercialization activity is positively related to the amount of the award, on the grounds that a greater award amount, *ceteris paribus*, represents a greater investment in new knowledge.

3.4.7 Scientist Life-Cycle

A large literature has emerged focusing on what has become known as the appropriability problem. The underlying issue revolves around how firms which invest in

the creation of new knowledge can best appropriate the economic returns from that knowledge (Arrow, 1962). Audretsch (1995) proposed shifting the unit of observation away from exogenously assumed firms to individuals — agents with endowments of new economic knowledge. When the lens is shifted away from the firm to the individual as the relevant unit of analysis, the appropriability issue remains, but the question becomes; *"How can scientists with a given endowment of new knowledge best appropriate the returns from that knowledge?"* Levin and Stephan (1991) suggest that the answer is, *It depends – it depends on both the career trajectory as well as the stage of the life-cycle of the scientist.*

The university or academic career trajectory encourages and rewards the production of new scientific knowledge. Thus, the goal of the scientist in the university context is to establish priority. This is done most efficiently through publication in scientific journals (Audretsch and Stephan, 2000). By contrast, with a career trajectory in the private sector, scientists are rewarded for the production of new economic knowledge, or knowledge which has been commercialized in the market, but not necessarily new scientific knowledge *per se*. In fact, scientists working in industry are often discouraged from sharing knowledge externally with the scientific community through publication. As a result of these differential incentive structures, industrial and academic scientists develop distinct career trajectories.

The appropriability question confronting academic scientists can be considered in the context of the model of scientist human capital over the life-cycle. Scientist life-cycle models suggest that early in their careers scientists invest heavily in human capital in order to build a scientific reputation (Levin and Stephan, 1991). In the later stages of their career,

the scientist trades or *cashes in* this reputation for economic return. Thus, early in her career, the scientist invests in the creation of scientific knowledge in order to establish a reputation that signals the value of that knowledge to the scientific community.

With maturity, scientists seek ways to appropriate the economic value of the new knowledge. Thus, academic scientists may seek to commercialize their scientific research within a life-cycle context. The life-cycle model of the scientist implies that, *ceteris paribus*, scientist age should play a role in the decision to commercialize. In the early stages of her career, a scientist will tend to invest in her scientific reputation. As she evolves towards maturity and the marginal productivity of her scientific research starts to hit diminishing returns, the incentive for cashing in through commercialization becomes greater.

Scientists working in the private sector are arguably more fully compensated for the economic value of their knowledge. This will not be the case for academic scientists, unless they cash out, in terms of Dasgupta and David (1994), by commercializing their scientific knowledge. This suggests that academic scientists seek commercialization within a life-cycle context. This life-cycle context presents two distinct hypotheses: both age and scientific reputation should influence the decision of a university scientist to engage in commercialization activities.

3.4.8 Locational and Institutional Contexts

Scientist location can influence the decision to commercialize for two reasons. First, as Jaffe (1989), Audretsch and Feldman (1996), Jaffe, Trajtenberg and Henderson (1993), and Glaeser, Kallal, Sheinkman and Shleifer (2002) show, knowledge tends to spill

over within geographically bounded regions. This implies that scientists working in regions with a high level of investments in new knowledge can more easily access and generate new scientific ideas. This suggests that scientists working in knowledge clusters should tend to be more productive than their counterparts who are geographically isolated. As Glaeser, Kallal, Scheinkman and Shleifer (1992, p. 1,126) have observed, "Intellectual breakthroughs must cross hallways and streets more easily than oceans and continents."

A second component of externalities involves not the technological knowledge, but rather behavioral knowledge. As Bercoviz and Feldman (2004) show for a study based on the commercialization activities of scientists at Johns Hopkins University and Duke University, the likelihood of a scientist engaging in commercialization activity, which is measured as disclosing an invention, is shaped by the commercialization behaviour of the doctoral supervisor in the institution where the scientist was trained, as well as the commercialization behaviour and attitudes exhibited by the chair and peers in the relevant department. Similarly, based on a study of 778 faculty members from 40 universities, Louis et al. (1998) find that it is the local norms of behaviour and attitudes towards commercialization that shape the likelihood of an individual university scientist to engage in commercialization activity, in their case by starting a new firm.

Thus, the location and institutional contexts can influence the propensity for scientists to engage in commercialization activities by providing access to spatially bounded knowledge spillovers and by shaping the institutional setting and behavioural norms and attitudes towards commercialization.

3.5 Estimation of a Probit Model

To shed light on the question; "*Why do some scientists commercialize their scientific research while others do not*?" a probit model was estimated for the unit of observation of the scientist identified in the NCI database where the dependent variable takes on the value of one if she has commercialized over the time period 1998-2004 and zero if she has not. As the previous section emphasized, there is no singular mode for scientist commercialization. Rather, scientists select across multiple modes of possible commercialization. Thus, the probit model was estimated for each of the main modes of commercialization – patents, licenses, new-firm startups, patent selling and SBIR discussed in the previous section. Each of these measures of commercialization is described and defined in Table 1. Because the sample size is large enough to warrant empirical estimation with a probit model, only four of the measures of commercialization- patents, licensing and startups, and commercializing -- could be used.

Table 3.1: Variable Description of The Modes of Commercialization

Dependent Variables	Description
Patenting Scientist	National Cancer Institute grant awarded scientist who patented from 1998 to 2004 (Sample 1693, *N*=392)
SBIR Grant Scientist	Scientist awarded an SBIR grant (Sample 1693, *N*=8)
Startup Scientist	Scientist who responded to survey question that she started new firm (Sample=140, *N*=36)
Licensing Scientist	Scientist who responded to survey question that she licensed (Sample=140, *N*=71)
Commercializing Scientist	Scientist who patented or licensed (Sample=140, N=83)
Patent Selling Scientist	Scientist who sold ownership of the patent (Sample=75, N=4)[14]

[14] Selling patents are dropped from the analysis due to the small number of patent sellers (N=4).

The previous section suggests five different types of factors shaping the decision by a scientist to commercialize her research: social capital, the TTO, resources, age, scientific human capital (quality), nature of the university, and location. These factors are empirically operationalized through the following measures:

Social Capital

Co-patents – This variable reflects the extent of social capital and linkages between scientists by measuring the number of patents where two NCI scientists shared a patent. It is expected to have a positive coefficient, reflecting the propensity for social capital to be positively related to scientist commercialization of research.

Board – This is a binary variable taking on the value of one if the scientist has sat on a scientific advisory board or the board of directors of a firm. A positive coefficient would indicate that social capital, as reflected by board membership, is conducive to the commercialization of university research.

Industry Co-publications – This variable reflects social capital and linkages between university scientists and their counterparts in industry and is measured as co-authorship between a university scientist and an industry scientist in the Science Citation Index using the Institute for Scientist Information (ISI) Web of Science citation database. The total count of papers coauthored with an industry scientist between the years of 1998 and 2004 was estimated using several search queries on the ISI database. Using the address fields within each publication value in the ISI database, Co-publications were identified as a private sector address if the terms *Co, Co Ltd, Inc,* or *LLC,* were found. Also, in order to not misidentify the University of **Co**lorado as a company, for example, the query forced

the previously mentioned search terms to be standalone words, and not part of larger words. The coefficient is expected to be positive, which would reflect that university-industry scientist interactions are conducive to commercialization.

Industry Co-publication Asia -- This variable reflects social capital and linkages between university scientists and their counterparts located in Asia. Scientist linkages are measured as co-authorship between a university and an Asian scientist in the Science Citation Index using the ISI Web of Science citation database. Using the address fields within each publication value of the ISI Web of Science citation index *Industry Co-publication Asia* was identified if any of the terms of *China*, *Japan*, *South Korea* and *Taiwan* were found in the ISI Web of Science address field. A binary variable was then created, taking on the value of one for all scientists with linkages in Asia and zero otherwise. The coefficient is expected to be positive which would reflect that interactions involving scientists located in Asia are conducive to commercialization.

Scientist Commercialization Route

Non TTO Assignee – This is a binary variable taking on the value of one for scientists who had at least one patent which was not assigned to their universities' TTO office, reflecting the TTO route to commercialization. According to the U.S. Patent Trademark Office a patent assignee may be defined as "The assignee, when the patent is assigned to him or her, becomes the owner of the patent and has the same rights that the original patentee had. The statute [of law] also provides for the assignment of a part interest, that is, a half interest, a fourth interest etc., in a patent."[15] Scientists not assigning a patent to their TTO are

[15] http://www.uspto.gov/web/offices/pac/doc/general

considered to choose the *entrepreneurial route* to commercialize their research. A positive coefficient would indicate that those scientists who have at least one non TTO assignee patent have a higher propensity to commercialize their research. A negative coefficient would suggest that those scientists choosing the *TTO route* are more likely to engage in commercializing their research.

Of the 392 patentees, 29.80 percent were determined to choose the entrepreneurial route to commercialization, in that they assigned at least one patent not to their university. For example, seven out of eight of Dr. Jon Doe's patent assignees belonged to the *Curators of the University of Missouri*. The eighth patent was assigned ownership to Pfizer, Inc. and not to the *Curators of the University of Missouri*. This example is typical of the *entrepreneurial route* to commercialization and was therefore categorized as a *Non TTO Patent Assignee*. In comparison, 70.20 percent of the 392 patenting scientist selected the TTO route to commercialization, in that they assigned all of their patents to the TTO.

Technology Transfer Office

TTO Helpful – This is a binary variable taking on the value of one for scientists who responded to the survey that their TTO directly helped them commercialize their research and zero otherwise. A positive coefficient would indicate that those scientists reporting that their TTO was helpful in commercializing their research have a higher propensity to commercialize their research.

TTO Age – This variable reflects the TTO age and is measured as the year in which the TTO was founded at the particular university. The measure is taken from the AUTM

database. Because more recent years indicate a younger TTO, a positive coefficient would reflect a negative relationship between TTO age and the propensity for scientists to commercialize.

TTO Employees – This variable measures the mean number of employees per year responsible for license and patent acquisitions. The measure is taken from the AUTM database. A positive relationship would suggest that a greater commitment of TTO employee resources yields a higher propensity for scientists to commercialize their research.

TTO Licensing Commitment – Dividing the number of employees dedicated to licensing technology by the number of administrative employees reflects the commitment of the TTO to licensing relative to other TTO functions. This measure is derived from the AUTM database. A positive relationship would suggest that allocating a greater share of TTO employees to licensing would increase scientist commercialization.

TTO Efficiency – The mean number of patents applied for is divided by the number of issued patents, which reflects the efficiency of the TTO. This measure is derived from the AUTM database. A positive coefficient would reflect that a higher yield of patent applications resulting in patents granted lead to greater scientist commercialization.

Scientific Human Capital

Scientist Citations – A specific computer program was designed to measure the citations of NCI scientists between 1998 and 2004 through the "Expanded Science Citation Index." A higher number of citations reflects a higher level of human capital and scientific reputation

(Audretsch and Stephan, 2000). A positive coefficient would reflect that the likelihood of commercialization is greater for more productive scientists.

Prior Patents – This variable is measured as the number of patents issued to a scientist prior to 1998. The variable is included to control for previous experience with commercialization activities. A positive coefficient would suggest that, even after controlling for the influences of social capital, the TTO, scientific human capital, resources, age, and locational and institutional contexts, previous commercialization experiences elevates the propensity of a scientist to engage in commercialization activity.

Resources

NCI Grant – This variable is the mean total NCI grant awarded to a scientist between 1998 and 2002. If external funding of scientific research is conducive to commercialization, a positive coefficient of the *NCI Grant* would be expected.[16]

Government Funding – This binary variable takes on the value of one for scientists responding to the scientist survey that they received additional funding in excess of $750,000 from government sources and zero otherwise. A positive coefficient would indicate that an increase in funding from the government facilitates scientist commercialization.

[16] The NCI grant coefficient was multiplied by 1,000 for presentation purposes

Scientist Life-Cycle

Scientist Age -- The age of the scientist, measured in terms of years, was obtained from the scientist survey. The Life-Cycle hypothesis of Stephan and Levin (1990) suggests a positive coefficient, which would reflect a higher propensity for more mature scientists to engage in commercialization activities.

Gender – This is a dummy variable assigned the value of one for males (1,310) of the overall 1,693 included in the NCI database. The gender of each scientist was obtained by "Googling" their names and finding their picture profile online. The estimated coefficient will reflect whether the gender of the scientist influences the propensity to commercialize research.

Locational and Institutional Contexts

Three different locational binary variables taking on the value of one for the *North East*, which includes all states on the Eastern Seaboard between Washington, D.C. and Maine (Washington, D.C., Connecticut, Rhode Island, New Hampshire, New Jersey, New York, Pennsylvania, Massachusetts, Maryland and Vermont), *California* and the *Great Lakes* (Ohio, Indiana, Illinois, Michigan and Wisconsin). Those regions which tend to have greater investments in research and science, and also have developed a culture more encouraging of university and scientist commercialization, such as California and the North East, might be expected to have a positive coefficient.

NCI Center – This is a binary variable taking on the value of one if the scientist is employed at one of the 39 nationally-recognized cancer centers, and zero otherwise. A

comprehensive cancer center integrates research activities across the three major areas of laboratory, clinical and population-based research. The comprehensive cancer centers generally have the mission to support research infrastructure, but some centers also provide clinical care and service, reflecting the priority that community outreach and information dissemination play at the centers.[17] A positive coefficient would reflect that being located at a comprehensive center facilitates commercialization.

Ivy League – A binary variable taking on the value of one for all scientists employed at Brown University, Cornell University, Columbia University, Dartmouth College, Harvard University, Princeton University, the University of Pennsylvania and Yale University, and zero otherwise.

Public Institution – A binary variable taking on the value of one for scientists employed at public universities and zero otherwise. Because they are at least partially financed by the public, state universities tend to have a stronger mandate for outreach and commercialization of research. This may suggest a positive coefficient.

The definitions of the independent variables are summarized in Table 2. The means and standard deviations of all variables are provided in Table 3. Table 4 provides a correlation matrix between all variables.

[17] http://www3.cancer.gov/cancercenters/description.html

Table 3.2: Description of Independent Variables

Independent Variables	**Description**
Co-patents	The number of times a patenting scientist shared a patent with another NCI scientist
Industry Co-publications	The number of publications an NCI scientist shared with a private industry scientist
Board	Binary variable, for scientists indicating that they sat on either a board of directors or science advisory board, Board=1
TTO Helpful	Binary variable, for scientists indicating that the "TTO directly helped you commercialize your research", TTO Helpful=1
Government Funding	Binary variable, for scientists indicating that they received at least $750,000 of funding from a governmental source, Government Funding=1
Non TTO Assignee	Binary variable, for scientists who had at least one patent where the assignee was not the scientist's university, Non TTO Assignee=1
Industry Co-publications Asia	Binary variable, for scientists who shared a co-publication with a scientist located in Asia, Industry Co-publications Asia=1
NCI Helpful	Binary variable, for scientists indicating that the NCI grant was helpful for patenting, NCI Helpful=1
TTO Age	Year when TTO was founded
TTO Employees	The mean annual number of TTO employees dedicated to licensing and patenting
TTO Licensing Commitment	The number of TTO employees dedicated to licensing and patenting divided by administrative employees
TTO Efficiency	The ratio of patent applications to patents issued by the TTO at the scientist's university
NCI Grant	Total amount of funding received by a scientist
Scientist Age	The age of the scientist
Gender	Binary variable, where a male=1
Scientist Citations	The number of citations a scientist had, 1998 - 2004
Prior Patents	The number of issued patents a scientist had, 1975 - 1998
NCI Center	Binary variable, for a scientist whose institution is recognized by NCI as a comprehensive center for cancer research, NCI Center=1
Ivy League	Binary variable, for a scientist whose institution is an Ivy League university, Ivy League=1
North East	Binary Variable, for a scientist's institution that is in CT, DC, MA, MD, NJ, NH, PA, RI or VT. North East=1
California	Binary variable, for a scientist's institution located in California, California=1
Great Lakes	Binary variable, for a scientist's institution that is located in IL, IN, MI, OH, or WI

Table 3.3: Means and Standard Deviations of All Variables

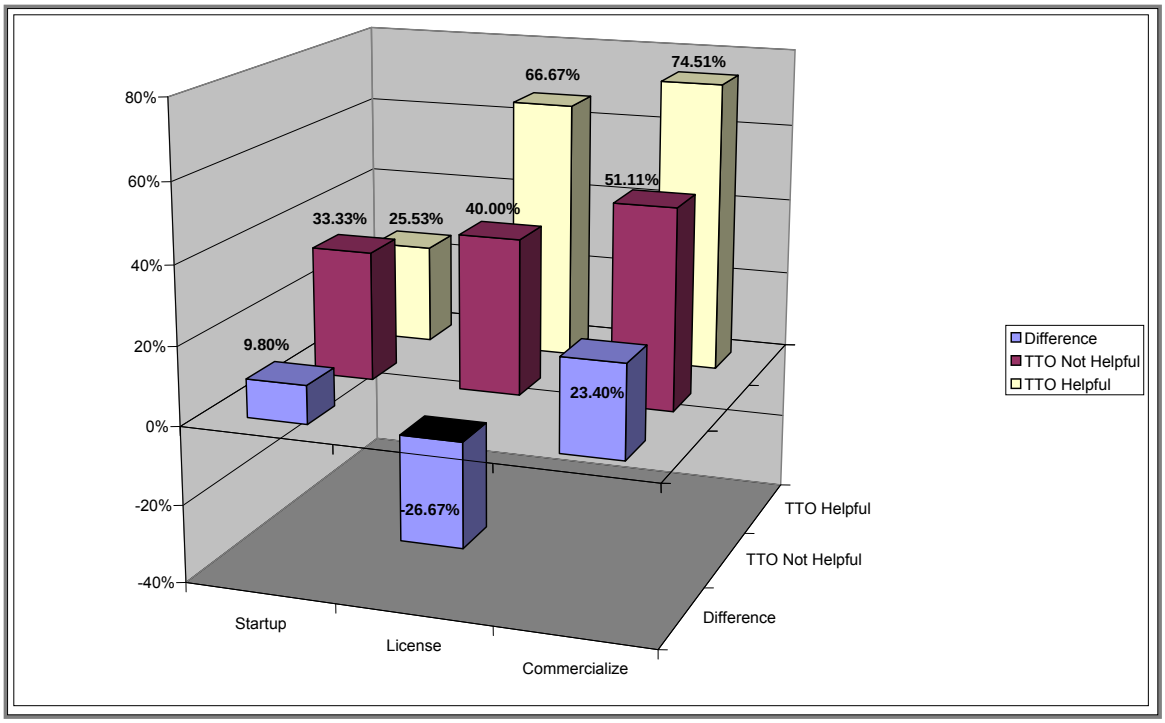
	NCI Scientist	SBIR Scientist	Patent Scientist	Interviewed Scientist
Variable	N=1693	N=8	N=392	N=140
Patent (%)	23.35 (0.42)	25.00 (0.46)	100.00	100.00
License (%)	-	-	-	50.71 (0.50)
Startup (%)	-	100	-	25.71 (0.44)
Commercialize (%)	-	100	-	59.29 (0.49)
Industry Co-publications	1.83 (3.57)	3.75	3.01 (4.89)	2.56 (3.73)
Asia Industry Co-publications (%)	37.00 (0.48)	50.00 (0.53)	48.00 (0.50)	8.50 (0.28)
Board (%)	-	-	-	58.00 (0.50)
Co-patents	-	-	3.13 (4.26)	1.18 (3.97)
Government Funding (%)	-	-	-	38.04 (0.49)
TTO Helpful (%)	-	-	-	53.13 (0.50)
Non TTO Assignee (%)	-	50.00 (0.70)	29.98 (0.45)	20.14 (0.40)
TTO Employees	8.66 (11.44)	9.45 (14.52)	9.14 (11.6)	8.95 (11.65)
TTO Age	1981.70 (11.35)	1986 (5.11)	1980.77 (11.29)	1980.74 (11.25)
TTO Licensing Commitment	1.68 (2.29)	1.76 (2.08)	1.31 (1.45)	1.22 (1.24)
TTO Efficiency (%)	0.32 (0.12)	0.306 (0.13)	0.343 (0.12)	0.372 (0.17)
NCI Grant (Dollars)	3,161,943 (3,196,918)	2,744,319 (1,533,956)	3,484,128 (3,795,993)	3,053,465 (2,674,288)
Gender (%)	77.87 (0.42)	87.50 (0.35)	87.85 (0.33)	88.57 (0.32)
NCI Helpful (%)	-	-	-	45.04 (0.50)
Scientist Age	-	-	-	56.76 (8.40)
Scientist Citations	1316.44 (2472.29)	3770.00 (9133.90)	1741.19 (2441.07)	1500.34 (1603.49)
Prior Patents	1.35 (4.92)	1.63 (1.18)	4.40 (9.28)	3.88 (6.47)
NCI Center (%)	55.86 (0.50)	75.00 (0.46)	56.50 (0.50)	50.70 (0.50)
Public Institution (%)	53.91 (0.50)	50.00 (0.53)	48.10 (0.50)	49.29 (0.50)
Ivy League (%)	10.24 (0.30)	0.00 -	12.15 (0.33)	15.00 (0.36)
North East (%)	34.84 (0.48)	37.50 (0.51)	37.22 (0.48)	41.43 (0.51)
California (%)	13.66 (0.34)	12.50 (0.35)	16.71 (0.37)	15.71 (0.37)
Great Lakes (%)	12.95 (0.34)	25.00 (0.46)	10.89 (0.31)	08.57 (0.28)

Table 3.4: Simple Correlation Matrix

	Startup	License	Commercial	Co-patent	Industry Co-pubs	Board	TTO Helpful	Gov't Funding	Non TTO Assignee	Asia Co-pub
Startup	1.000									
License	0.203	1.000								
Commercial	0.520	0.802	1.000							
Co-patent	-0.077	0.148	0.092	1.000						
Industry Co-pubs	0.166	0.127	0.220	0.049	1.000					
Board	0.446	0.305	0.340	-0.080	0.031	1.000				
TTO Helpful	-0.113	0.284	0.280	0.149	0.007	0.014	1.000			
Gov't Funding	0.135	0.101	0.147	-0.014	0.021	0.057	0.015	1.000		
Non TTO Assign	0.130	-0.276	-0.048	-0.071	-0.078	-0.141	-0.109	0.152	1.000	
Asia Co-pubs	-0.080	0.132	0.191	-0.070	0.000	0.011	-0.074	-0.112	-0.103	1.000
TTO Age	-0.182	-0.083	-0.044	-0.108	-0.047	-0.206	-0.134	-0.024	0.046	0.106
TTO Employees	-0.015	0.051	-0.018	0.359	0.143	0.091	0.147	0.075	-0.144	-0.100
TTO Commit	0.006	0.059	0.004	0.368	0.126	0.089	0.139	0.094	-0.113	-0.095
TTO Efficiency	0.054	0.161	0.085	-0.127	0.133	-0.054	-0.033	-0.229	0.077	-0.112
NCI Grant	-0.053	-0.066	-0.031	0.165	0.073	0.120	0.250	0.031	-0.043	-0.027
NCI Helpful	0.277	0.265	0.333	0.051	-0.010	0.213	0.343	0.027	-0.156	0.053
Scientist Age	-0.137	-0.100	-0.167	0.125	-0.166	-0.066	0.051	0.049	-0.127	-0.044
Gender	0.157	-0.050	0.024	0.039	-0.017	0.315	0.027	0.023	0.007	0.091
Scientist Citations	-0.066	0.083	0.041	0.191	0.066	0.104	-0.052	0.085	-0.188	-0.073
Prior Patents	-0.051	0.156	0.156	0.583	-0.042	0.035	0.194	0.085	-0.028	-0.074
NCI Center	-0.057	0.124	0.113	0.091	0.237	-0.093	0.153	-0.254	-0.265	0.032
Public Institution	-0.075	-0.135	-0.203	0.100	-0.067	-0.031	-0.213	0.219	0.068	0.046
Ivy League	-0.007	0.248	0.264	-0.061	0.048	-0.100	0.175	-0.056	0.098	0.067
North East	0.082	0.194	0.263	-0.108	-0.003	-0.012	0.104	-0.190	-0.055	0.127
California	0.015	0.018	-0.015	0.250	0.217	0.130	0.099	0.020	-0.185	-0.126
Great Lakes	-0.108	0.067	0.005	0.028	0.087	0.052	0.075	0.055	0.030	0.119
	TTO Age	TTO Emply	TTO Commitment	TTO Efficiency	NCI Grant	NCI Helpful	Scientist Age	Gender	Scientist Citations	Prior Patents
TTO Age	1.000									
TTO Employees	-0.189	1.000								
TTO Commit	-0.166	0.983	1.000							
TTO Efficiency	-0.154	-0.194	-0.193	1.000						
NCI Grant	-0.315	0.150	0.134	-0.072	1.000					
NCI Helpful	-0.090	0.205	0.200	-0.007	0.106	1.000				
Scientist Age	-0.008	-0.038	-0.041	-0.169	0.041	0.004	1.000			
Gender	-0.043	-0.015	-0.007	0.081	-0.058	0.086	0.056	1.000		
Scientist Citation	-0.318	0.070	0.078	0.116	0.193	0.090	-0.103	0.053	1.000	
Prior Patent	-0.017	0.133	0.142	-0.121	0.090	0.159	0.289	0.028	0.228	1.000
NCI Center	0.143	0.232	0.268	0.150	-0.089	0.079	-0.099	-0.145	0.022	-0.040
Public Institution	0.266	0.278	0.292	-0.196	0.073	0.132	0.259	0.181	-0.193	-0.023
Ivy League	0.004	-0.152	-0.138	0.521	0.015	0.122	-0.214	-0.007	0.127	0.030
North East	-0.164	-0.213	-0.206	0.298	0.026	0.000	-0.221	-0.182	0.250	0.179
California	-0.179	0.791	0.746	-0.101	0.038	0.136	-0.027	0.052	0.026	-0.004
Great Lakes	0.209	-0.137	-0.123	-0.242	-0.091	-0.195	0.091	-0.059	-0.082	-0.010
	NCI Center	Public Institution	Ivy League	North East	California	Great Lakes				
NCI Center	1.000									
Public Institution	-0.108	1.000								
Ivy League	0.175	-0.376	1.000							
North East	0.213	-0.511	0.480	1.000						
California	0.167	0.123	-0.174	-0.363	1.000					
Great Lakes	-0.121	-0.105	-0.107	-0.224	-0.139	1.000				

Figure 3.5 compares the likelihood of scientist commercialization between the two modes of commercialization — startup and licensing — for those 54 scientists perceiving they were helped by their TTO offices and the 47 scientist perceiving they were not helped. The likelihood of licensing intellectual property is greater for scientists helped by the TTO than for those not helped. By contrast, the likelihood of starting a new firm is less for those scientists helped by the TTO than for those scientists not helped. This results in a difference for not being helped by the TTO that is positive for startups but negative for licensing.

Figure 3.5: TTO Helpfulness to Scientist by Commercialization Mode



Similarly, Figure 3.6 compares the likelihood of scientist commercialization between startups and licensing for the 111 scientists choosing the TTO route to commercialize their research, and the 29 scientists selecting the entrepreneurial route to commercialization. The likelihood of licensing intellectual property is greater for the scientists assigning all of their patents to their TTO. By contrast, the likelihood of starting a new firm is greater for those scientists not assigning all of their patents to their TTO. Thus, those scientists selecting the TTO commercialization route have a higher propensity to license, while those scientists choosing the entrepreneurial route to commercialziation have a higher propensity to start a new firm.

Figure 3.6: Scientist Commercialization Route by Commercialization Mode

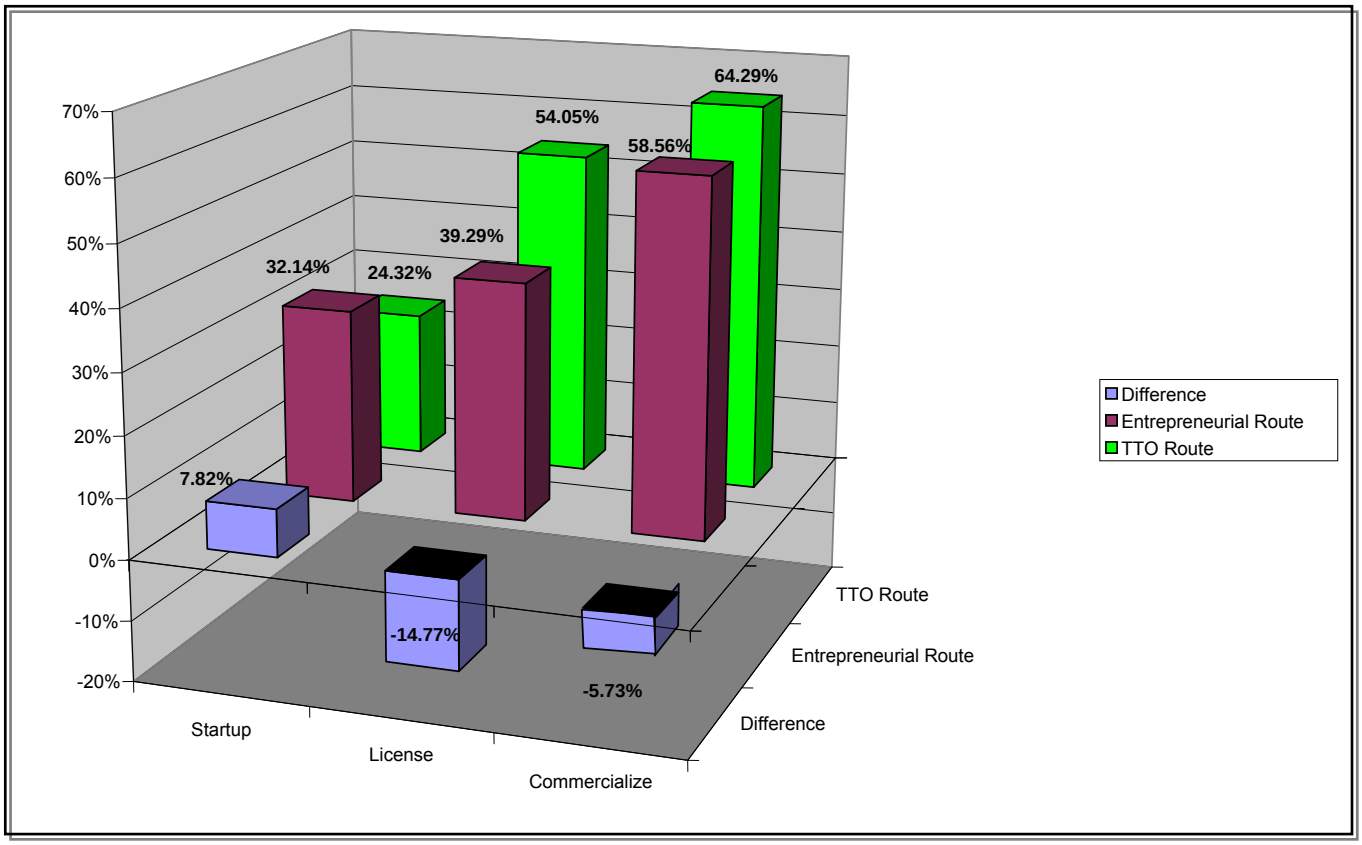
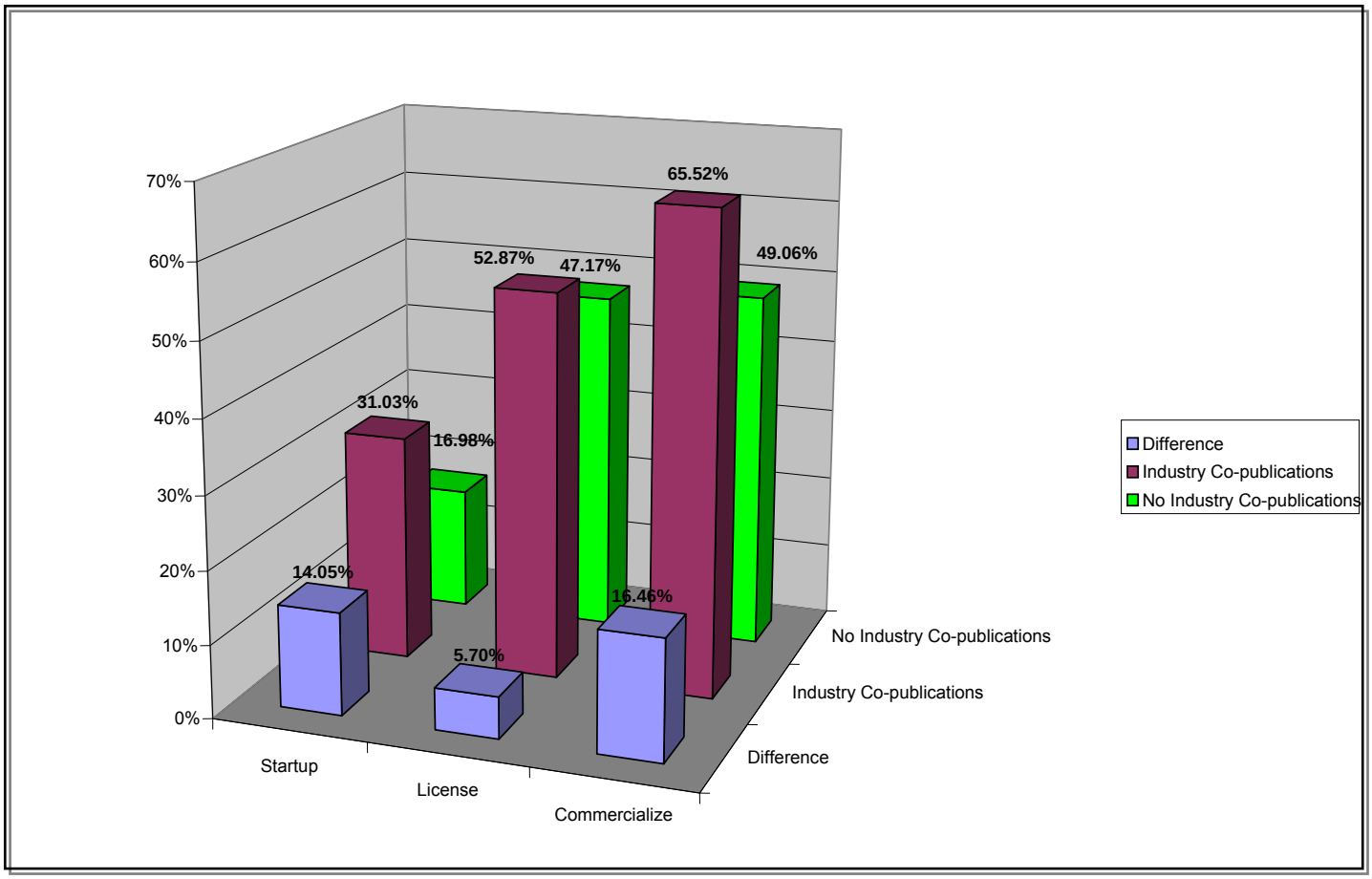


Figure 3.7 shows how one of the measures of social capital, co-publication with a scientist in industry, impacts the commercialization mode. Scientists with social capital, measured as having at least one co-publication with industry (N=88), exhibit a higher propensity to start a new firm, license their intellectual property, and commercialize their research, than do their colleagues with low social capital (N=54). Thus, there is at least some evidence suggesting that the impact of social capital on entrepreneurship is greater than on licensing.

Figure 3.7: Social Capital by Commercialization Mode



3.6 Empirical Results

The results from estimating the probit model using the mode of scientist commercialization as starting a new firm are provided in Table 5. Because of multicollinearity, not all of the control variables could be included in the same estimation model.

Table 3.8: Probit Regression Results Estimating Scientist Commercialization - Startups

	1	*2*	*3*	*4*
Co-patents	0.141 **(1.76)***	0.155 **(1.65)***	0.155 **(1.67)***	0.191 **(1.77)***
Industry Co-publications	0.102 **(1.72)***	0.17 **(1.77)***	0.158 **(1.72)***	0.191 **(1.84)***
Board	1.696 **(3.40)*****	1.663 **(2.44)****	1.721 **(2.55)****	2.204 **(2.43)****
TTO Helpful	-1.319 **(2.65)*****	-1.665 **(2.50)****	-1.646 **(2.53)****	-1.602 **(2.23)****
Government Funding	0.892 **(1.91)***	1.328 **(2.13)****	1.298 **(2.13)****	1.602 **(2.14)****
Non TTO Patent Assignee	-	-	-	1.598 **(1.80)***
Asia Co-publications	-1.304 **(1.77)***	-0.899 (1.01)	-0.733 (0.88)	-0.684 (0.75)
TTO Age	-0.022 (1.09)	-0.042 (1.23)	-0.028 (0.85)	-0.042 (1.25)
TTO Employees	-0.025 (1.52)	-0.022 (0.58)	-	-0.032 (0.78)
TTO Licensing Commitment	-	-	-0.208 (0.83)	-
TTO Efficiency	-0.017 (0.01)	0.069 (0.04)	0.853 (0.51)	-0.742 (0.50)
NCI Grant	-0.001 (0.93)	-0.028 (1.07)	-0.022 (1.03)	0.001 (1.14)
NCI Helpful	1.67 **(3.39)*****	1.913 **(2.99)*****	1.932 **(3.06)*****	2.122 **(3.04)*****
Age	-	-0.009 (0.25)	0 (-0.01)	0.025 (0.60)
Gender	-	1.616 (1.24)	1.354 (1.09)	1.409 (1.03)
Scientist Citations	-0.37 **(2.16)****	-0.025 **(2.30)****	-0.032 **(2.38)****	-0.029 **(1.73)***
Prior Patents	-0.072 (1.41)	-0.078 (1.29)	-0.08 (1.33)	-0.101 (1.46)
NCI Center	-	0.091 (0.16)	-0.106 (0.19)	0.419 (0.64)
Public Institution	-	-0.742 (0.91)	-1.137 (1.48)	-0.552 (0.65)
Ivy League	-	-0.934 (0.84)	-1.255 (1.08)	-2.211 (1.38)
North East	0.918 **(1.99)****	1.234 (1.57)	1.156 (1.52)	1.677 **(1.76)***
California	-	-0.053 (0.05)	-0.591 (0.75)	0.113 (0.09)
Great Lakes	-	-0.095 (0.07)	-0.468 (0.36)	0.210 (0.17)
Constant	42.081 (1.04)	79.973 (1.19)	53.664 (0.81)	78.756 (1.17)
LR chi2	**44.26*****	**46.9*****	**47.26*****	**51*****
R-squared adjusted	0.42	0.48	0.48	0.52
Observations	83	76	76	76

Absolute value of z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

The first column provides results where the scientist-specific characteristics of age and gender, and the binary variables reflecting institution type and location are not included in the estimation. The estimated coefficient of all three measures of social capital, co-patents, co-publications and serving as a member of an industry board are positive and statistically significant. This suggests that for these three measures reflecting different dimensions of social capital, a greater degree of linkages and interactions, both with other academic scientists, with scientists in industry, and with industrial firms, tends to be conducive to scientist entrepreneurship.

While engaging in co-publications increases the likelihood of a scientist becoming an entrepreneur, there is at least some evidence suggesting that this measure of social capital may not be homogenous but rather sensitive to the location of the co-author. As the negative and statistically significant coefficient suggests, if the co-author is located in Asia, the propensity of a scientist to become an entrepreneur becomes lower. Thus, there is at least some evidence suggesting that measures of social capital may be highly nuanced and heterogeneous.

The negative and statistically significant coefficient of *TTO Helpful* suggests that the likelihood of starting a business is lower for those scientists indicating that the TTO at their university was helpful in commercializing their research, but higher for their counterparts indicating that their TTO was not helpful in commercializing research. Thus, if the scientist perceives the TTO as not being helpful with commercialization activities, the likelihood of starting a firm is greater.

Additional funding from (non-NCI) government agencies is conducive to scientist entrepreneurship, as reflected by the positive and statistically significant coefficient of *Government Funding*. None of the measures reflecting either TTO-specific characteristics or the amount of the NCI grant can be considered to be statistically significant. However, as the positive and statistically significant coefficient suggests, those scientists indicating that the NCI grant was helpful have a greater propensity to become an entrepreneur.

The negative and statistically significant coefficient of scientist citations suggests that more highly cited scientists have a systematically lower propensity to become entrepreneurs. Similarly, while prior patenting has no significant influence on scientist entrepreneurial behaviour, the positive and statistically significant coefficient of the binary variable for scientists at universities located in the North East suggests that those scientists located between Washington, D.C. and Maine tend to be more entrepreneurial.

In the second column, probit regression results estimating the likelihood of scientist startups are presented, where the scientist-specific characteristics of age and gender are included along with the measures of university type. Inclusion of these additional control variables leaves the main results reflecting the positive impact of the three measures reflecting social capital and the negative impact of a helpful TTO on the likelihood of scientist entrepreneurship virtually unchanged. The main difference in the results is that the location of a co-author in Asia and the Northeast dummy variable are no longer statistically significant. In the third column the measure reflecting the TTO commitment to licensing is substituted for the number of TTO licensing employees. Again, the main results remain the same.

The binary measure reflecting the route to commercialization, measured as patents not assigned to the TTO, is included in the probit model presented in the fourth column. The positive and statistically significant coefficient of *Non TTO Patent Assignee* suggests that those scientists choosing the entrepreneurial commercialization route, that is not through the TTO, have a higher likelihood of starting a new firm. Those scientists selecting the TTO commercialization route have a lower propensity to start a new firm. All of the other coefficients remain virtually unchanged.

Thus, the results estimating the likelihood of an NCI scientist starting a firm provide consistent and compelling evidence that social capital promotes scientist entrepreneurship, while having a helpful TTO and assigning the patent to the TTO are associated with a lower propensity for scientists to become entrepreneurs. These results might suggest that starting a new firm is a prevalent mechanism for scientists resorting to commercializing their research through the entrepreneurial commercialization route and the TTO route to commercialization.

A different mode of commercializing is licensing, and is examined in Table 6, which reports probit results from estimating the likelihood of scientists licensing their intellectual property. The coefficient of the social capital measuring co-publications cannot be considered to be statistically different from zero. However, the positive and statistically significant coefficient of the binary variable for scientists belonging to either a Scientific Board of Advisors (SAB), or Board of Directors of a private firm and co-patenting does provide at least some evidence suggesting that social capital promotes the likelihood of a scientist licensing her intellectual property.

Table 3.9: Probit Regression Results Estimating Scientist Commercialization - License

	1	*2*	*3*	*4*
Co-patents	0.154 (1.25)	0.400 **(2.25)****	0.388 **(2.20)****	0.470 **(2.51)****
Industry Co-publications	0.025 (0.64)	0.068 (1.02)	0.072 (1.12)	0.092 (1.19)
Board	1.123 **(2.99)*****	1.965 **(3.16)*****	1.946 **(3.19)*****	2.279 **(3.17)*****
TTO Helpful	0.769 **(2.16)****	1.261 **(2.45)****	1.264 **(2.45)****	1.413 **(2.45)****
Government Funding	0.681 **(1.90)***	0.883 **(1.78)***	0.873 **(1.76)***	1.346 **(2.21)****
Non TTO Patent Assignee	-	-	-	-2.978 **(2.54)****
Asia Industry Co-publications	1.343 **(1.72)***	2.165 (1.62)	2.223 **(1.67)***	2.497 (1.42)
NCI Helpful	0.277 (0.78)	0.565 (1.15)	0.554 (1.14)	0.478 (0.91)
TTO Age	0.025 (1.58)	-0.004 (0.15)	0.001 (0.01)	0.001 (0.02)
TTO Employees	0.004 (0.22)	-0.015 (0.43)	-	0.006 (0.16)
TTO Licensing Commitment	-	-	0.019 (0.12)	-
TTO Efficiency	2.281 **(2.25)****	2.744 **(1.95)***	2.932 **(1.90)***	4.300 **(2.42)****
NCI Grant	0.007 (0.14)	-0.004 **(2.50)****	-0.004 **(2.51)****	-0.005 **(2.58)*****
Scientist Age	-	-0.014 (0.40)	-0.01 (0.30)	-0.045 (1.13)
Gender	-	-2.173 **(2.42)****	-2.134 **(2.40)****	-2.505 **(2.48)****
Scientist Citations	-0.002 (0.24)	-0.002 (0.30)	-0.001 (0.320)	-0.010 (0.66)
Prior Patents	-0.02 (0.47)	-0.01 (0.18)	-0.013 (0.23)	-0.006 (0.11)
NCI Center	-	0.033 (0.06)	-0.047 (0.09)	-0.691 (1.04)
Public Institution	-	0.685 (0.87)	0.476 (0.74)	0.111 (0.12)
Ivy League	-	0.329 (0.38)	0.243 (0.26)	1.175 (0.97)
North East	0.416 (1.08)	0.448 (0.60)	0.325 (0.48)	-0.076 (0.08)
California	-	-0.26 (0.24)	-0.636) (0.92)	-1.301 (0.97)
Great Lakes	-	1.002 (0.93)	0.885 (0.83)	0.072 (0.06)
Constant	51.347 **(1.65)***	7.189 (0.14)	-0.201 (0.00)	0.584 (0.01)
LR chi2	**31.76*****	**44.02*****	**43.84*****	**54*****
R-squared adjusted	0.28	0.42	0.42	0.52
Observations	83	76	76	76

Absolute value of z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

As for the commercialization mode of startups, the coefficient of the TTO being helpful with scientist commercialization is statistically significant. However, the sign of the coefficient is actually the opposite, i.e. positive, suggesting that those scientists who indicate that they are helped by the TTO have a higher propensity to license their intellectual property, which is in stark contrast to the findings in Table 6 indicating a lower propensity to become an entrepreneur. This might suggest an asymmetric effect of TTOs on scientist entrepreneurship versus scientist licensing. The TTOs appear to be more helpful to a scientist in licensing their intellectual property than for starting a new firm.

While the positive and statistically significant coefficient of *Government Funding* is similar to that found for the mode of startups, the positive and statistically significant coefficient of the variable measuring co-publications with an industry co-author located in Asia is the opposite. This might indicate that while having a co-author located in Asia reduces the likelihood of starting a firm it actually increases the propensity for U.S. based scientists to license their intellectual property.

The coefficients of the variables measuring the helpfulness of the *NCI Grant* towards commercialization, *TTO Age*, and number of TTO employees are not statistically significant. However, the positive and statistically significant coefficient of *TTO Efficiency* indicates that those scientists located at a university where the TTO is more efficient exhibit a higher likelihood of licensing their intellectual property. None of the remaining variables, *Scientist Citations*, *Prior Patents*, or *Northeast*, are found to have statistically significant impact on the likelihood of scientist licensing.

The second column reports regression results where measures reflecting scientist age, gender, and university type and location are included in the estimation model. There are three main differences. First, the coefficient of *Co-patents* becomes statistically significant and positive, indicating that, for the entrepreneurship mode of commercialization, this dimension of social capital is positively related to the likelihood of licensing intellectual property.

Second, the coefficient of *NCI Grant* becomes negative and statistically significant, suggesting that the higher the NCI grant award, the lower is the likelihood of a scientist licensing their intellectual property. Finally, the coefficient of *Gender* is negative and statistically significant. The negative coefficient of this binary variable may seem surprising, given that a slightly higher share of male scientists license their intellectual property than do their female colleagues.[18] However, one interpretation of the negative coefficient is that if female scientists had the same degree of co-patenting with other scientists, participation on boards, help from the TTO, additional funding from non-NCI government agencies, and level of efficiency at their universities' TTO, they would actually exhibit a higher propensity to license than do their male colleagues. According to this interpretation, what explains the gender gap, in terms of licensing behaviour, is not gender *per se*, but rather access to and participation in social capital, such as sitting on scientific advisory boards and boards of directors, as well as co-patenting with other academic scientists. The measure of *TTO Licensing Commitment* is substituted for *TTO Employees* in the regression results presented in the third column. The results remain virtually identical to those reported in column two.

[18] 51 percent of the patenting male scientists licensed their intellectual property and 49 percent of the patenting female scientists licensed their intellectual property.

The measure reflecting the scientist commercialization route is included in the fourth column. As the negative and statistically significant coefficient of *Non TTO Patent Assignee* suggests, those scientists choosing the entrepreneurial route to commercialize their research exhibit a lower likelihood of licensing their intellectual property. In comparison, those scientists selecting the TTO commercialization route have a higher propensity to license.

Overall, the results reported from estimating scientist licensing reveal several striking similarities but also differences from those estimating scientist entrepreneurship. First, the impact of social capital is positive for both entrepreneurship and licensing. Co-patenting with other academic scientists as well as sitting on a scientific advisory board or board of directors of a private company increases the likelihood of a scientist both starting a business and licensing her intellectual property. However, co-publishing with scientists in industry spurs scientist entrepreneurship, while it has no impact on licensing behaviour.

Second, scientist perception that the TTO is helpful in commercializing research leads to disparate results between the two modes of commercialization. While those scientists indicating that the TTO was helpful exhibited a higher propensity to license their intellectual property, they also were less entrepreneurial in that they have a lower likelihood to start a new firm. However, those scientists indicating that the TTO was not helpful were less likely to license their intellectual property, but had a higher propensity to start a new business. This is also consistent with the finding that TTO efficiency promotes scientist licensing but not entrepreneurship. These disparate findings may suggest that the impact of the TTOs is not symmetric across difference modes of commercialization.

Third, the particular commercialization route chosen by the scientist influences the mode of commercialization. Those scientists choosing the TTO commercialization route exhibit a higher likelihood of licensing but a lower propensity to start a new firm. By contrast, scientists choosing the entrepreneurship route to commercialize their research have a greater propensity to start new firms rather than license their intellectual property. Entrepreneurship in the form of a new firm startup apparently serves as a substitute for licensing when scientist commercialization is through the entrepreneurial route and not the TTO route.

In Table 7 the two modes of commercialization, entrepreneurship and licensing, are combined to identify the likelihood of a scientist commercializing her research. There is at least some evidence suggesting that social capital promotes scientist commercialization. While co-patenting with other academic scientists seems to have no significant impact on commercialization behaviour, both co-publishing with an industry scientist and sitting on a board of a firm are found to increase the likelihood that a scientist commercializes her research.

Table 3.10: Probit Regression Results Estimating Scientist Commercialization - Commercialize

	1	*2*	*3*	*4*
Co-patents	0.097 (1.17)	0.272 (1.46)	0.152 (0.96)	0.306 (1.59)
Industry Co-publications	0.140 **(2.11)****	0.206 **(2.00)****	0.191 **(2.13)****	0.215 **(2.00)****
Board	1.335 **(3.25)*****	1.532 **(2.76)*****	1.586 **(2.93)*****	1.496 **(2.62)*****
TTO Helpful	0.571 (1.43)	0.552 (1.00)	0.706 (1.34)	0.503 (0.90)
Government Funding	0.910 **(2.14)****	0.936 **(1.87)***	0.904 **(1.85)***	0.768 (1.46)
Non TTO Patent Assignee	-	-	-	0.922 (1.03)
NCI Helpful	0.907 **(2.26)****	1.433 **(2.44)****	1.140 **(2.26)****	1.393 **(2.30)****
TTO Age	0.021 (1.26)	-0.016 (0.50)	0.009 (0.30)	-0.018 (0.57)
TTO Employees	-0.017 (0.92)	-0.066 (1.45)	-	-0.073 (1.53)
TTO Licensing Commitment	-	-	-0.298 **(1.67)***	-
TTO Efficiency	0.970 (0.90)	0.712 (0.54)	1.827 (1.15)	0.916 (0.66)
NCI Grant	0.004 (0.64)	-0.003 (1.46)	-0.003 (1.32)	-0.003 (1.47)
Scientist Age	0.002 (0.65)	-0.043 (1.22)	-0.031 (0.94)	-0.049 (1.33)
Previous Patents	-0.018 (0.41)	-0.913 (1.05)	-0.552 (0.70)	-0.943 (1.06)
Citations	-	0.010 (1.38)	0.020 (1.06)	0.012 (1.47)
Previous Patents	-	0.001 (0.02)	-0.011 (0.21)	0.015 (0.25)
NCI Center	-	-0.005 (0.01)	-0.167 (0.32)	0.070 (0.12)
Public Institution	-	0.053 (0.07)	-0.717 (1.11)	0.125 (0.17)
North East	0.881 **(2.20)****	1.234 **(1.71)***	0.821 (1.34)	1.303 **(1.77)***
California	-	1.095 (0.82)	-0.714 (1.01)	1.352 (0.97)
Great Lakes	-	0.705 (0.54)	-0.165 (0.13)	0.536 (0.37)
Constant	-44.366 (1.31)	32.443 (0.52)	-16.937 (0.28)	37.238 (0.59)
LR chi2	**39.22*****	**44.87*****	**45.30*****	**46.06*****
R-squared adjusted	0.37	0.46	0.46	0.47
Observations	83	76	76	76

Absolute value of z statistics in brackets
* significant at 10%;** significant at 5%; *** significant at 1%

There is no statistically significant evidence that being at a university where the scientist indicates that the TTO is helpful with commercialization efforts actually impacts the likelihood of that scientist commercializing. However, the results do suggest that additional funding from non-NCI government agencies, as well as the NCI grant itself increases the propensity of scientists to commercialize their research.

Since the measure of scientist commercialization combines two modes of commercialization, entrepreneurship and licensing, it may not be surprising that the results generally reflect a combination of the individual findings for startups and licensing.

It is also possible to provide a comparison between the two modes of commercialization and patenting behaviour. However, since the survey was administered to the 140 respondents from the 392 NCI scientists who had patented, it is not possible to apply the variables formed from the survey instrument to the larger sample of 1,431 NCI scientists. The results from estimating the likelihood of a scientist patenting are reported in Table 8. As the positive and statistically significant coefficients of *Co-publications* indicate, there is evidence suggesting that measures of social capital increase the scientist propensity to patent as well as license and become an entrepreneur. Furthermore, the location of the co-author apparently influences the propensity to patent. If the co-author is located in Asia, the likelihood of a U.S. based scientist patenting in the U.S. is greater.

Table 3.11: Probit Regression Results Estimating Scientist Commercialization - Patents

	1	*2*	*3*
Co-publications	0.061 **(5.82)*** **	0.043 **(3.45)*** **	0.055 **(5.06)*** **
Asia Co-publications	0.269 **(3.47)*** **	0.228 **(2.64)*** **	0.222 **(2.78)*** **
TTO Employees	0.042 **(1.75)***	-0.006 (-1.00)	0.039 (-1.51)
TTO Efficiency	1.006 **(3.23)*** **	0.894 **(2.41)** **	**0.867** **(2.60)*** **
TTO Age	-0.015 **(3.40)*** **	-0.004 (0.76)	-0.010 **(2.14)** **
Scientist Citations	-	0.045 (0.33)	0.022 (1.45)
NCI Grant	-	0.007 (0.55)	0.004 (0.36)
Gender	-	0.245 **(2.30)** **	0.397 **(3.95)*** **
Public Institution	-	-0.129 (1.24)	-0.175 **(1.94)***
NCI Center	-	0.021 (0.24)	0.018 (0.22)
Ivy League	-	-0.082 (0.53)	0.042 (0.30)
North East	-	0.013 (0.11)	0.087 (0.79)
California	-	0.262 (1.25)	0.154 (1.31)
Great Lakes	-	0.048 (0.35)	0.064 (0.50)
Previous Patents	-	0.230 **(12.14)*** **	-
Constant	27.50 **(3.25)*** **	6.343 (0.60)	19.142 **(1.98)** **
Observations	1431	1431	1431
LR chi2	**83.75*** **	**341.44*** **	**112.65*** **
R-squared adjusted	0.05	0.22	0.07
Absolute value of z statistics in brackets * significant at 10%; ** significant at 5%; *** significant at 1%			

The other consistent result involves *TTO Efficiency*. Those scientists working at universities with a more efficient TTO exhibit a higher propensity to patent. There is also at least some evidence suggesting that older and more established TTOs and larger TTOs, as measured by employment, tend to be associated with a higher scientist propensity to patent.

Because the samples of scientists are not the same, comparisons across these different commercialization modes must be qualified and considered to be provisional at best. Still, there are at least some indications suggesting that social capital promotes all modes of commercialization, but perhaps entrepreneurship the strongest. By contrast, the TTO seems to be most effective in promoting first and foremost patents and then licensing, but much less startups.

To further probe the impact that the TTO plays in facilitating different commercialization modes, the sample of survey respondents is decomposed into those scientists indicating that they were helped with their commercialization efforts by the TTO and those that were not. Based on these two sub-samples, regression results estimating the likelihood of a scientist licensing are reported in Table 9. Results for the sub-sample of scientists indicating that they were helped by the TTO are reported in the first two columns, while those not helped are reported in the last two columns.

Table 3.12: Probit Regression Results Estimating Scientist Licensing by Helpfulness of TTO

	TTO Helped Scientist		TTO Did Not Help Scientist	
	1	2	3	4
Startup	-2.957 **(1.90)***	-	2.507 **(2.13)****	-
Co-patents	1.384 **(2.22)****	1.065 **(2.25)****	0.353 (0.62)	0.181 (0.66)
Industry Co-pubs	0.192 (1.31)	0.125 (0.98)	-0.296 **(1.65)***	-0.081 (0.84)
Government Funding	4.795 **(2.22)****	1.897 **(2.19)****	-0.495 (0.50)	0.011 (0.02)
NCI Helpful	-0.053 (0.07)	-0.200 (0.28)	2.931 **(1.72)***	2.526 **(2.79)*****
TTO Efficiency	4.797 **(1.73)***	3.366 (1.59)	4.938 (1.41)	2.807 (1.58)
TTO Employees	0.005 (0.15)	0.011 (0.33)	-0.114 (1.41)	-0.068 (1.58)
TTO Age	-0.234 **(2.34)****	-0.104 **(1.77)***	-0.046 (0.67)	-0.012 (0.28)
Scientist Age	0.093 (1.43)	0.039 (0.86)	-0.168 **(1.97)****	-0.093 (1.61)
North East	0.682 (0.84)	0.000 **(2.32)****	0.000 (0.99)	0.000 (0.62)
Great Lakes	3.362 **(1.92)***	0.680 (0.95)	0.263 (0.19)	0.287 (0.31)
NCI Grant	-0.007 **(2.35)****	2.258 (1.59)	3.122 **(1.66)***	1.703 (1.36)
Constant	457.962 **(2.33)****	203.606 **(1.75)***	99.986 (0.71)	29.158 (0.31)
LR chi2	**28.15****	**23.27****	**28.54*****	**21.45****
R-squared adjusted	0.55	0.45	0.61	0.46
Observations	41	41	35	35

Absolute value of z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

The first column also includes a binary variable taking on the value of one if the scientist started a new firm. As the negative and statistically significant coefficient of this variable suggests, those scientists indicating they were helped by TTO and started a new firm exhibited a lower likelihood of licensing their intellectual property. The positive and statistically significant coefficient of this binary variable in the third column suggests that of those scientists not helped by the TTO, starting a firm increases the likelihood of licensing. Taken together, these results might suggest that for those scientists helped by the TTO, entrepreneurship and licensing tend to be substitutes. Scientists tend to do one or the other, but not both. By contrast, for those scientists not helped by the TTO, entrepreneurship and licensing tend to be complements. Those scientists who start a new business also tend to license their intellectual property.

3.7 Conclusions

A consequence of globalization in the most developed countries, such as the United States, has been to shift the comparative advantage away from traditional manufacturing industries and towards new knowledge-based economic activity. But where is this knowledge to come from? At this point, the answer is uncertain, but along with education and human capital, as well as critical research and development (R&D) by private industry and government agencies, research undertaken by universities is sure to play a prominent role. As research and knowledge become perhaps the most crucial component to generating economic growth and competitive jobs in globally-linked markets, universities emerge as a key factor in determining the future well-being of the country. After all, it ranks among the most important tasks of universities to create new scientific knowledge.

In addition, the magnitude of resources being invested in university research, including some of the most capable and creative scientists in the country, is the envy of the world.

The massive investment in university research can impact economic growth only if knowledge can be transformed into actual innovations and new and better products through the commercialization process. That is, the extent to which university research becomes commercialized. It matters for economic growth, for jobs and for global competitiveness.

Thus, a large literature has emerged trying to gauge and analyze the extent to which university research spills over into commercial activity. Much, if not most, of this previous research has been restricted to focusing on the activities emanating from Technology Transfer Offices, which have provided systematic and consistent documentation of their efforts over a fairly long period of time. Analyses of these data have typically led to conclusions suggesting that while patents and licenses from university research have increased over time, the typical TTO does not generate significant commercialization of university research. However, an important qualification is that, by restricting themselves to TTO generated data, such studies are not able to consider any commercialization activities not emanating from the TTOs.

This chapter has taken a different approach. Rather than focus on what the TTOs do, it instead focuses on what university scientists do. Thus, the findings about the commercialization of university research are based on actual university scientists and not the TTOs. The results are revealing. In particular, while all modes of commercialization are important, scientist entrepreneurship emerges as an important and prevalent mode of commercialization of university research. More than one in four patenting NCI scientists

has started a new firm. This is a remarkably high rate of entrepreneurship for any group of people, let alone university scientists. Thus, the extent to which university research is being commercialized and entering the market may be significantly greater than might have been inferred from studies restricted only to the commercialization activities of the TTO. Scientist entrepreneurship may prove to be the sleeping giant of university commercialization.

Second, the mode of commercialization is apparently not independent of the commercialization route. Nearly one-third of patenting NCI scientists rely on the entrepreneurial commercialization route, in that they do not assign all of their patents to the university. These scientists exhibit a higher likelihood of starting a new firm but a lower propensity to license. By contrast, scientists choosing the TTO commercialization route exhibit a higher propensity to license but a lower likelihood to start a new firm.

Third, we find that the determinants of scientist commercialization vary considerably according to the specific mode of commercialization. Social capital, measured in terms of co-patenting with other NCI scientists, co-publishing with industry scientists, and sitting on a scientific advisory board (SAB) or board of directors, generally promotes all modes of commercialization, although the impact seems to be the strongest for scientist entrepreneurship. However, the role of the TTO is sharply divided depending upon the commercialization mode. Having a TTO that is perceived to be helpful for commercialization seems to increase the likelihood of a scientist licensing but decrease the propensity of the scientist to start a new firm. By contrast, having a TTO that is perceived not to be helpful reduces the licensing activity of scientists but increases their likelihood of

becoming entrepreneurs. Thus, licensing and entrepreneurship appear to be substitutes when the TTO is helpful to the scientists and complements when not.

How are scientists able to start a business without TTO support? There is at least some evidence indicating that social capital can serve as a mechanism to compensate for lack of TTO help when starting a new firm. This would suggest that university governance and public policy facilitating participation in scientific networks may be a valuable investment accruing positive returns in terms of knowledge spillovers and technology transfer, ultimately leading to commercialization, innovation and economic growth.

Future research needs to further probe why and how scientists choose to commercialize their research, what commercialization route they select, what mode of commercialization is most effective, and how university governance and public policy can best promote such commercialization efforts. A host of pressing questions remain. For example, are all social networks equivalent, that is are they homogeneous, or do some facilitate scientist commercialization more than others? Similarly, do non-patenting scientists engage in commercialization activities, particularly entrepreneurship, or does their lack of patented intellectual propensity preclude commercialization of their research? Whatever answers to these and other crucial questions future research can uncover, the sleeping giant of scientist entrepreneurship may prove to be one giant that is worth waking up.

3.8 Appendix A: Breakdown of Patents by U. S. Patent and Trademark Office Classification

Classification of Patents by USPTO Category	Percentage of total NCI patents	Title
435	0.352%	Chemistry: molecular biology and microbiology
514	0.184%	Drug, bio-affecting and body treating compositions
424	0.152%	Drug, bio-affecting and body treating compositions
530	0.060%	Chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products
536	0.038%	Organic compounds -- part of the class 532-570 series
128	0.017%	Surgery
436	0.014%	Chemistry: analytical and immunological testing
250	0.013%	Radiant energy
382	0.012%	Image analysis
600	0.011%	Surgery
800	0.010%	Multicellular living organisms and unmodified parts thereof and related
324	0.008%	Electricity: measuring and testing
549	0.008%	Organic compounds -- part of the class 532-570 series
604	0.006%	Surgery
548	0.006%	Organic compounds -- part of the class 532-570 series
364	0.005%	Electric power conversion systems
606	0.004%	Surgery
528	0.004%	Synthetic resins or natural rubbers -- part of the class 520 series
422	0.004%	Chemical apparatus and process disinfecting, deodorizing, preserving, or sterilizing
560	0.004%	Organic compounds -- part of the class 532-570 series
546	0.003%	Organic compounds -- part of the class 532-570 series
564	0.003%	Organic compounds -- part of the class 532-570 series
356	0.002%	Optics: measuring and testing
378	0.002%	X-ray or gamma ray systems or devices
210	0.002%	Liquid purification or separation
385	0.002%	Optical waveguides
568	0.002%	Organic compounds -- part of the class 532-570 series
623	0.002%	Prosthesis (i.e., artificial body members), parts thereof, or aids and accessories therefor
556	0.002%	Organic compounds -- part of the class 532-570 series
359	0.002%	Optical: systems and elements
426	0.002%	Food or edible material: processes, compositions, and products
73	0.001%	Measuring and testing
260	0.001%	Chemistry of carbon compounds
362	0.001%	Illumination
544	0.001%	Organic compounds -- part of the class 532-570 series

*Note, the top 95% of the patent breakdown is shown

Chapter 4: Academic Entrepreneurship: The Role of Novel and General Heterogonous Innovation

4.1 Introduction

Perhaps triggered by passage of the Bayh-Dole Act, and the subsequent proliferation of technology transfer offices at universities around the world, a recent literature has exploded focusing on the transfer and spill over of university research (Shane, 2002 and Shane and Stuart, 2002). This research has typically examined what universities do, particularly in terms of patented inventions (Herderson, Jaffe and Trajtenberg, 1998; Colyvas et al., 2002; and Thursby and Thursby, 2002).

However, much less attention has been given to what the scientists themselves do themselves, in terms of commercialization, either with or without the assistance of the technology transfer office (TTO). As Shane (2004, p.4) points out, "Sometimes patents, copyrights and other legal mechanisms are used to protect the intellectual property that leads to spinoffs, while at other times the intellectual property that leads to a spinoff company formation takes the form of know how or trade secrets. Moreover, sometimes entrepreneurs create university spinoffs by licensing university inventions, while at other times the spinoffs are created without the intellectual property being formally licensed from the institution in which it was created. These distinctions are important for two reasons. First it is harder for researchers to measure the formation of spinoff companies created to exploit intellectual property that is not protected by legal mechanisms or that has not been disclosed by inventors to university administrators."

The few studies that have analyzed the commercialization activities of scientists have focused on characteristics specific to the scientists, such as age and gender (Stephan and Levin 1991 and Audretsch and Stephan, 1996), as well as the scientist's human capital (measured in terms of publications and citations) (Zucker, Darby and Brewer, 1998; Audretsch and Stephan, 1996) and social capital. In addition, several studies have considered the impact of the technology transfer office on the propensity for scientists to become an entrepreneur (Feldman et al. 2002, Zucker et al. 2002). These studies generally find that a higher degree of human capital, or scientist knowledge, as measured in terms of publications and citations, leads to a higher propensity to commercialize that knowledge in the form of a patented invention of becoming an entrepreneur.

However, a very different literature suggests that the knowledge underlying a patented invention may not be homogenous in nature. Rather, Trajtenberg, Jaffe and Henderson (1997) and Agarwal and Henderson (2002) suggest that knowledge is remarkably heterogeneous. They introduce a method for distinguishing between and measuring the extent to which knowledge reflects originality or novelty, rather than being incremental in nature. Similarly, they are able to distinguish between knowledge that is general versus specific knowledge.

The purpose of this chapter is to examine whether the type of knowledge underling a scientist's patent, rather than the more traditional measures reflecting characteristics specific to the scientist, influences the likelihood that she will become an entrepreneur. In particular, this chapter links to characteristics of a scientist's patents, novelty and generality, to the propensity that scientist will become an entrepreneur. Based on a large data set of scientists awarded a research grant from the National Cancer

Institute (NCI) and holding patents, this chapter finds that scientist holding a patent that is more original and general have a higher likelihood of becoming an entrepreneur that those with a patent that reflects incremental knowledge and specific knowledge. Thus, the empirical evidence suggests that the type of knowledge underlying a patent may influence the decision for a scientist to become an entrepreneur, rather than characteristics specific to the entrepreneur found in previous literature.

4.2 Scientist Entrepreneurship

The focus of the growing literature on scientist entrepreneurship has been to address the question of why some scientists choose to become entrepreneurs while others do not. In seeking an answer, studies have generally focused on five factors. The first factor is the amount of knowledge or human capital associated with the scientist. If new knowledge drives new commercial opportunities, then scientists with more knowledge should have a greater propensity to become an entrepreneur. In an important study, Zucker et al. (2002) find that startup activity tends to be greater where star scientists, measured in terms of scientific output, is greater.

The second factor influencing the decision by scientists to become an entrepreneur involves the social capital accessed by the capital or linkages to important networks. Social capital refers to meaningful interactions and linkages the scientist has with others. While *physical capital* refers to the importance of machines and tools as a factor of production (Solow, 1956), the endogenous growth theory (Romer 1986, 1990; Lucas 1988) puts the emphasis on the process of knowledge accumulation, and hence the creation of *knowledge capital*. The concept of *social capital* (Putnam, 1993 and Coleman, 1988) can be considered a further extension because it adds a social component to those factors shaping economic growth and prosperity. According to Putnam

(2000, p.19), “Whereas physical capital refers to physical objects and human capital refers to the properties of individuals, social capital refers to connections among individuals – social networks. By analogy with notions of physical capital and human capital – tools and training that enhance individual productivity – social capital refers to features of social organization, such as networks that facilitate coordination and cooperation for mutual benefits.”

A large and robust literature has emerged attempting to link social capital to entrepreneurship (Aldrich and Martinez, 2003; Aldrich, 2005; and Thorton and Flynn, 2003). According to this literature, entrepreneurial activity should be enhanced where investments in social capital are greater. Interactions and linkages, such as working together with industry, are posited as conduits not just of knowledge spillovers but also for the demonstration effect providing a flow of information across scientists about how scientific research can be commercialized (Thursby and Thursby, 2004).

Nicolaou and Birley (2003) examine the influences of social networks on university spin-outs. Their data base consists of 45 spin- outs comprising 111 inventors originating from Imperial College London. They find that a high level of non redundancy in the academic’s institutional business discussion networks, coupled with a high strength of ties, increases the propensity for a scientist to become an entrepreneur.

Rappert et al. (1999) find empirical evidence supporting the importance of linkages with industry for academic entrepreneurs. Based on detailed interviews with 94 individuals from 59 university spin-offs in the United Kingdom, they find that linkages play a crucial role. Similarly, Murray (2004), using data from 23 U.S. biotechnology firms, finds that the academic inventors’ social capital contributes to entrepreneurial capabilities. In analyzing the impact of star scientists on the success of biotechnology in

Japan, Zucker and Darby (2001) identify collaboration between the scientists and industry plays an important role. Based on a survey of 291 university scientists involved in biotechnology in Isreal, Oliver (2004) finds that scientists with significantly more industrial collaborations were more likely to submit patent applications. Thus, there are both compelling theoretical reasons as well as supporting empirical evidence linking social capital to scientist entrepreneurship.

The third factor influencing the decision to become an entrepreneur by a scientist is the institutional context in which she works. One of the important mechanisms facilitating the entrepreneurial activities of universities is the technology office of the university (TTO), which has a mandate to facilitate and promote the commercialization of university science. As the President of the Association of American Universities observed, "Before Bayh-Dole, the federal government had accumulated 30,000 patents, of which only 5% had been licensed and even fewer had found their way into commercial products. Today under Bayh-Dole more than 200 universities are engaged in technology transfer, adding more than $21 billion each year to the economy,"[19] and the Commission of the U.S. Patent and Trademark Office claimed, "In the 1970s, the government discovered that inventions that resulted from public funding were not reaching the marketplace because no one could make the additional investment to turn basic research into marketable products. That finding resulted in the Bayh-Dole Act, passed in 1980. It enabled universities, small companies, and nonprofit organizations to commercialize the results of federally funded research. The results of Bayh-Dole have been significant.

[19] cited in Mowery (2005, p. 2).

Before 1981, fewer than 250 patents were issued to universities each year. A decade later universities were averaging approximately 1,000 patents a year."[20]

Research has found that the TTO influences entrepreneurial activities emanating from university scientists. For example, Leitch and Harrrison (2005) undertook a series of interviews with the directors of TTOs and found that the TTO can influence start-up ventures. Link and Scott (2005) found that the proximity of the university to a research park facilitates the ability of a TTO to generate spinoffs. Jensen and Thursby (2001) examined 62 TTOs at U.S. universities and concluded that the ability of the TTO to license inventions increases the speed to which intellectual property becomes commercialized. Markman et al. (2004) interviewed 128 TTO directors and found a link between the compensation of TTO personnel and entrepreneurial activity generated by the TTO.

The fourth factor influencing scientist entrepreneurship involves characteristics specific to the particular scientist, in particular age. The university or academic career trajectory encourages and rewards the production of new scientific knowledge. Thus, the goal of the scientist in the university context is to establish *priority*. This is done most efficiently through publication in scientific journals (Audretsch and Stephan, 2000). By contrast, with a career trajectory in the private sector, scientists are rewarded for the production of new economic knowledge, or knowledge which has been commercialized in the market, but not necessarily new scientific knowledge *per se*. In fact, scientists working in industry are often discouraged from sharing knowledge externally with the

[20] cited in Mowery (2005, p. 2)

scientific community through publication. As a result of these differential incentive structures, industrial and academic scientists develop distinct career trajectories.

The appropriability question confronting academic scientists can be considered in the context of the model of scientist human capital over the life-cycle. Scientist life-cycle models suggest that early in their careers scientists invest heavily in human capital in order to build a scientific reputation (Levin and Stephan, 1991). In the later stages of their career, the scientist trades or *cashes in* this reputation for economic return. Thus, early in her career, the scientist invests in the creation of scientific knowledge in order to establish a reputation that signals the value of that knowledge to the scientific community.

With maturity, scientists seek ways to appropriate the economic value of the new knowledge. Thus, academic scientists may seek to commercialize their scientific research within a life-cycle context. The life-cycle model of the scientist implies that, *ceteris paribus*, scientist age should play a role in the decision to commercialize. In the early stages of her career, a scientist will tend to invest in her scientific reputation. As she evolves towards maturity and the marginal productivity of her scientific research starts to hit diminishing returns, the incentive for cashing in through commercialization becomes greater.

Scientists working in the private sector are arguably more fully compensated for the economic value of their knowledge. This will not be the case for academic scientists, unless they cash out, in terms of Dasgupta and David (1994), by commercializing their scientific knowledge. This suggests that academic scientists seek commercialization

within a life-cycle context, where they are more likely to enter into entrepreneurship as they mature.

The fifth factor influencing scientist entrepreneurship is geography. Scientist location can influence the decision to commercialize for two reasons. First, as Jaffe (1989), Audretsch and Feldman (1996), Jaffe, Trajtenberg and Henderson (1993), and Glaeser, Kallal, Sheinkman and Shleifer (2002) show, knowledge tends to spill over within geographically bounded regions. This implies that scientists working in regions with a high level of investments in new knowledge can more easily access and generate new scientific ideas. This suggests that scientists working in knowledge clusters should tend to be more productive than their counterparts who are geographically isolated. As Glaeser, Kallal, Scheinkman and Shleifer (1992, p. 1126) have observed, "Intellectual breakthroughs must cross hallways and streets more easily than oceans and continents."

A second component of externalities involves not the technological knowledge, but rather behavioural knowledge. As Bercoviz and Feldman (2004) show for a study based on the commercialization activities of scientists at Johns Hopkins and Duke University, the likelihood of a scientist engaging in commercialization activity, which is measured as disclosing an invention, is shaped based on the commercialization behaviour of the doctoral supervisor in the institution where the scientist was trained, as well as the commercialization behaviour and attitudes exhibited by the chair and peers at the relevant department. Similarly, based on a study of 778 faculty members from 40 universities, Louis et al. (1989) find that it is the local norms of behaviour and attitudes towards commercialization that shape the likelihood of an individual university scientist to engage in commercialization activity, in their case by starting a new firm.

Audretsch and Stephan (1996) find that geography matters more in certain economic relationships than in others. In particular, from a data set of 54 beiotechnology firms affiliated with 445 university scientists, they find that the probability of a scientist-firm contact being local is shaped by the role played by the scientists: (i) Proximity matters more in the case of founders and chairs of scientific advisory board (SABs); (ii) Proximity does not matter as much in the case of members of SABs; (iii) When knowledge is transmitted through formal ties, geographic proximity is not necessary. Zucker et al. (1998) examine 327 star sciences in the life sciences and 751 U.S. firms and find that the location of new dedicated biotechnology firms and new biotech subunits of existing firms are primarily explained by the presence of academic star scientists. Thus, the locational context can influence the propensity for scientists to engage in commercialization activities by providing access to spatially bounded knowledge spillovers and by shaping the behavioural norms and attitudes towards entrepreneurship.

While extant research has identified these five factors – human capital, social capital, institutional context, age and geography – the impact of the type of knowledge associated with the scientist on entrepreneurship has largely been neglected. Even though the first factor considers the amount of knowledge, it typically is measured in terms of the quantity of publications and citations and is therefore considered to be homogeneous. In the next section we will suggest that, in fact, knowledge emerging from scientific research is remarkably heterogeneous in such a manner as to influence the decision of scientists to become an entrepreneur.

4.3 Novelty and Generality

The previous section identified a growing literature suggesting that the knowledge embodied in a scientist is an in important factor influencing the likelihood of her becoming an entrepreneur. In particular, the degree to which the knowledge is novel versus incremental should influence the decision to become an entrepreneur in order to commercialize that knowledge. Knowledge that is more incremental in nature can be characterized more by risk, where the outcomes are known along with their associated probability distributions. By contrast, knowledge that is novel is characterized more by uncertainty where not only are the outcomes not known but no associated probability distributions can be assigned (Alvarez, 2003, Barney, 1986 and Alvarez and Barney, 2005 and 2006).

The cost of the scientist transferring incremental knowledge through a license or consulting contract is relatively low because the associated risk can be calculated and incorporated into the contract. By contrast, it is very difficult for a scientist to transfer novel knowledge through the standard instruments of licensing or consulting because of the inherent uncertainty which cannot be written into a contract. Thus, as Alvarez (2003), Barney (1986) and Alvarez and Barney (2005 and 2006) point out, entrepreneurial opportunities tend to be more highly associated with knowledge characterized by uncertainty rather than risk, or in this case novel knowledge rather than incremental knowledge.

Arrow (1962) and Williamson (1975) argued that when knowledge created outside of incumbent firms cannot be easily transferred to those incumbent firms, as a result of agency and bureaucracy problems, the holder of such knowledge is not able to

transfer that knowledge via a licensing or consulting contract but must rather start her own firm in order to appropriate the expected returns on that knowledge. This reflects what Winter (1984, p. 297) termed as an entrepreneurial technological regime where, "An entrepreneurial regime is one that is favorable to innovative entry and unfavorable to innovative activity by established firms."

Winter's (1982) entrepreneurial regime corresponds to Alvarez and Barney's (2007) high uncertainty context associated with novel knowledge. This would suggest that scientists with knowledge that can be characterized as being relatively novel rather than incremental would more likely choose to become entrepreneurs.

Similarly, knowledge that is more general in nature and less specific to a particular application is also characterized by a greater degree of uncertainty. It is very difficult for a scientist to know all of the ways in which general knowledge can be applied and commercialized. Thus, general knowledge would also be expected to be more conducive to entrepreneurship than would very specific knowledge. This leads to the hypotheses that the likelihood of a scientist becoming an entrepreneur should be higher if she holds patents reflecting more novel knowledge as well as more general knowledge.

4.4 Measurement Issues

In order to link the propensity for a scientist to become an entrepreneur to the nature of her underlying intellectual property, a new data base was created based on scientists awarded a research grant by the National Cancer Institute between 1998 and 2002. Of those research grant awards, the largest twenty percent, which included 1,693 scientist awardees, were taken to form the database used in this chapter. The National

Cancer Institute (NCI) awarded a total of $5,350,977,742 to the top 1,693 scientists in the United States from 1998 to 2002.

To match the patent records with the 1,692 NCI recipient scientists, Structured Query Language (SQL) and Python programming languages were written to extract and manipulate data. A match between the patentee and NCI awardee databases was considered to be positive if all four of the following necessary conditions were met:

(1) A positive match was made with the first, middle, and last name. If, for example, the scientist did not have a middle name listed on either the NCI award database or the patent database, but did have a positive first and last name, this first condition was considered to be fulfilled.

(2) The second criterion involved matching the relevant time periods between the two databases. Observations from both databases were matched over the time period 1998-2004, which corresponds to the initial year in which observations were available from the NCI database (1998-2002) and the final year in which patents were recorded in the patent database (1975-2004). Because applications of patents may take anywhere from three months to two years to be issued, the 2003 and 2004 USPTO patent records were included in our query. Issued patents from 1998 to 2004 by NCI scientists fulfilled the second criterion.

(3) The third criterion was based on location. If the patentee resided within an approximate radius of 60 miles from the geographic location of the university, the third condition was fulfilled.

(4) The fourth criterion was based on USPTO patent classification. Using the USPTO patent classification code, all patents were separated into respective coding groups. Patents which did not fall under the traditional categories of biotechnology were identified. All non biotech patents were evaluated and patents such as “Bread Alfalfa Enhancer” were rejected as an NCI scientist patent (see Appendix A for a distribution of patent categories). Based on these four match criteria, a subset of 398 distinctly issued patentees were identified between 1998 and 2004 with a total of 1,204 patents.

Since the focus of this chapter is to link the propensity of scientists to become entrepreneurs to the type of knowledge involved in their patented inventions, patent data for each scientist was obtained from the United States Patent and Trade Office (USPTO). The patent records span 1975 to 2004. The inventor patent data included identification of the patent number of the invention, the name and address of the inventor, and the inventor sequence number.

However, the USPTO records do not identify whether the scientist holding the patent has become an entrepreneur in the form of founding a new business. To identify whether the scientist had become an entrepreneur, a series of interviews with each scientist were undertaken, where the scientists was asked whether she had founded a company between 1998 and 2004. The dependent variable in the estimated probit regressions takes on the value of one if the scientist also started a new firm or zero otherwise.

4.4.1 Measuring Generality and Originality

We follow Trajtenberg, Jaffe and Henderson (1997) to measure the extent to which a patent reflects novelty and the extent to which it reflects generality. This second concept, generality, refers to the extent to which the forward patents citations are spread across different technological fields, rather than being concentrated in just a few technological fields. We compute a measure of generality of technology on the basis of a herfindahl index of concentration, where the number of citations in each 3 digit patent classification plays the same role as the sales of each firm in the traditional industrial organization measure.

Two measures reflecting, "Generality" and "Originality," as suggested by Trajtenberg, Jaffe and Henderson (1997) were created, where *nii j ij Generality* 1 *s*2 ,where *sij* denotes the percentage of citations received by patent *i* that belong to patentclass *j*, out of *ni* patent classes (note that the sum is the Herfindahl concentration index). Thus as written in Trajtenberg, Jaffe and Henderson:

"if a patent is cited by subsequent patents that belong to a wide range of fields the measure will be high, whereas if most citations are concentrated in a few fields it will below (close to zero). Thinking of forward citations as indicative of the impact of a patent, a high generality score suggests that the patent presumably had a widespread impact, in that it influenced subsequent innovations in a variety of fields (hence the "generality" label). "Originality" is defined the same way, except that it refers to the backward citations issued. Thus, if a patent cites previous patents that belong to a narrow set of technologies the originality score will be low, whereas citing patents in a wide range of fields would render a high score. Note that these measures depend of course upon the patent classification system: a finer classification system would render higher measures, and conversely for a coarser system." P.2 (2001)

Several other variables were included in estimating the probit model to control for influences on the propensity for a scientist to become an entrepreneur already identified

in the literature. These measures include the age of the scientist, gender, number of co-authored publications with a scientist employed by industry, the mean number of citation between 1998 and 2004, the total amount of funding received by the scientist, a dummy variable taking on the value of one if the scientist had a history of being awarded a patent prior to 1998, a dummy variable taking on the value of one if the scientist was employed at a university with a comprehensive center for cancer research, a dummy variable taking on the value of one if the university has ivy league status, the age of the technology transfer office (TTO), and the size of the TTO, measured in terms of number of full-time employees. The variable definitions are provided in Table One.

Table 4.1: Description of Variables

Variables	**Description**
Startup	Binary variable, where if the scientist responsed to "did you found a company" =1
Originality	The number of times a patenting scientist shared a patent with another NCI scientist
Generality	The number of publications an NCI scientist shared with a private industry scientist
Scientist Age	Count variable where scientists age is recorded
Gender	Binary variable, where a male=1
Industry Copublications	Count of copublications a scientists had with industry from 1998 – 2004
Citations per publication	The average citations per publication with 1998 – 2004
NCI Grant	Total amount of funding received by a scientist from 1998 to 2004
Prior Patentee	Binary variable, where if a scientist had an issued patent prior to 1998 =1
NCI Center	Binary variable, for a scientist whose institution is recognized by NCI as a comprehensive center for cancer research, NCI Center=1
Ivy League	Binary variable, for a scientist whose institution is an Ivy League university, Ivy League=1
Public Institution	Binary variable, where a university is a publicly funded university =1
TTO Age	Year when University Technology Transfer Office was founded
TTO Employees	The mean annual number of Technology Transfer Office employees dedicated to licensing and patenting
Patent Classification	Using the USPTO patent classification system, patents were controlled for the type of Intellectual Property they belonged to. Patents were controlled for

	their 3 and 6 digit controls system used by the USPTO. See Apendix A for breakdown of classification.

The means and standard deviations of each variable are provided in Table two. It should be emphasized that, as the table shows, the correlation between the measures reflecting patent novelty and generality are quite low, suggesting that these measures reflect very different aspects of knowledge.

Table 4.2: Means and Deviations of Variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Startup	360	.2444444	.4303555	0	1
Originality	297	.3189348	.276184	0	.826087
Generality	220	.2196009	.2567887	0	.8526077
Scientist Age	337	57.69139	1.148.756	41	95
Gender	360	2.172.222	1.030.771	0	102
Industry Copublications	360	3.408.333	4.509.654	0	34
Citations per publication	360	2.584.525	2.076.277	0	1.303.651
NCI Grant	360	3125040	2626173	0	1.37e+07
Prior Patentee	360	.7972222	.5438878	0	4
Public Institution	360	.4666667	.499582	0	1
Ivy League	360	.1194444	.3247621	0	1
NCI Compcenter	354	.5084746	.5006358	0	1
TTO Employees	359	9.438.062	1.245.584	0	4.235.714
TTO Age	359	1982.17	9.135.026	1940	2004
cat11	360	.1916667	.39416	0	1
cat12	360	.0527778	.2239007	0	1
cat14	360	.0388889	.1935992	0	1

cat21	359	.0557103	.2296815	0	1
cat22	359	.0724234	.2595494	0	1
cat25	359	.2785515	.4489119	0	1
cat26	359	.0362117	.1870773	0	1
cat27	359	.4011142	.4908081	0	1

The correlation coefficient for each variable pair is shown in Table three.

Table 4.3: Correlation Table of Variables

1	startup	1	2	3	4	5	6	7	8	9	10	11
2	Originality	0.1746	10.000									
3	Generality	0.1209	0.1810	10.000								
4	Scientist Age	0.1063	0.0575	0.0498	10.000							
5	Gender	0.0420	0.0032	-0.0595	0.0101	10.000						
6	Industry Copublications	0.0136	-0.0433	-0.0618	-0.0148	-0.0080	10.000					
7	Citations per Publication	-0.1621	-0.2771	0.0258	-0.1637	0.1159	0.2129	10.000				
8	NCI Grant	-0.1876	-0.1041	-0.0061	0.0093	-0.0426	-0.1011	0.3558	10.000			
9	Prior Patentee	-0.1484	0.0679	0.0256	0.1794	-0.0733	0.0848	0.0587	0.0968	10.000		
10	Public Institution	-0.1863	0.0251	0.0994	0.0419	0.1262	-0.0649	-0.0094	0.2602	-0.1540	10.000	
11	Ivy League	0.0714	0.0344	0.1588	-0.1242	-0.1830	0.0529	0.1401	0.2126	0.0807	-0.3258	10.000
12	NCI Center	-0.0543	-0.0239	-0.0222	-0.0801	-0.0035	0.1621	0.2711	0.1169	0.0861	-0.0501	0.0988
13	TTO Employees	-0.1845	0.0075	-0.0752	0.0187	0.0231	0.1858	0.3170	0.4247	0.1369	0.3521	-0.1247
14	TTO Age	-0.1895	0.0212	0.1805	0.1801	-0.0337	-0.0411	-0.2284	-0.1277	0.0573	0.1924	-0.0472
15	Patent cat11	-0.0620	0.1090	0.0058	-0.0176	-0.0275	0.0107	-0.0210	-0.0400	0.0302	0.0638	0.0195
16	Patent cat12	-0.1533	0.1353	-0.0802	0.2021	0.1088	0.0235	-0.1857	-0.1580	0.1077	-0.2160	-0.1121
17	Patent cat14	0.1031	0.1784	0.2985	-0.1338	0.0112	-0.0688	-0.0587	-0.0466	0.0096	0.1384	0.0600
18	Patent cat21	0.0693	0.0778	0.1100	-0.0200	0.0700	-0.0146	0.0498	-0.1312	-0.0461	-0.0728	0.1155
19	Patent cat22	-0.0557	0.0574	-0.1394	-0.1714	-0.0664	0.1658	0.1832	-0.0244	-0.0500	-0.0041	0.1358
20	Patent cat25	0.2020	-0.0537	-0.1959	0.2331	-0.0898	-0.1028	-0.2181	-0.2159	-0.0904	-0.0973	-0.1314
21	Patent cat26	-0.1086	-0.0255	0.0176	-0.1311	0.0888	-0.0688	-0.0987	0.0103	-0.0500	0.0434	-0.0158
22	Patent cat27	0.0083	-0.1811	-0.0106	-0.0836	0.0211	0.1124	0.2678	0.3281	0.0762	0.0627	0.0473
23	Patent cat29	0.0237	0.0903	0.0775	-0.1061	-0.1423	0.0139	-0.1150	0.0538	0.0142	-0.0491	0.1355
24	Patent cat210	-0.0617	0.1169	0.1098	0.0067	0.0700	-0.0608	-0.1674	-0.1392	0.1016	0.0449	-0.0721

12	NCI Center	12	13	14	15	16	17	18	19	20	21	22
13	TTO Employees	0.4182	10.000									
14	TTO Age	-0.0487	-0.2418	10.000								
15	cat11	0.1165	-0.0249	-0.0004	10.000							
16	cat12	-0.2826	-0.0992	0.1331	-0.1281	10.000						
17	cat14	0.1035	0.1203	0.0450	-0.1046	-0.0832	10.000					
18	cat21	0.0547	-0.0877	-0.0174	0.0025	-0.0656	-0.0535	10.000				
19	cat22	0.0080	-0.0377	-0.1730	0.2381	-0.0832	-0.0679	-0.0535	10.000			
20	cat25	-0.0693	-0.1861	0.0357	0.0556	-0.1950	-0.1591	-0.1254	-0.1591	10.000		
21	cat26	-0.0397	-0.1354	0.1932	-0.1046	-0.0014	0.0292	-0.0535	-0.0679	-0.1591	10.000	
22	cat27	0.1950	0.2925	-0.2885	-0.0491	-0.2122	-0.1732	-0.1365	-0.1732	-0.4059	-0.1732	10.000
23	cat29	0.0232	0.0280	0.0101	-0.0761	0.0485	0.2095	-0.0389	-0.0494	-0.1158	-0.0494	-0.1260
24	cat210	-0.0044	-0.0728	0.1384	0.0873	0.0357	0.3072	-0.0422	-0.0535	-0.1254	-0.0535	-0.1365

25	cat29	1	26
26	cat210	-0.0389	10.000

4.6 Empirical Results

To test the hypothesis that the propensity for a scientist to become an entrepreneur is influenced by the extent to which her intellectual property can be characterized as being novel and by being general, a probit model was estimated where the dependent variable takes on the value of one if the scientist started a new firm and zero if she did not (table three) and a marginal affects table is provided (table four).

Table 4.4: Clustered Probit Estimate of Scientist Entrepreneurship

v1	**v2**	**v2**	**v2**	**v2**
COEFFICIENT	short	full	no tto	no ncicomp
Originality	**1.099e+00*** **	**1.168e+00** **	**1.242e+00*** **	**1.145e+00** **
	[4.150e-01]	[4.637e-01]	[4.667e-01]	[4.583e-01]
Generality	**9.294e-01* **	**1.278e+00** **	**1.105e+00** **	**1.329e+00** **
	[4.832e-01]	[5.273e-01]	[4.914e-01]	[5.451e-01]
Scientist Age	1.141e-02	3.271e-02*	3.135e-02	3.042e-02
	[1.934e-02]	[1.978e-02]	[2.058e-02]	[1.938e-02]
Gender	5.168e-01	7.004e-01	8.004e-01	6.875e-01
	[5.894e-01]	[5.497e-01]	[5.811e-01]	[5.667e-01]
Industry Copublications		5.187e-02*	3.884e-02	5.184e-02*
		[2.832e-02]	[2.893e-02]	[2.770e-02]
Citations per Publication		-2.335e-02*	-1.656e-02	-2.402e-02*
		[1.358e-02]	[1.329e-02]	[1.293e-02]
NCI Grant		-1.074e-07	-9.719e-08	-9.615e-08
		[1.082e-07]	[1.052e-07]	[1.011e-07]
Prior Patentee		-6.870e-01*	**-8.057e-01** **	-6.584e-01
		[4.125e-01]	[4.003e-01]	[4.088e-01]
Public Institutions		-6.296e-01	-8.719e-01*	-5.816e-01
		[4.843e-01]	[4.549e-01]	[4.760e-01]
Ivy League		2.732e-01	2.079e-01	2.050e-01
		[5.988e-01]	[6.011e-01]	[5.745e-01]
NCI Center		-2.228e-01	-4.095e-01	-
		[4.921e-01]	[4.537e-01]	
TTO Employees		-2.476e-02	-1.182e-02	-2.930e-02
		[2.320e-02]	[2.038e-02]	[2.181e-02]
TTO Age		-4.084e-02*	-	-4.367e-02*
		[2.391e-02]		[2.280e-02]
cat11	-5.268e-01	-4.661e-01	-4.361e-01	-5.042e-01
	[3.647e-01]	[3.848e-01]	[3.567e-01]	[3.896e-01]
cat12	-3.111e-01	-1.175e+00	-1.131e+00	-1.089e+00
	[8.398e-01]	[9.252e-01]	[1.017e+00]	[8.829e-01]
cat14	**1.070e+00** **	**1.370e+00** **	**1.554e+00*** **	**1.296e+00** **
	[4.769e-01]	[5.548e-01]	[5.457e-01]	[5.595e-01]
cat21	1.129e+00*	3.182e-01	6.138e-01	2.850e-01
	[6.587e-01]	[7.471e-01]	[7.235e-01]	[7.502e-01]
cat22	1.091e+00	4.880e-01	9.632e-01	4.921e-01
	[6.956e-01]	[7.136e-01]	[7.668e-01]	[7.023e-01]
cat25	**1.587e+00*** **	9.161e-01*	1.131e+00*	8.989e-01*
	[5.563e-01]	[5.325e-01]	[5.813e-01]	[5.324e-01]
cat26	-2.738e-01	-9.249e-01*	**-9.272e-01** **	-9.296e-01*
	[4.221e-01]	[5.245e-01]	[4.387e-01]	[5.599e-01]
cat27	**1.123e+00** **	7.880e-01	**1.155e+00** **	7.352e-01
	[4.930e-01]	[5.448e-01]	[5.368e-01]	[5.440e-01]
cat29	7.424e-01	2.968e-01	3.363e-01	2.384e-01

	[5.996e-01]	[5.951e-01]	[5.657e-01]	[5.647e-01]
cat210	-5.384e-01	**-1.070e+00****	**-1.014e+00****	**-1.065e+00****
	[5.006e-01]	[4.666e-01]	[4.755e-01]	[4.526e-01]
Constant	**-3.355e+00****	7.821e+01*	**-2.895e+00****	8.388e+01*
	[1.339e+00]	[4.733e+01]	[1.449e+00]	[4.512e+01]
Observations	174	173	173	173
R-squared	.	.	.	.
LR chi2	43.68	92.79	74.03	90.72
R-squared adjusted	0.175	0.346	0.319	0.343
Observations	174	173	173	173
r2_p	0.175	0.346	0.319	0.343
chi2	43.68	92.79	74.03	90.72
df_m	14	23	22	22
Ll	-84.54	-66.82	-69.61	-67.08
ll_0	-102.5	-102.2	-102.2	-102.2
N_clust	75	74	74	74
Robust standard errors in brackets				
*** p<0.01, ** p<0.05, * p<0.1				

As the positive as statistically significant coefficient of originality indicates, a scientist is more likely to become an entrepreneur if the patent reflects original knowledge rather than incremental knowledge. Similarly, as the positive and statistically significant coefficient of generality suggests, a scientist has a higher propensity to start a new firm is her knowledge is more general than specific. These results are found to hold across four different specifications of the probit model, based on the inclusion of different control variables.

The control variables are generally not statistically significant. Scientist age is statistically significant in only one of the four specifications, and gender is never statistically significant. Neither, human capital, as measured by citations, nor social capital, as measured by co-authored publications with an industry scientist, is statistically significant. The characteristics of the technology transfer office (TTO), also do not have

any statistically significant impact on the likelihood of a scientist becoming an entrepreneur.

Table 4.5: Marginal Affects Table of Scientist

	Coefficients
	Scientist
Dependent Variable	Startups
Originality	**1.168e+00****
	[4.637e-01]
Generality	**1.278e+00****
	[5.273e-01]
Scientist Age	3.271e-02*
	[1.978e-02]
Gender	7.004e-01
	[5.497e-01]
Industry Copublications	5.187e-02*
	[2.832e-02]
Citations per Publication	-2.335e-02*
	[1.358e-02]
NCI Grant	-1.074e-07
	[1.082e-07]
Prior Patentee	-6.870e-01*
	[4.125e-01]
Public Institutions	-6.296e-01
	[4.843e-01]
Ivy League	2.732e-01
	[5.988e-01]
Nci Center	-2.228e-01
	[4.921e-01]
TTO Employees	-2.476e-02
	[2.320e-02]
TTO Age	-4.084e-02*
	[2.391e-02]
cat11	-4.661e-01
	[3.848e-01]
cat12	-1.175e+00
	[9.252e-01]
cat14	**1.370e+00****
	[5.548e-01]
cat21	3.182e-01
	[7.471e-01]
cat22	4.880e-01
	[7.136e-01]
cat25	9.161e-01*
	[5.325e-01]
cat26	-9.249e-01*

	[5.245e-01]
cat27	7.880e-01
	[5.448e-01]
cat29	2.968e-01
	[5.951e-01]
cat210	**-1.070e+00****
	[4.666e-01]
Constant	7.821e+01*
	[4.733e+01]
Observations	173
R-squared	.
LR chi2	92.79
R-squared adjusted	0.346
Observations	173
Xmfx_y	0.167
N_clust	74
ll_0	-102.2
Ll	-66.82
df_m	23
chi2	92.79
r2_p	0.346
Robust standard errors in brackets	
*** p<0.01, ** p<0.05, * p<0.1	

As shown in Table four, the marginal affects are only significant for originality and generality. Indicating that with one lest patent citation for originality, there is a 116% change of a scientist starting a company while with one more forward patent citation in generality equaling a 127% likelihood of a scientist starting a firm.

4.7 Conclusion

The empirical results provide a striking contrast to previous studies. Rather than pointing to characteristics specific to the scientist, such as age and gender, or characteristics specific to her human capital and social capital, such as citations and co-publications with industry scientists, or even characteristics specific to the TTO, this

chapter has found that it is the nature of the knowledge and technology inherent in the patent that influences whether or not a scientist becomes an entrepreneur.

In particular, this chapter has found two characteristics reflecting the knowledge underlying a patented invention influence scientist entrepreneurship. The first is the degree of originality or novelty of the patent. The empirical results of this chapter suggest that the more original or novel the patent, the more likely a scientist is to become an entrepreneur. This empirical finding is consistent with the view that knowledge which is highly novel or original is characterized by a greater extent of uncertainty, making it more difficult for the holder of that knowledge, i.e. the scientist, to appropriate the value of her ideas using some alternative mode of commercialization. Similarly, the degree of generality also increases the likelihood of a scientist becoming an entrepreneur. Again, more general knowledge is associated with a greater degree of uncertainty, making it more difficult for the holder of that knowledge to appropriate its value through traditional modes of technology transfer.

Thus, the results of this chapter suggest that while the amount of human capital and social capital may be important in generating entrepreneurship from universities, it is the type of knowledge underling inventive activity that may also be important in understanding why some scientists choose to become entrepreneurs while others do not. Knowledge that is highly uncertain, in that it reflects originality and generality, increases the likelihood of a scientist becoming an entrepreneur. There may, in fact, be other characteristics of knowledge that do not have a neutural effect on scientist entrepreneurship. Subsequent research might prove fruitful in considering not just the

amount of knowledge generated by scientific work, but also other dimensions shaping the type of knowledge generated, and how it is linked to scientist entrepreneurship.

Chapter 5: Scientist Commercialization as a Conduit of Knowledge Spillovers

5.1 Introduction

Why and how will scientists decide to combine to commercialize their academic research? The answers to this question are not only important to institutions and scientists engaged in research. The New Endogenous Growth models and theories highlight the central role that investments in science and research play in generating economic growth (Romer, 1985; and Lucas, 1993). But more recently, public policy makers, ranging from local communities, to states and even entire countries have pointed out that such investments in knowledge and research do not automatically spill over into commercialized new products and innovations. Rather, what Acs et al. (2004) and Audretsch et al. (2005) term as *the knowledge filter* effectively impedes the spillover and commercialization of investments in knowledge, thereby limiting the rate of return in terms of employment creation and economic growth accruing from public and private investments in science and research. In the presence of a high knowledge filter, investments in science and research do not automatically spill over and become commercialized, resulting in vigorous rates of economic growth and employment generation, as assumed in models of endogenous growth. The combination of high investments in science and research but low rates of economic growth and employment generation led first to what was termed as the Swedish Paradox and somewhat later adapted by European Commission as *The European Paradox*. Audretsch et al. (2005) and Acs et. al (2004) identify activities that involve the commercialization of science and

research as the *Missing Link* in the process of economic growth. In the absence of scientist commercialization of research, investments in science and research will not generate an adequate rate of return, in terms of economic growth and job creation.

5.2 How and Where are Scientists Creative?

Why will a scientist choose to combine her scientific creativity with entrepreneurial creativity? A number of theories and hypotheses have posited why some scientists choose to commercialize research while others do not, and some compelling insights have been garnered through previous empirical studies. These include the scientist life-cycle, which highlights the role of reputation, the knowledge production function, which highlights the role of scientific human capital and resources, and the regional and university contexts, which highlight the role of geographically bounded spillovers and institutional incentives.

A large literature has emerged focusing on what has become known as the appropriability problem. The underlying issue revolves around how firms which invest in the creation of new knowledge can best appropriate the economic returns from that knowledge (Arrow, 1962). Audretsch (1995) proposed shifting the unit of observation away from exogenously assumed firms to individuals – agents with endowments of new economic knowledge. When the lens is shifted away from the firm to the individual as the relevant unit of analysis, the appropriability issue remains, but the question becomes; *"How can scientists with a given endowment of new knowledge best appropriate the returns from that knowledge?"* Levin and Stephan (1991) suggest that the answer is, *It*

depends – it depends on both the career trajectory as well as the stage of the life-cycle of the scientist.

The university or academic career trajectory encourages and rewards the production of new scientific knowledge. Thus, the goal of the scientist in the university context is to establish *priority*. This is done most efficiently through publication in scientific journals (Audretsch and Stephan, 2000). By contrast, with a career trajectory in the private sector, scientists are rewarded for the production of new economic knowledge, or knowledge which has been commercialized in the market, but not necessarily new scientific knowledge *per se*. In fact, scientists working in industry are often discouraged from sharing knowledge externally with the scientific community through publication. As a result of these differential incentive structures, industrial and academic scientists develop distinct career trajectories.

The appropriability question confronting academic scientists can be considered in the context of the model of scientist human capital over the life-cycle. Scientist life-cycle models suggest that early in their careers scientists invest heavily in human capital in order to build a scientific reputation (Levin and Stephan, 1991). In the later stages of their career, the scientist trades or *cashes in* this reputation for economic return. Thus, early in her career, the scientist invests in the creation of scientific knowledge in order to establish a reputation that signals the value of that knowledge to the scientific community.

With maturity, scientists seek ways to appropriate the economic value of the new knowledge. Thus, academic scientists may seek to commercialize their scientific research

within a life-cycle context. The life-cycle model of the scientist implies that, *ceteris paribus*, scientist reputation should play a role in the decision to commercialize

An implication of the knowledge production function formalized by Zvi Griliches (1978) is that those scientists with a greater research and scientific prowess have the capacity for generating a greater scientific output. But how does scientific capability translate into observable characteristics that can promote or impede commercialization efforts? Because the commercialization of scientific research is particularly risky and uncertain (Audretsch and Stephan, 2000), a strong scientific reputation, as evidenced through vigorous publication and formidable citations, provides a greatly valued signal of scientific credibility and capability to any anticipated commercialized venture or project. This suggests a hypothesis linking measures of the quality of the scientist, or her scientific reputation as measured by citations and publications, to commercialization.

Scientist location can influence the decision to commercialize for two reasons. First, as Jaffe (1989), Audretsch and Feldman (1996), Jaffe, Trajtenberg and Henderson (1993), and Glaeser, Kallal, Sheinkman and Shleifer (2002) show, knowledge tends to spill over within geographically bounded regions. This implies that scientists working in regions with a high level of investments in new knowledge can more easily access and generate new scientific ideas. This suggests that scientists working in knowledge clusters should tend to be more productive than their counterparts who are geographically isolated. As Glaeser, Kallal, Scheinkman and Shleifer (1992, p. 1126) have observed, “Intellectual breakthroughs must cross hallways and streets more easily than oceans and continents.”

A second component of externalities involves not the technological knowledge, but rather behavioural knowledge. As Bercoviz and Feldman (2004) show for a study based on the commercialization activities of scientists at Johns Hopkins and Duke University, the likelihood of a scientist engaging in commercialization activity, which is measured as disclosing an invention, is shaped based on the commercialization behaviour of the doctoral supervisor in the institution where the scientist was trained, as well as the commercialization behaviour and attitudes exhibited by the chair and peers at the relevant department.

Thus, the locational and institutional contexts can influence the propensity for scientists to engage in commercialization activities by providing access to spatially bounded knowledge spillovers and by shaping the institutional setting and behavioural norms and attitudes towards commercialization.

5.3 Measurement Issues

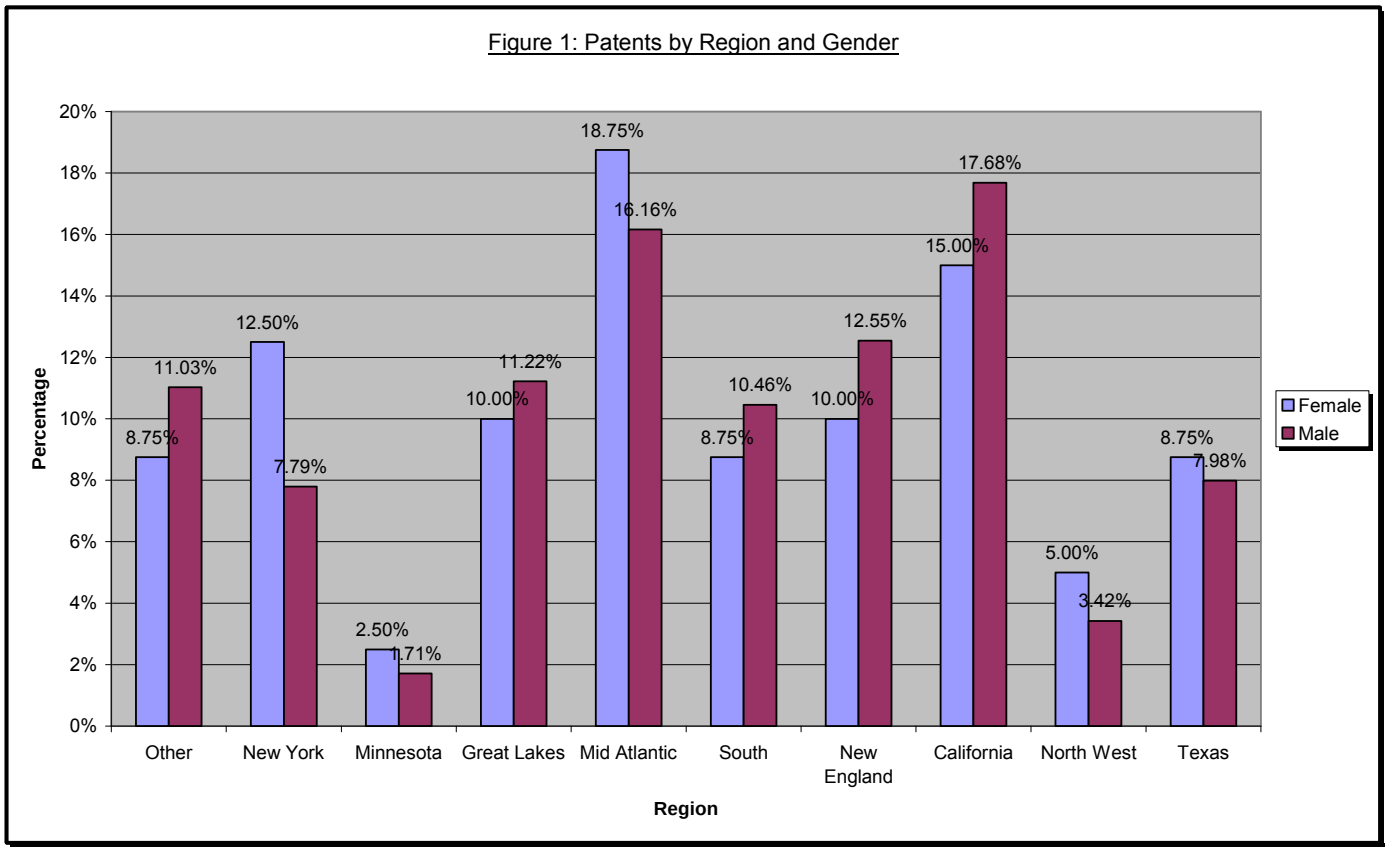
The commercialization activity of university scientists was measured by starting with those scientists awarded a research grant by the National Cancer Institute between 1998 and 2002. Of those research grant awards, the largest twenty percent, which included 1,693 scientist awardees, were taken to form the database used in this chapter. The National Cancer Institute (NCI) awarded a total of $5,350,977,742 to the top 1,693 scientists in the United States from 1998 to 2002.

Since the focus of this chapter is on the propensity for scientists to commercialize their research, commercialization must be operationalized and measured. The most common measure of commercialization of research is patents. Thus, the propensity for

NCI recipient scientists to patent was analyzed by obtaining patent data from the United States Patent and Trade Office (USPTO). The patent database spans 1975 to 2004. The inventor patent data included identification of the patent number of the invention, the name and address of the inventor, and the inventor sequence number.

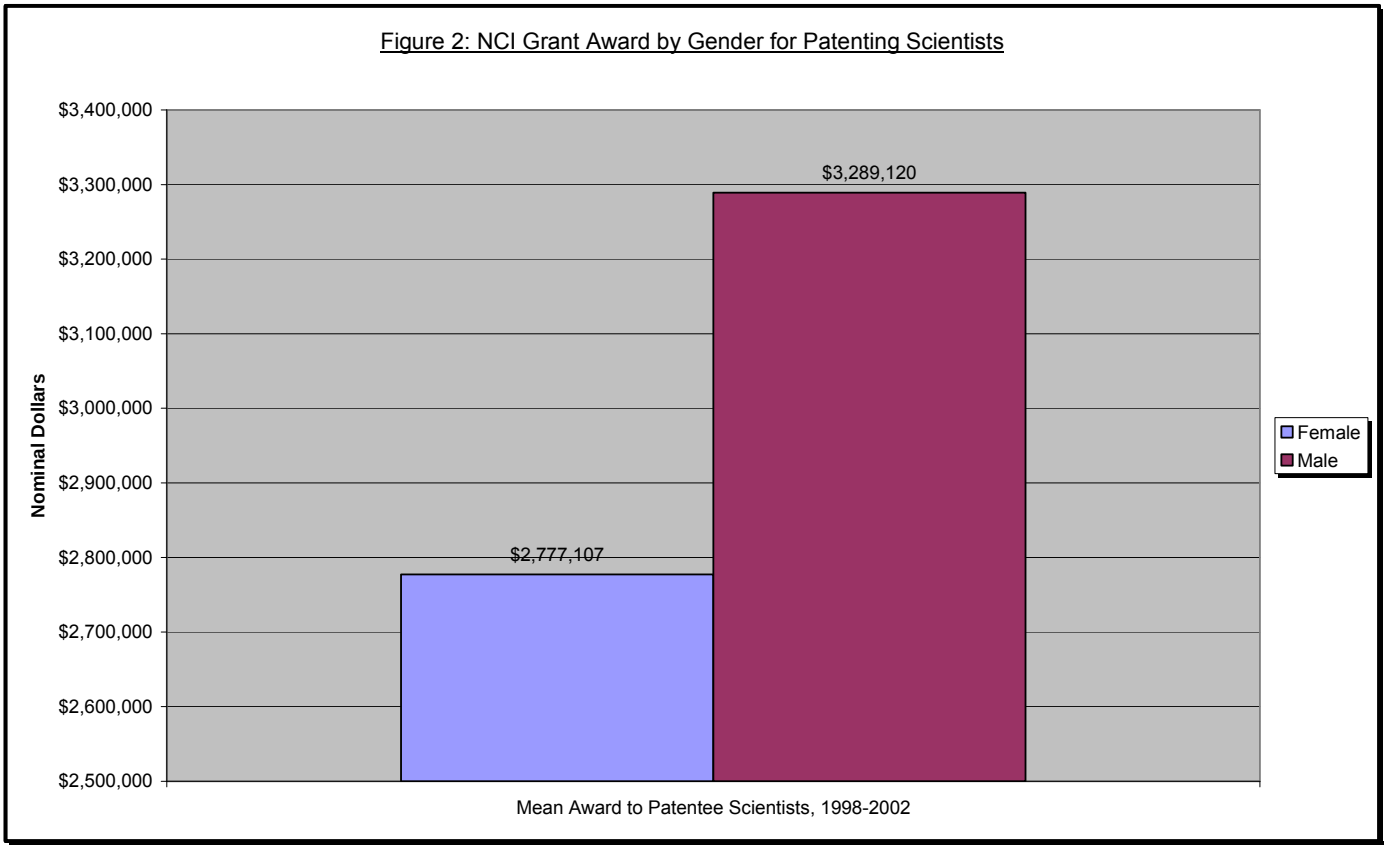
Figure 1 shows that the geographic distribution of patentees varied both across regions as well as by gender. In some regions, such as New York, Mid-Atlantic, the North West and Texas, the propensity for females to patent exceeded that of their male colleagues. By contrast, in other regions, such as California, New England and the Great Lakes, male scientists exceeded a greater propensity to patent.

Figure 1: Patents by Region and Gender



Gender also clearly played a role in a number of other dimensions. For example, Figure 2 shows that the mean amount of the NCI grant was considerably greater for male scientists who patented than for their female counterparts.

Figure 2: NCI Grant Award by Gender for Patenting Scientists



To shed light on the question; "*Why do some scientists patent their scientific research while others do not*?" a logit model was estimated for the unit of observation of the scientist identified in the NCI database where the dependent variable takes on the value of one if she has patented over the time period 1998-2004 and zero if she did not.

The previous section suggests five different types of factors shaping the decision by a scientist to commercialize her research – resources, personal characteristics, scientific human capital, nature of the university, and location. These factors are empirically operationalized through the following measures:

Award Amount – This variable is the mean total NCI awarded to the scientist between 1998 and 2002. The award amount was obtained from the original NCI award excel sheet. If external funding of scientific research is conducive to commercialization, a positive coefficient of the *Award Amount* would be expected.

Male –This is a dummy variable assigned the value of one for males (1,310) of the overall 1,693 included in the NCI database. The gender of each scientist was obtained by "Googling" their names. The estimated coefficient will reflect whether the gender of the scientist influences the propensity to commercialize research.

Location --Ten different locational dummy variables were created taking on the value of one for *Texas*, *California*, *New York*, *Minnesota*, *Great Lakes* (Ohio, Indiana, Illinois, Michigan and Wisconsin), *North West* (Oregon and Washington), *New England* (Maine, Vermont, New Hampshire, Connecticut, Rhode Island and Massachusetts), *South Atlantic* (Virginia, North Carolina, South Carolina, Georgia and Florida), *Mid Atlantic* (Washington DC, Maryland, Pennsylvania), and *Other* (Arizona, Alabama, New Mexico, Colorado, Nebraska, Hawaii and Iowa.) Those regions which tend to have greater investments in research and science, and also have developed a culture more encouraging university and scientist commercialization, such as California and New England, might be expected to have a positive coefficient.

University Type

Ivy League – A dummy variable was created taking on the value of one for all scientists employed at Brown University, Cornell University, Columbia University, Dartmouth

College, Harvard University, Princeton University, the University of Pennsylvania and Yale University.

Public Universities – A dummy variable was created taking on the value of one for scientists employed at public universities and zero otherwise. Because they are at least partially financed by the public, state universities tend to have a stronger mandate for outreach and commercialization of research. This may suggest a positive coefficient.

Carnegie Classifications – *The Carnegie Classification of Universities* (2000 edition) provides a comprehensive study classifying universities by types of degree offered. Each type of institution is defined according to the types and numbers of degrees offered in different fields. The categories are:

1. *Special Medical Institution* (graduate only that specializes in medical degrees (i.e. doctors and nurses)

2. *Research Intensive University* (grants doctoral degrees in three fields and fewer than 50 annually)

3. *Research Extensive University* (grants doctoral degrees in more than three fields and more degrees than 50 annually)

4. *Bachelors and Masters College* (grants only BA/BS and masters degrees but no Ph.D.s)

5. *Associate's College* (two year institution)

Scientist Human Capital

Citations – A specific computer program was designed to measure the citations of the 1,693 scientists through the "Expanded Science Citation Index." A higher number of citations reflex a higher level of human capital and scientific reputation (Audretsch and Stephan, 2000). A positive coefficient would reflect that the likelihood of commercialization is greater for more productive scientists.

Publications – A specific computer program was designed to measure the publications of the scientist, which should also reflect the level of human capital and scientific reputation (Audretsch and Stephan, 2000).

Star Scientist – A scientist is classified as being a star if she is in the top ten percent of publications. A dummy variable was created taking on the value of one for those scientists with a star classification and zero otherwise. Star scientists may be able to attract resources for commercialization, suggesting a positive coefficient (Audretsch and Stephan, 1996).

The results from estimating the logit model using the patent measure for scientist commercialization are provided in Table 1.

Table 1: Probit Estimation of Scientist Knowledge Diffusion - Patents

	(1)	(2)	(3)	(4)
Male	.884 **(6.33)****	.896 **(6.43)****	.878 **(6.27)****	.878 **(6.29)****
Medical University	.248 (1.52)	-	.228 (1.16)	-
Extensive University	-	.020 (0.14)	-	-
Intensive University	-.140 (-0.63)	-	-.171 (-0.77)	-
Star Scientist	.298 **(1.75)***	-	-	-
Citations	-	-	.643 **(2.97)****	.644 **(2.96)****
Papers Published	-	-.010 (-0.05)	-	-
NCI Total Award	.992 (0.951)	-.342 (-0.02)	-.297 (-0.18)	-.003 (-0.19)
Public Institutions	-.182 (-1.44)	-.202 (-1.62)	-.164 (-1.29)	-.209 **(-1.69)***
Ivy League	.219 (1.13)	.171 (0.89)	.227 (1.16)	-
Texas	-	.191 (0.438)	-.593 **(-2.01)****	.259 (1.11)
North West	-.361 (-1.29)	-.406 (-1.48)	-.966 **(-3.32)****	-.283 (-0.97)
California	.597 **(3.00)****	.485 **(2.80)****	-	.587 **(2.97)****
New England	.463 **(0.048)****	.375412 **(1.73)***	-.153 (-0.67)	.526 **(2.31)****
South	.134 (0.64)	-	.472 **(-2.21)****	.169 (0.78)
Mid Atlantic	.090 (0.47)	-.137 (-1.57)	-.504 **(-2.55)****	.184 (0.94)
Great Lakes	-	-	-.666 **(-3.27)****	-
Minnesota	-.659 **(-1.79)***	-.580 (-1.57)	-1.264 **(-3.23)****	-.510 (-1.35)
New York	-.162 (-0.70)	-.211 (-0.95)	-.741 **(-3.14)****	-.062 (-0.27)
Other			-0.637 (-3.03)**	0.033 (0.874)
Intercept	-1.388 **(-6.41)****	-1.286 **(-5.44)****	-0.828 **(-3.97)****	-1.432 **(-6.82)****
Psuedo R^2	0.04	.037	.043	.041
>CHI-Squared	0.000	0.000	0.000	0.000
Sample Size	1683	1683	1683	1683

Notes: t-statistic in brackets.

* Statistically significant at the two-tailed test for 90 percent level of confidence

** Statistically significant at the two-tailed test for 95 percent level of confidence

The various measures of scientist human capital, or scientist quality, are highly correlated and therefore including them in the same estimated model may result in multicollinearity. Thus, the first column presents results when the measure of star scientist is used, while the second column includes the measure of publications, and the third and fourth column citations. As the positive and statistically significant coefficient of start scientist suggests, those scientists with a prolific publication record tend to have a higher propensity to commercialize research through patents. Similarly, those scientists with greater citations also have a greater likelihood of filing for a patent.

There is also considerable statistical evidence suggesting that the gender of a scientist influences the likelihood of commercialization in the form of patents. In particular, being a male will elevate the propensity for a scientist to patent. The evidence concerning the impact on university type on the patenting activities of scientists is weaker and more ambiguous. There is at least some evidence suggesting that being employed in a public university may actually reduce the likelihood of a scientist patenting. Finally, the region in which the scientist is located apparently influences her propensity to patent. In particular, those scientists located in California and New England exhibit a greater likelihood of patenting, even after controlling for the other main factors, such as scientist quality and gender.

5.4 Conclusions

Globalization has triggered a shift in the comparative advantage of leading developed countries away from the factor of capital and towards knowledge. For the factor of knowledge to be effective in generating employment, economic growth and international competitiveness, it must spill over to become commercialized. As Acs et al. (2003) and Audretsch et al. (2006) emphasize, such knowledge spillovers are not automatic and cannot be assumed to exist. Thus, in terms of Richard Florida's insights about creativity, investments in scientific creativity need to be combined with commercial creativity to facilitate the spillover of such knowledge that can ultimately contribute to economic growth. Such scientific creativity can be combined with commercial creativity by scientists who choose to commercialize their research.

This chapter has identified why some scientists choose to combine scientific and commercial creativity while others do not. In particular, the human capital and reputation of the scientist play an important, as does the context, in terms of location and particular type of institution where the scientist is employed. The evidence suggests that it is those scientists with the greatest amount of knowledge who have a higher propensity to commercialize their research. However, such scientist commercialization is conditioned by both the type of university as well as the region

Chapter 6: Radical Innovation: Literature Review and Development of an Indicator

6.1 Introduction

Since the early days of Joseph Schumpeter in the 1920s, the concept of radical innovation in economic theory has been a driving force for economic growth. Yet the term offers an abundance of concepts and definitions that can be difficult for policy-makers and scholars hoping to identify *ex ante* radical innovations to expedite and facilitate growth. Building a universal and compelling concept and methodology to identify radical innovation remains elusive and problematic for scholars for several reasons. First, terminology of the definition has varied from really new to breakthrough, discontinuous, generational and, finally, radical innovation. The differing etymology is, in part, due to the differing fields of research involved in the study of radical innovation. The differing terms each carry the spirit of what radical innovation creates, yet they are unable to provide a unifying foundation for distinguishing radical innovation.

The second problem relates to the difficulty associated with quantifying or recognizing what actually constitutes a radical innovation *ex ante*, (the famous "I know it when I see it issue.") Traditionally, policy-makers and scholars have been unable to identify nascent radical innovations *ex ante*. Given the difficulty of identifying innovations *ex ante*, how can one aggregate radical innovations' contribution to economic growth for a region or country? For this reason, most

scholars have left the definition abstract and instead have focused their research on the concept and the *ex post* impact of singular fields of radical innovative activity.

This chapter will define innovation and provide a brief description of and distinction between radical innovation and incremental innovative activity. It then applies the Dahlin and Behrens (2005) heterogeneous classifications of radical innovations found in the literature. The classifications identify the different forms of radical innovation that are found in the literature. Finally, the chapter offers conclusions and suggestions to identify radical innovations *ex ante* in a uniform manner.

6.2 Origins of Radical Innovation

The concept of innovation, at least implicitly, dates back at least to Joseph Schumpeter's seminal 1934 treatise, *The Theory of Economic Development; and Inquiry into Profits, Capital, Credit, Interest and the Business Cycle*. His term, the "process of creative destruction," conceptually and literally began a radical revolution in economic theory and commercial orientation. The process, as Schumpeter argued, was one where large firms were destroyed by the entrepreneur who seizes commercial opportunities from inventors. Entrepreneurs enter the market with such commercial competitive advantages, due to their potential innovations, that they not only compete but "destroy" incumbent firms and their respective economies of scale due to the entrepreneur's superior innovation. Schumpeter's work on creative destruction created the foundation for innovation.

As McCraw (2007) points out, at the centre of Schumpeter's intellectual contribution was a focus on innovation. Schumpeter, more than any of the great economists before him, viewed innovation as the driving force of progress and development. But Schumpeter also emphasized that innovation, and therefore economic progress, comes at a price — creative destruction. Just as the factory wiped out the blacksmith shop and the car superseded the horse and buggy, incumbents will be displaced by innovating entrepreneurs. As McCraw (2007, p. 6) concludes about Schumpeter, "He knew that creative destruction fosters economic growth but also that it undercuts cherished human values. He saw that poverty brings misery but also that prosperity cannot assure peace of mind."

Schumpeter did not distinguish explicitly between radical innovation and other types of innovative activity, however. While one may infer that Schumpeter's creative destruction replaces old technologies and expands new commercial opportunities, the concept of radical innovation must refer to a much more specific type of innovation that is traditionally identified in *ex post* analysis.

Along with Schumpeter, many other scholars applied *ex post* identification of radical innovations for their empirical investigation. This method, however, creates several problems for both scholars as well as policy-makers. As will be discussed below, *ex post* identification causes two problems. Firstly, in a practical sense, one would ideally wish to identify an emerging radical innovation at an early stage in order to expedite commercial entry into the market. Secondly, and more importantly, studies based on *ex post* analysis have inherent methodological problems. According to Dahlin and Behrens (2005, p. 718), "basing identification

of radical inventions on market success by only including innovations in a study, for instance, ignoring inventions that never reach the market, creates a selection bias; indeed, technologies might be radical in a technological sense without having significant market impact, since the market impact of a technology is affected by many non-technological conditions."

6.2.1 Firm Size and Radical Innovations

In order to understand where radical innovations originate, we will first offer a brief summary of radical innovations to better understand how heterogeneous the sources of radical innovations are.

Small Firm Entrepreneurship

As illustrated in Table 1, radical innovations delivered by small firm entrepreneurs up until 1995 are substantial. Since 1995, many new drivers of economic growth have emerged; for example, information technology (e.g. Microsoft, Dell, Skype and eBay) and renewable resource technology (hybrid motor, wind technology) have been placed on the impressive list. While there is no empirical investigation of how the radical technologies were developed, one can *ex post* immediately appreciate their value-added to economies.

Table 1: Radical Innovations from Small Firm Entrepreneurs

Air conditioning	Heart valve	Pre-stressed concrete
Air passenger service	Heat sensor	Prefabricated housing
Airplane	Helicopter	Pressure-sensitive tape
Articulated tractor chassis	High-resolution CAT scanner	Programmable computer
Cellophane artificial skin	High-resolution digital X-ray	Quick-frozen food
Assembly line	High-resolution X-ray microscope	Reading machine
Audio tape recorder	Human growth hormone	Rotary oil drilling bit
Bakelite	Hydraulic brake	Safety razor
Biomagnetic imaging	Integrated circuit	Six-axis robot arm
Biosynthetic insulin	Kidney stone laser	Soft contact lens
Catalytic petroleum cracking	Large computer	Solid fuel rocket engine
Computerized blood pressure controller	Link trainer	Stereoscopic map scanner
Continuous casting	Microprocessor	Strain gauge
Cotton picker	Nuclear magnetic resonance scanner	Strobe lights
Defibrillator	Optical scanner	Supercomputer
DNA fingerprinting	Oral contraceptives	Two-armed mobile robot
Double-knit fabric	Outboard engine	Vacuum tube
Electronic spreadsheet	Overnight national delivery	Variable output transformer
Freewing aircraft	Pacemaker	Vascular lesion laser
FM radio	Personal computer	Xerography
Front-end loader	Phototypesetting	X-ray telescope
Geodesic dome	Polaroid camera	Zipper
Gyrocompass	Portable computer	Blackberry

Source: Baumol (2004)

6.2.2 Large Firm Innovation

The origins of radical innovations are more complex than the traditional belief of inventors in a garage coming up with a new idea. There are many cases where large and successful corporations have developed, implemented and profited

from in-house radical innovations (e.g. Nokia and the cellphone; Kodak and the digital camera; Apple Computers and the iPhone). As illustrated in Table 2, there is a large field of radical innovation where large firms have invented and delivered products to the market.

Table 2 Radical Innovations from Large Firms

AM radio	Wireless Telegraph and Signal Co.
Analogue answering machine	American Telegraphone Co.
Analogue quartz watch	Seiko
Black-and-white celluloid roll camera	Eastman Dry Plate & Film Co.
Camcorder	Sony
Cassette tape player	Phillips
Compact disc player	Phillips and Sony
Cellular telephone	Motorola
Digital answering machine	Sharp
Digital camera	Sony
Digital high-definition television	Panasonic
Digital video disc (DVD) player	Toshiba
Disposable shaver	Bic Corp.
Electric blanket	General Electric
Electronic colour television	RCA
Electronic desktop calculator	Sharp
Laptop computer	Tandy Corp. (Radioshack)
Laser disc player	Phillips
Laser printer	IBM
Microwave	Raytheon
Mini-disc player	Sony
Palm computer	Amstrad

Source: Chandy and Tellis (2000)

6.3 Characteristics of Radical Innovation vis-à-vis Incremental Innovation

Dahlin and Behrens (2005) explicitly link the extent to which an *invention* is radical to the nature of the ideas upon which the innovative activity is based, and the extent to which the innovative activity involves information that is codified or knowledge that is inherently tacit in nature. Information refers to facts that can be codified and where the valuation across different agents, or employees, and layers of decision-making bureaucracy within the organization is relatively constant.

Innovative activity based on economic information tends to be incremental in nature in that it generally involves an organizational consensus about the potential value and impact of the innovation. Thus, incremental innovation tends to support and enhance the status quo organization.

By contrast, radical innovation is based on knowledge involving tacit ideas that not only defy codification, but also whose economic value remains highly uncertain and asymmetric and tends to generate radical innovations. The expected value of any new idea is highly uncertain, and has a much greater variance than would be associated with innovative activity based on information. When it comes to radical innovation, there is uncertainty about whether the new producer service can be produced, how it can be produced, and whether sufficient demand for that visualized new product or service might actually materialize (Arrow, 1962).

In addition, new ideas constituting tacit knowledge are typically associated with considerable asymmetries. For example, in order to evaluate a proposed new idea concerning a new biotechnology product, the decision maker might not only need to have a PhD in biotechnology, but also a specialization in the exact scientific area. Differences in education, background and experience can result in divergence in the expected value of a new project or variance in the outcomes anticipated from pursuing that new idea, both of which can lead to divergence in recognition and evaluation of opportunities between economic agents and decision-making hierarchies. Such divergence in the valuation of new ideas will become even greater if the new idea is not consistent with the core competence and technological

direction of the incumbent firm. Thus, radical innovation tends to be disruptive to the status quo organization and strategy of the firm.

In fact, what actually constitutes a radical innovation and distinguishes it from an incremental innovation may depend upon the question being asked and the perspective in which innovative activity is being considered. Table 3 presents a broad spectrum of perspectives on what distinguishes a radical innovation from an incremental innovation. For example, in terms of the time frame, the impacts of incremental innovations tend to be realized over a shorter time period than those of radical innovations. Similarly, the source and process of idea generation and opportunity recognition varies between incremental and radical innovations.

Table 3 Distinguishing between Incremental and Radical Innovations

Focus	Incremental Innovation	Radical Innovation
Time frame	Short term — 6 to 24 months	Long term — usually 10 years or more
Development strategy	Step by step from conception to commercialization, high levels of certainty	Discontinuous, iterative, setbacks, high levels of uncertainty
Idea generation and opportunity recognition	Continuous stream of incremental improvement; critical events largely anticipated	Ideas often pop up unexpectedly and from unexpected sources, slack tends to be required; focus and purpose might change over the course of development
Process	Formal, established, generally with stages and gates	A formal, structured process might hinder
Business case	A complete business case can be produced at the outset, customer reaction can be anticipated	The business case evolves throughout development and might change; predicting customer reaction is difficult
Players	Can be assigned to a cross-functional team with clearly assigned and understood roles; skill emphasis is on making things happen	Skill areas required; key players may come and go; finding the right skills often relies on informal networks; flexibility, persistence and willingness to experiment are required
Development structure	Typically, a cross-functional team operates within an existing business unit	Tends to originate in research and development (R&D); tends to be driven by the determination of one individual who pursues it wherever he or she is
Resources and skill requirements	All skills and competences necessary tend to be within the project team; resource allocation follows a standardized process	It is difficult to predict skill and competence requirements; additional expertise from outside might be required; informal networks; flexibility is required
Operating unit involvement	Operating units are involved from the beginning	Involving operating units too early can again lead to great ideas becoming small

Source: Stamm (2003)

6.4 Entrepreneurship, Radical Innovation and the Knowledge Filter

An important and broadly accepted strand of literature suggests that small and new firms will be at a competitive disadvantage with respect to generating innovative activity in general and radical innovations in particular. According to Griliches' (1979) model of the knowledge production function, innovative activity is the direct result of investments made by a firm in knowledge inputs, such as R&D and human capital. Since larger firms generally invest significantly more in R&D than small and new firms, they would be expected to generate more innovative activity.

Since radical innovation generates more value than incremental innovation, some scholars have assumed, and even developed elaborate theoretical models to explain why, large firms, which have large R&D departments, will generate more radical innovations than small and new firms, which are constrained by size in their ability to invest in R&D (Cohen and Klepper, 1992a, b).

Five factors favouring the innovative advantage of large enterprises have been identified in the literature. First is the argument that innovative activity requires a high fixed cost. As Comanor (1967) observes, R&D typically involves a "lumpy" process that yields scale economies. Similarly, Galbraith (1956, p. 87) argues, "Because development is costly, it follows that it can be carried on only by a firm that has the resources which are associated with considerable size."

Second, only firms that are large enough to attain at least temporary market power will choose innovation as a means for maximization (Kamien and Schwartz, 1975). This is because the ability of firms to appropriate the economic returns accruing from R&D and other knowledge-generating investments is directly related to the extent of that enterprise's market power (Levin et al., 1985, 1987; Cohen et al., 1987; Cohen and Klepper, 1991).

Third, R&D is a risky investment; small firms engaging in R&D make themselves vulnerable by investing a large proportion of their resources in a single project. However, their larger counterparts can reduce the risk accompanying innovation through diversification into simultaneous research projects. The larger firm is also more likely to find an economic application for the uncertain outcomes resulting from innovative activity (Nelson, 1959).

Fourth, scale economies in production may also provide scope economies for R&D. Scherer (1991) notes that economies of scale in promotion and distribution facilitate penetration of new products, enabling larger firms to enjoy greater profit potential from innovation. Finally, an innovation yielding cost reductions of a given percentage results in higher profit margins for larger firms than for smaller firms.

There is also substantial evidence that technological change, or rather one aspect of technological change, R&D, is, in fact, positively related to firm size. The abundance of empirical studies relating R&D to firm size is thoroughly reviewed in

Acs and Audretsch (2003). The empirical evidence is generally consistent with the hypothesis that large firms invest in proportionately more R&D.

Using a direct measure of innovative output from the U.S. Small Business Administration's innovation data base, Acs and Audretsch (1990) and Pavitt et al. (1987), in a similar study for the U.K., show that the most innovative U.S. firms are large corporations. Furthermore, the most innovative American corporations also tend to have large R&D laboratories and be R&D intensive. At first glance, these findings, based on direct measures of innovative activity, seem to confirm the conventional wisdom. However, in the most innovative four-digit standard industrial classification (SIC) industries, large firms, defined as enterprises with at least 500 employees, contributed more innovations in some instances, while in other industries small firms produced more innovations. For example, in the area of computers and process control instruments, small firms contributed the bulk of innovations. By contrast, in the area of pharmaceutical preparation and aircraft industries, large firms were much more innovative.

Probably the best measure of innovative activity is the total innovation rate, which is defined as the total number of innovations per thousand employees in each industry. The innovation rate for large firms is defined as the number of innovations made by firms with at least 500 employees divided by the number of employees (thousands) in large firms. Similarly, the innovation rate for small firms is defined as the number of innovations made by firms with fewer than 500 employees divided by the number of employees (thousands) in small firms.

Innovation rates, or the number of innovations per thousand employees, have the advantage that they measure innovative activity in large and small firms relative to the presence of large and small firms in any given industry. Thus, for example, while large firms in manufacturing introduced 2445 innovations and small firms contributed slightly fewer (1954), employment in small firms was only half that in large firms, yielding an average innovation rate in manufacturing of 0.309 for small firms compared with an average innovation rate of 0.202 for large firms (Acs and Audretsch, 1988, 1990).

What explains this innovation paradox, where small and new firms are empirically found to generate more innovative activity than would be expected given their meagre R&D resources? Resolution of this paradox lies again in considering both the nature of knowledge within the context of the organizations creating that knowledge and the role of entrepreneurship, or what Audretsch et al. (2006) term the knowledge spillover theory of entrepreneurship.

Because of the conditions inherent in radical innovation based on knowledge — high uncertainty, asymmetries and transactions cost — decision-making hierarchies can reach the decision not to commercialize new ideas that individual economic agents, or groups of economic agents, think are potentially valuable and should be pursued. The characteristics of knowledge that distinguish it from information — a high degree of uncertainty combined with non-trivial asymmetries, combined with a broad spectrum of institutions, rules and regulations — distinguish radical innovation from incremental innovation.

Thus, not all potential innovative activity, especially radical innovations created through scientific discoveries and inventions, is fully appropriated within the firm making investments to create that knowledge in the first place. Various constraints on the ability of a large firm to determine the value of knowledge prevent it from fully exploiting the inherent value of its knowledge assets (Moran and Ghoshal, 1999). In fact, evidence suggests that many large, established companies find it difficult to take advantage of all the opportunities emanating from their investment in scientific knowledge (Christensen and Overdorf, 2000). For example, Xerox's Palo Alto research centre succeeded in generating a large number of scientific breakthroughs (a superior personal computer, the facsimile machine, the Ethernet and the laser printer, among others), yet failed to commercialize many of them and develop them into innovations (Smith and Alexander, 1988; Chesbrough and Rosenbloom, 2002).

The knowledge conditions inherent in radical innovation impose what Audretsch et al. (2006) and Acs et al. (2004) term *the knowledge filter*. The knowledge filter is the gap between knowledge that has potential commercial value and knowledge that is actually commercialized in the form of innovative activity. The greater the knowledge filter, the more pronounced the gap between new knowledge and commercialized knowledge in the form of innovative activity.

An example of the knowledge filter confronting a large firm is provided by the response of IBM to Bill Gates, who approached IBM to see if it was interested in purchasing the then struggling Microsoft. They weren't interested. IBM turned down, "the chance to buy ten percent of Microsoft for a song in 1986, a missed

opportunity that would cost $3 billion today."[21] IBM reached its decision on the grounds that "neither Gates nor any of his band of thirty some employees had anything approaching the credentials or personal characteristics required to work at IBM."[22]

Thus, the knowledge filter serves as a barrier impeding investments in new knowledge from being pursued and developed to generate innovative activity. In some cases, a firm will decide against developing and commercializing new ideas emanating from its knowledge investments even if an employee, or group of employees, think they have a positive expected value. As explained above, this divergence arises because of the inherent conditions of uncertainty, asymmetries and high transactions costs which create the knowledge filter.

While Griliches' model of the knowledge production function focuses on the decision-making context of the firm concerning investments in new knowledge, Audretsch (1995) proposed shifting the unit of analysis from the firm to the individual knowledge worker (or group of knowledge workers). This shifted the fundamental decision-making unit of observation in the model of the knowledge production function away from exogenously assumed firms to individuals, such as scientists, engineers or other knowledge workers — agents with endowments of new economic knowledge. Shifting the focus away from the firm to the individual as the relevant unit of observation also shifts the appropriation problem to the individual, so that the relevant question becomes how economic agents with a given

[21] "System Error," *The Economist*, September 18, 1993, p. 99.
[22] Paul Carrol, "Die Offene Schlacht," *Die Zeit*, No. 39, September 1993, p.18.

endowment of new knowledge can best appropriate the returns from that knowledge. If an employee can pursue a new idea within the context of the organizational structure of the incumbent firm, there is no reason to leave the firm. If, on the other hand, employees place greater value on their ideas than the decision-making hierarchy of the incumbent firm, they may face forgoing what has been determined to be a good idea. Such divergences in the valuation of new ideas force workers to choose between forgoing ideas or starting a new firm to appropriate the value of their knowledge.

By focusing on the decision-making context confronting the individual, the knowledge production function is actually reversed. Knowledge becomes exogenous and embodied in a worker. The firm is created endogenously in the workers' efforts to appropriate the value of their knowledge through innovative activity. Typically, an employee in an incumbent large corporation, often a scientist or engineer working in a research laboratory, will have an idea for an invention and ultimately for an innovation. Accompanying this potential innovation is an expected net return from the new product. The inventor would expect compensation for the potential innovation accordingly. If the company has a different, presumably lower, valuation of the potential innovation, it may decide either not to pursue its development or that it merits a lower level of compensation than that expected by the employee.

In either case, employees will weigh the alternative of starting their own firm. If the gap in the expected return accruing from the potential innovation between the inventor and the corporate decision maker is sufficiently large, and if

the cost of starting a new firm is sufficiently low, the employee may decide to leave the large corporation and establish a new enterprise. Since the knowledge was generated in the established corporation, the new start-up is considered to be a spinoff from the existing firm. Such start-ups typically do not have direct access to a large R&D laboratory. Rather, the entrepreneurial opportunity emanates from the knowledge and experience accrued from the R&D laboratories of the previous employer. Thus, entrepreneurship is an endogenous response to opportunities created by investments in new knowledge that are not commercialized because of the knowledge filter. By resorting to starting up a new firm to actualize the commercialization of ideas that otherwise might remain dormant in the incumbent firm, entrepreneurship serves as a conduit for knowledge spillovers.

Knowledge created in one organizational context that remains uncommercialized due to the knowledge filter provides an important source of new entrepreneurial opportunities. It is new knowledge and ideas created in one context but left uncommercialized or not vigorously pursued by the organization actually creating those ideas, such as a research laboratory in a large corporation or research undertaken by a university, that serves as the source of knowledge generating entrepreneurial opportunities. Thus, entrepreneurship can serve as an important mechanism facilitating the spillover of knowledge. The incumbent organization creating the knowledge and opportunities is not the same firm that actually exploits the opportunities. If the exploitation of those opportunities by the entrepreneur does not involve full payment to the firm for producing those opportunities, such as a

licence or royalty, then the entrepreneurial act of starting a new firm serves as a mechanism for knowledge spillovers.

Thus, new knowledge generating opportunities for entrepreneurship is the duality of the knowledge filter. The higher the knowledge filter, the greater the divergence in the valuation of new ideas between economic agents and the decision-making hierarchies of incumbent firms. Entrepreneurial opportunities are generated not just by investments in new knowledge and ideas, but by the propensity for only a distinct subset of those knowledge opportunities to be fully pursued and commercialized by incumbent firms. Thus, entrepreneurship is important in generating innovative activity in general and radical innovations in particular by serving as an important conduit of knowledge spillovers.

6.5 Measuring and Defining Radical Innovation

6.4.1 Expert Panels

There is a long tradition of relying on industry experts to identify innovative activity. The first serious attempt to directly measure innovative output was made by a panel of industry experts assembled by the Gellman Research Associates (1976) for the National Science Foundation. The Gellman panel identified 500 major innovations that were introduced into the market between 1953 and 1973 in the United States, the United Kingdom, Japan, West Germany, France and Canada. The database was compiled by an international panel of experts who identified those innovations representing the “most significant new industrial products and

processes, in terms of their technological importance and economic and social impact" (National Science Board, 1975, p. 100).

A second and comparable database once again involved an expert panel assembled by the Gellman Research Associates (1982), this time for the U.S. Small Business Administration. In their second study, the Gellman panel identified 635 U.S. innovations, including 45 from the earlier study for the National Science Foundation. The remaining 590 innovations were selected from 14 industry trade journals for the period 1970–1979. About 43 percent of the sample was selected from award-winning innovations described in *Industrial Research and Development* magazine.

A third data source to directly measure innovation activity was compiled at the Science Policy Research Unit (SPRU) of the University of Sussex in the United Kingdom.[23] The SPRU data consist of a survey of 4378 innovations that were identified over a period of 15 years. The survey was compiled by writing to experts in each industry and requesting them to identify "significant technical innovations that had been successfully commercialized in the United Kingdom since 1945, and to name the firm responsible" (Pavitt et al., 1987, p. 299).

Another study conducted by Acs and Audretsch (1990) looked at 4938 innovations and their levels of significance (Table 4): (1) the innovation established an entirely new category of product, (2) the innovation is the first of its type on the market in a product category already in existence, (3) the innovation represents a

[5] The SPRU innovation data are explained in detail in Pavitt et al. (1987), Townsend et al. (1981), Robson and Townsend (1984) and Rothwell (1989).

significant improvement in technology, and (4) the innovation is a modest improvement designed to update an existing product (Acs and Audretsch, 1990).

Table 4 Distribution of Innovations of Large and Small Firms According to their Level of Significance (percentages in parentheses)

Level of Significance	**Description**	**Number of Innovations**				
		Large Firms			**Small Firms**	
1	Established a new product category	(0.00)	(0.00)		(0.00)	(0.00)
2	First of its type on the market in an existing product category	50	(1.76)		30	(1.43)
3	Significant improvement in existing technology	360	(12.70)		216	(10.27)
4	Modest improvement designed to update an existing product	2434	(85.53)		1959	(88.31)
Total		2834	(99.99)		2104	(100)

Source: Audretsch and Acs (1990)

Acs and Audretsch (1990) found that while none of the innovations were at the highest level of significance, they did find that small firms make up a considerable portion of the innovations within the field. There appears to be little

difference in the "quality" and significance of innovations between large and small firms.

The most recent and ambitious major database providing a direct measure of innovative activity is the U.S. Small Business Administration's Innovation Data Base (SBIDB). The database consists of 8074 innovations commercially introduced in the U.S. in 1982. A private firm, The Futures Group, compiled the data and performed quality-control analyses for the U.S. Small Business Administration by examining more than 100 technology, engineering and trade journals spanning every industry in manufacturing. Industry experts were relied upon to identify innovations as well as their significance. From the sections in each trade journal listing innovations and new products, a database consisting of innovations by four-digit standard industrial classification (SIC) industries was established. Many of the innovations were classified according to four distinct levels of significance, ranging from incremental, which referred to quality improvement, to most significant, which presumably referred to a radical innovation.[24]

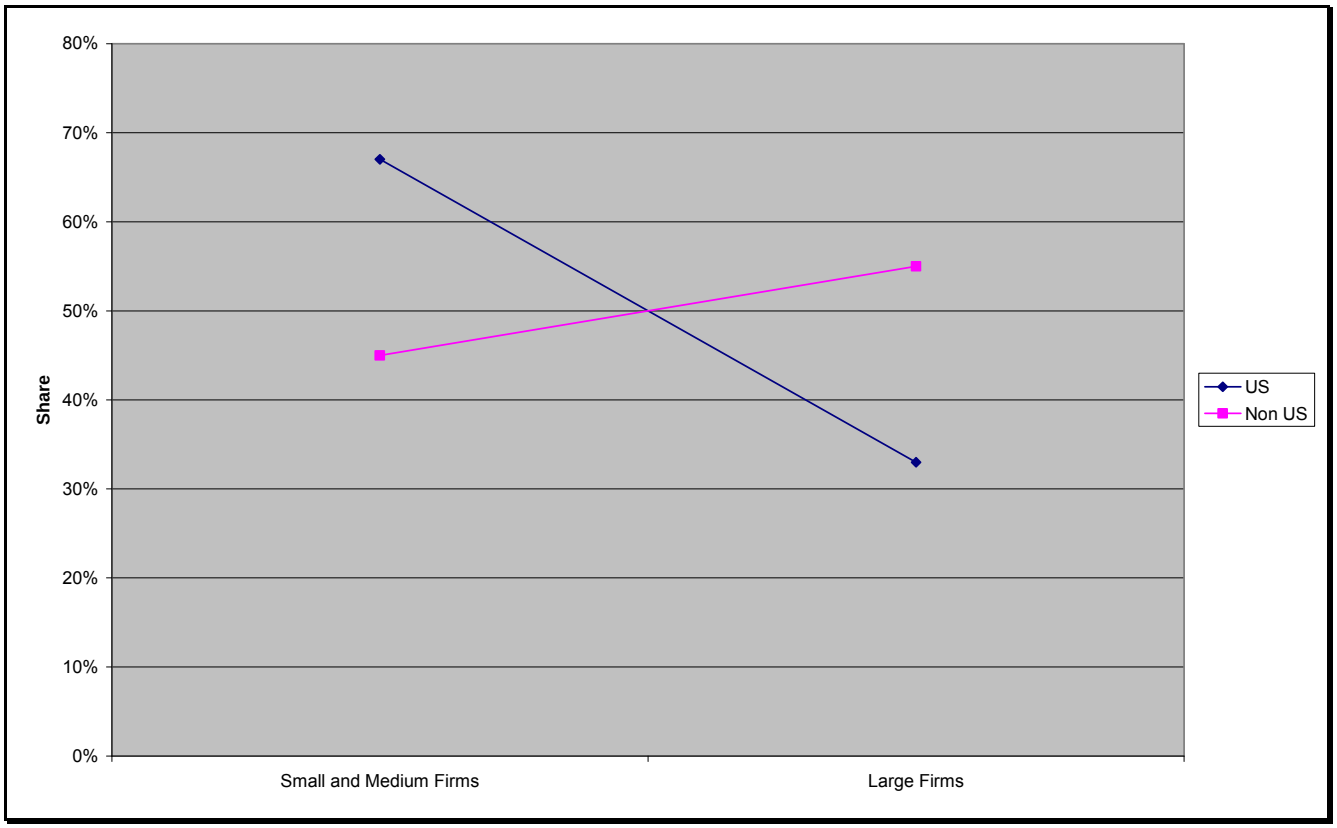
Dewar and Dutton similarly relied upon an *ex post* study of experts to identify specific radical innovations and suggest that, "the major difference captured by the labels radical and incremental is the degree of novel technical process content embodied in the innovation and hence, the degree of new knowledge embedded in the innovation" (Dewar and Dutton, 1986, p. 1429). This distinction is consistent with those researchers who define technology in terms of its

[6] A detailed description of the U.S. Small Business Administration's Innovation Data Base can be found in Chapter 2 of Acs and Audretsch (1990).

knowledge component (Dutton and Thomas, 1985). Although radical and incremental pertain to distinctions along a theoretical continuum of the level of new knowledge embedded in an innovation, the middle values of this continuum are difficult to interpret (Baumol 2004).

Another expert panel study found that there are large discrepancies between innovations by small and large firms among U.S. and non-U.S. companies. As shown by Chandy and Tellis (2000) in Figure 1, only 45 percent of non-U.S. small firms created radical innovations, while 66 percent of U.S. small firms created radical innovations.

Figure 1: Share of Radical Innovations by Firm Size and Country for Consumer Durables and Office Products

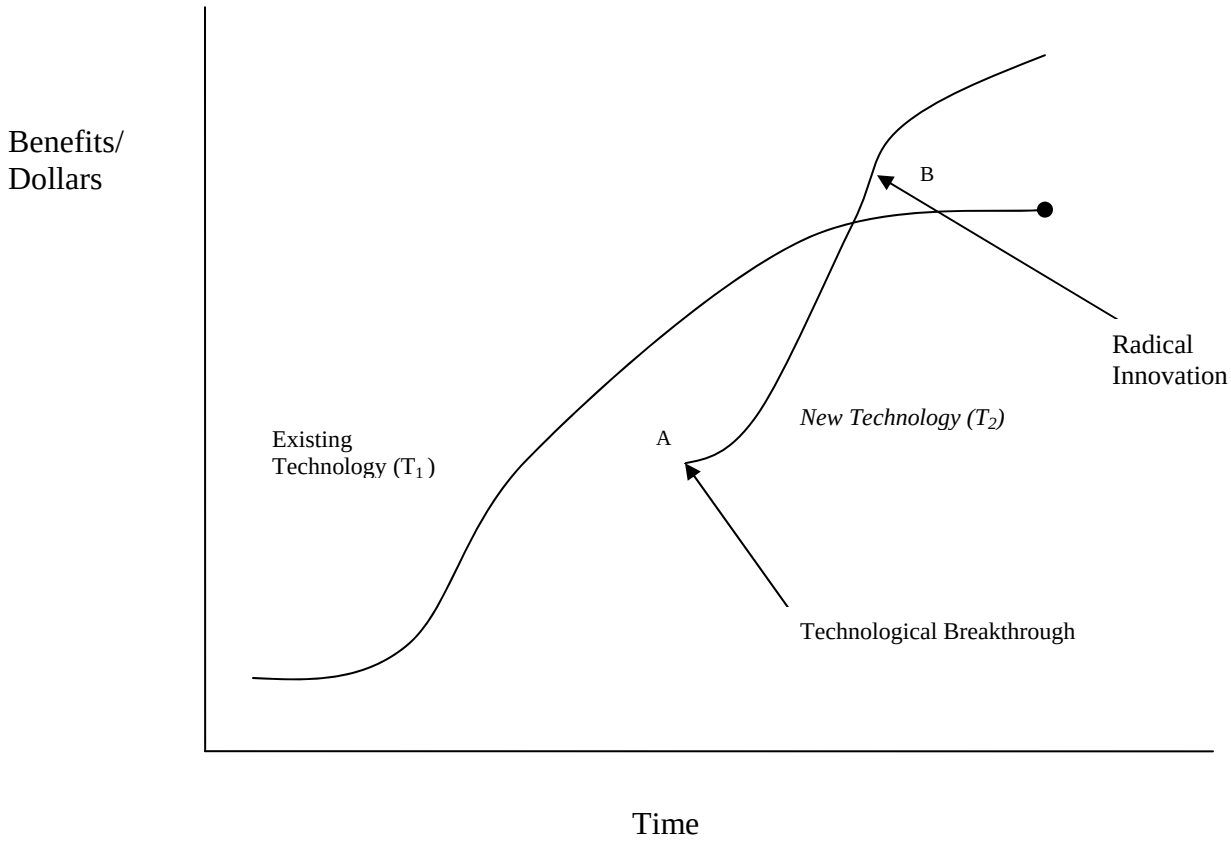


Source: Chandy and Tellis (2000)

6.4.2 S-Curves and Technological Trajectories

Dosi (1982) enters the theoretical discussion by describing how discontinuous and continuous technological trajectories can be distinguished. Much of the foundation for this area of research uses Schumpeterian economic evolution to understand the innovation process. In particular, Dosi develops a framework for distinguishing radical innovation from incremental innovation based on the technological push and consumer demand for innovation. Dosi suggests that an incremental innovation extends an existing technological paradigm. By contrast, a radical innovation creates a new technological paradigm. According to Dosi (1982, p. 150), "Technological paradigms have a powerful *exclusion effect*: the efforts and the technological imagination of engineers and the organizations they are in are focuses in rather precise direction while they are, so to speak, 'blind' with respect to other technological possibilities. At the same time, technological paradigms define also some idea of 'progress'." As shown in Figure 2, there are two points of innovation.

Figure 2: S-Curve of Radical Innovation



Source: Chandy and Tellis (2000, p. 3)

At point A, there is a technological breakthrough. This breakthrough allows the firm to properly estimate how and when it may introduce the innovation to the market. This new technology over time succeeds the existing technology. Once the technological breakthrough enters (point B) into the existing technological curve, it provides greater value added and supersedes the existing technology.

As Dahlin and Bohrens (2004) rightly point out: “A related approach suggests that the development of technologies subsequent to the introduction of a radical innovation will follow the path of an S-curve. However, as is the case for technological trajectories, S-curves do not offer a precise manner for mapping technologies. Neither do they help us identify, or define, the radical invention that will start a new S-curve. In effect, whereas one needs to have good ideas about what the important performance criteria are a priori, such ideas appear to us only a fortiori in Dosi and Foster’s framework analyzing radical innovations.”

6.4.3 Hedonic Price Models

This strand of literature stems from Henderson and Clark (1990) and Henderson (1993), where price is the empirical measure used to determine radical innovation. Henderson studies the lithographic industry. While hedonic pricing traditionally limits itself to technological fields, it provides a quantifiable means to understand the impact of variables on price. For example, instead of just comparing the price of a black-box camera with a digital camera, the model would adjust for incremental improvements in the process, such as a flash or quicker shutter speed. Therefore, it provides a simple way to understand how supplementary additions in the quality of a product affect price. Henderson (1993, p. 258) finds that “prior experience is significantly and negatively correlated with realized market share for radical innovation, providing strong support for the hypothesis that incumbents attempting to introduce products that require quite different organizational capabilities were severely handicapped.”

There are multiple problems with this method. The most crucial problem is that the method is unable to test for new fields that are dormant or in an emerging field. Indeed, 15 years prior to her study, the radical innovation of the digital camera was already owned and operated by the Kodak Eastman Company.[25] Other problems with the method, for example, are that the hedonic price index approach incorporates the productivity of individuals, and multiple product levels can be tested. However, one must pre-select what product characteristics might predict the degree to which an innovation is radical. Another problem is that the willingness to pay may be more likely with incremental changes (Tellis and Golder, 1996; Shane, 2001).

6.4.4 Codified Innovation: Patents

Over the past 20 years, patents have become one of the most common means of measuring the degree to which an innovation is radical or incremental. Patents have become an important metric in the innovation literature because of an easy and open paper trail of patent citations. This trail leaves a clearly defined origin of ideas and represents a clear lineage of where ideas go when they are cited in the future. This lineage comes in two forms: forward citations and backward citations. Patent citations also indicate a clear economic value to start-ups and economic growth (Trajtenberg, 1990). Since patent citations are equitable to a patent monopoly, there are strict procedures to ensure that appropriate citations are issued, creating a platform for researchers to apply empirical investigation for radical innovation.

6.4.5 Forward Patent Citation Radicalness

Forward patent citation involves future citations of a patent. These citations come from United States patent examiners. These professionals cite the previous patent only when there is a legitimate reason to cite the previous patent's intellectual property. These future citations are called forward patent citations. Rosenkopf and Nerkar (2001) measure the degree of radicalness by examining the computer disk industry to investigate the impact patents have on future citations in domains of patent classification. Patent domains are maintained and categorized by the United States Patent and Trademark Office (USPTO). The authors' show how incremental patents are often more narrowly cited within a certain domain of patents and radical patents are often cited by multiple domains of patents.

The forward patent count that Rosenkopf and Nerkar (2001) use is, in many ways, comparable to forward citations in scholarly journals. There are, however, two detrimental differences when using citations. First, there is a motivation from the patent inventor to cite as little as possible from previous work. The less work that is cited in the grant application, the more intellectual property (IP) monopoly is granted to the inventor. Second, a patent examiner is required to assign relevant patent citations to the patent application. For a greater understanding of deficiencies in the U.S. patent-examining process, see Graham and Harhoff (2006) and Harhoff et al. (2002). Drawing on patent citations creates other problems as well. As Rosenberg and Nekar (2001, p. 290) define radical innovation: "'radical'

exploration builds upon distant technology that resides outside of the firm. The technological subunit utilizes knowledge from a different technological domain and does not obtain that knowledge from other subunits with the firm."

The definition of radicalness holds innovation exogenous to the human capital and tacit knowledge of the firm. As Klepper and Graddy (1990) suggest, new and radical innovations can come from subunits within the firm. The distant technology can often be found within the incumbent firm. However, the firm is unwilling to either operationalize the potential radical innovation due to managerial disagreements or commit resources to a new and uncertain venture.

6.4.6 Backward Patent Classification and Citations

Backward patent citations are citations given to prior work. These citations are issued by patent examiners where examiners cite previous patents, thereby giving the citations a clear line of intellectual property rights. Shane (2001) shows, through a unique data set from Massachusetts Institute of Technology (MIT) inventors involving 1397 licensed MIT patents, that the more radical the invention, the more likely it was made by a small firm. As Shane (2001, p. 208) explains, radical innovations will tend to originate from small firms and large firms: "First, radical technologies destroy the capabilities of existing firms because they draw on new technical skills. Since organizational capabilities are difficult and costly to create (Nelson and Winter, 1982; Hannan and Feeman, 1984), established firms are organized to exploit established technologies. Firms find it difficult to change their activities to exploit technologies based on different technical skills." Shane (2001)

finds that research suggests that radical patent citations and a lack of patent classification are positive to start-ups for the MIT-based patents. As one may note from Table 5, Shane's method of radical identification is one of many ways to identify radical innovations.

Table 5: Literature Summary of Radical Innovations

Commonly used definitions of radical versus incremental changes		
Studies in chronological order	**Industries studied**	**Definition of novelty**
Cooper and Schendel (1976)	Locomotives, fountain pens, vacuum tubes, fossil fuel boilers, safety razors, propellers, leather	None. Selected industries in which almost full substitution occurred when innovation was introduced
Dosi (1982)	Theory paper	Technological paradigm = "model" and a "pattern" of solution of selected technological problems, based on selected principles derived from natural sciences and on selected material technologies (p. 152); radical change; paradigm shift
Foster (1985)	Multiple examples, e.g., watches, artificial hearts, textile fibres, semiconductors	Discontinuity = gap between two S-curves at a point where one technology replaces another
Dewar and Dutton (1986)	Shoe manufacturing	Radical innovations require adopting firm to process new information
Anderson and Tushman (1990)	Glass, cement and minicomputers	Two dimensions: (1) order-of-magnitude change in price-performance ratio; (2) competence-enhancing versus competence-destroying
Henderson and Clark (1990)	Theory paper	Two dimensions: (1) design architecture is reinforced or changed; (2) core technological concepts in componentry are reinforced or changed
Henderson (1993)	Photolithographic alignment equipment	Two dimensions: (1) degree of substitutability; (2) competence-enhancing versus competence-destroying
Das (1994)	Theory paper	Two dimensions: (1) knowledge same or different; (2) competence-enhancing versus competence-destroying

Christensen and Rosenbloom (1995)	Disk drives	Radical = launching new direction in technology versus Incremental = making progress along established path
Christensen and Bower (1996)	Disk drives	Radical = disrupts or redefines a performance trajectory Incremental = sustains the industry's rate of improvement in product performance
Tripsas (1997)	Graphical typesetting	None
Chandy and Tellis (2000)	Consumer durables and office products	"a new product that incorporates a substantially different core technology and provides substantially higher customer benefits relative to previous products in the industry" (p. 2)
Rosenkopf and Nerkar (2001)	Optical disk technology	"Radical exploration builds upon distant technology that resides outside of the firm." (p. 290)
Shane (2001)	MIT-licensed patents	"I measure the radicalness of the patent as a time-invariant count of the number of three-digit patent classes in which *previous* patents cited by the given patent are found, but the patent is not classified" (p. 210)
Ahuja and Lampert (2001)	Chemicals	Radical/breakthrough inventions "serve as the basis of 'future' technologies, products and services." (p. 522)
Dahlin and Behrens (2005)	Tennis racquets	Three criteria: (1) the invention must be novel: it needs to be dissimilar from prior inventions; (2) the invention must be unique: it needs to be dissimilar from current inventions; (3) the invention must be adopted: it needs to influence the content of future inventions

Adapted from Dahlin and Behrens (2005)

6.4.6 Dahlin and Behrens Metric for Radical Innovations

As one can see, radical innovations come in multiple paths and trajectories. Whether through small or large firms, these innovations are able to transform the nature of the market to the advantage of the radically innovative firm. The best

method to identify an *ex ante* radical innovation, therefore, is through the only available paper trail of patents. As mentioned earlier, analysis has used either forward patent or backward patent citations, but has never used both to dynamically analyze the data. Dahlin and Behrens (2005) use patents from the tennis racquet industry to show that there is not only a way to *ex ante* identify whether an invention is radical, but also a way to systematically analyze a product market to determine whether the innovation is radical.

Dahlin and Behrens offer an attractive means to identify incipient radical innovations a priori, or before they are actually fully developed and introduced. They create a three-stage metric process that distinguishes between radical invention and radical innovation. This is an important process. As mentioned in previous sections, other methods were unable to identify radical inventions and therefore the potential radical innovation in the pipeline. As mentioned above, for example, innovations from large firms, such as the Kodak digital camera, were not recognized as radical inventions due to a lack of proper identification metrics. This method offers a needed predictive power of identifying patents that have the potential to be radical innovations. The model offers three criteria and is based on the structure of patent citations and replication of new patent citations.

The Dahlin and Behrens model identifies radical inventions as inventions that heavily influence and affect the future content of patent families. Therefore, the patent must be unique to other patents in terms of its patent structure and future citations. This uniqueness is identified by the criteria presented in Table 5.

Dahlin and Behrens' model places emphasis on how dissimilar the patent is to past and current inventions. Therefore, when new patents are filed, the new patents' citations are compared with the identified radical invention. If the new patents replicate a similar patent structure to the identified radical patent, the radical patent is then classified as a radical innovation. In Table 6, the advantages of using the Dahlin-Behrens model are examined.

Table 6: Characterizing Each Definitional Form of Radical Innovation

	S-Curves	**Hedonic Price Models**	**Expert Panels**	**Patent Measures**	**Dahlin-Berhens**
Practical problems					
1. Lacks quantifiable measurement indicating when an invention is radical	Yes — need expert help to determine if a new trajectory/curve is started	Yes — focuses on price increases as a function of technical criteria, but any price increase counts	No — uses scales of expert perceptions	No — but cut-off points often arbitrary and not defined a priori	No — uses patent citations
2. Difficulty of timing — when to compare innovations	No — assumes multiple time comparisons	No — allows for multiple time comparisons	Yes — focuses on experts at one point in time	Yes — for forward citations; no — for backward citations	No — analyzes both past and currentinnovation structure
3. Difficulty in accessing data	Difficult	Medium difficulty	Easy	Easy	No — data are freely accessible
4. A priori key characteristic determined?	Yes — model is predefined as effort and technical impact	No — models are variable	No — varies from expert to expert	Yes — patent citations	Yes — patent citations
Conceptual problems					
1. Performance-comparison issues	Allows for continuous comparisons over time since multiple trajectories/curves	Medium, easy to test multiple criteria simultaneously	Depends on questionnaire	Yes — for forward citations, mainly timing issues	No — one may track the performance of the citations
2. Impact-based definition	No	Yes — if no effect on demand (price higher), not considered radical	Standard questions have impact bias, could be removed	Yes — for forward citations; no — for backward citations	No — impact is based on citations and noton actual commercial output
3. Assumptions of firm homogeneity	No	No — focus on product characteristics	Standard questions have impact bias, could be removed	Yes — for forward citations, ignoring the likelihood ofbeing cited is afunction of firm status; no — for backwardscitations	Yes — for forward citations, ignoring the likelihood of being cited is a function of firm status; no — for backwards citations
4. Selection bias	Depends on data source and how trajectories/curves are identified	Yes — only characteristics in products with market success will be included	Yes — recency and success biases also likely	No	No

6.5. Conclusions

In this chapter, we offer a literature review of how radical innovation is quantified and the metrics applied for identifying radical innovation. As suggested in the literature, there are conflicting empirical metrics identifying radical innovation. Consequently, there is conflicting empirical evidence on the propensity for small and large firms to engage in radical innovation. After all, according to the literature, it surely cannot be that both large firms are "incompetent" and small firms are "inferior" with respect to radical innovations. These empirical inconsistencies lie, to some degree, in how one identifies a radical invention.

While not perfect, the Dahlin-Behrens model provides policy-makers with an easily accessible and identifiable means to properly identify radical innovations *ex ante*. This identification requires that the radical innovation 1) be dissimilar to previous patent citations, 2) differ from existing patent citations, and 3) affect future patent citation structures. The three-stage definition offers explicit advantages over previous identification regimes. Specifically, technical content is identified and tracked over time. The definition also eliminates many of the problems found in other identification metrics, such as 1) definition and measurement, 2) ability to identify an invention that is still in the development phase, and 3) identification is not measured by *ex post* analysis.

While it will continue to be unclear what share of radical innovation originates from small and large firms, the ability to identify the invention will be the critical aspect for policy-makers and then to identify whether the invention is from a large or small firm. Therefore, the authors believe that radical innovation should not

necessarily be analyzed under the large or small firm unit of analysis, but rather radical innovations should be identified and tracked within and coming out of the pipeline.

Chapter 7: Summary and Conclusions

7.1 Summary

A result of globalization and investment in knowledge has led countries to shift their comparative advantage away from traditional industries such as manufacturing and large scale firm production towards new territories of knowledge-based economic activity. But how and where will policy makers turn for new forms of knowledge-based activity? While the overall answers remains clouded, one area where policy makers will be turning their heads is toward university knowledge and scientist entrepreneurship.

As research and knowledge become perhaps the most crucial component to generating economic growth and competitive jobs in globally-linked markets, universities emerge as a key factor in determining the future well-being of the country. After all, it ranks among the most important tasks of universities to create new scientific knowledge. In addition, the magnitude of resources being invested in university research, including some of the most capable and creative scientists in the country, is the envy of the world.

The massive investment in university research can impact economic growth only if knowledge can be transformed into actual innovations and new and better

products through the commercialization process. That is, the extent to which university research becomes commercialized. It matters for economic growth, for jobs and for global competitiveness.

This book has taken a different approach towards addressing where knowledge-based entrepreneurship may manifest itself. Rather than focus on what the TTOs do, it instead focuses on what university scientists do. Thus, the findings about the commercialization of university research are based on actual university scientists and not the TTOs. The results are revealing. In particular, while all modes of commercialization are important, scientist entrepreneurship emerges as an important and prevalent mode of commercialization of university research. More than one in four patenting NCI scientists has started a new firm. This is a remarkably high rate of entrepreneurship for any group of people, let alone university scientists. Thus, the extent to which university research is being commercialized and entering the market may be significantly greater than might have been inferred from studies restricted only to the commercialization activities of the TTO. Scientist entrepreneurship may prove to be the sleeping giant of university commercialization.

7.2 Future research

There are three primary areas of future research. The first area needs to further probe why and how scientists choose to commercialize their research, what commercialization route they select, what mode of commercialization is most effective, and how university governance and public policy can best promote such commercialization efforts. A host of pressing questions remains. For example, are all

social networks equivalent, that is are they homogeneous, or do some facilitate scientist commercialization more than others? Similarly, do non-patenting scientists engage in commercialization activities, particularly entrepreneurship, or does their lack of patented intellectual propensity preclude commercialization of their research? Whatever answers to these and other crucial questions future research can uncover will be highly important.

Another stream of research will require similar studies in other fields of technology. While Oncology research is a critical area for commercialization, it remains to be seen whether other fields of knowledge share similar variables for entrepreneurship and economic growth. Indeed, given that Oncology has a relatively development field, other fields such as Green Technology may have a very different fate for commercialization.

The third area of future research is to fully understand how managing intellectual property (IP) at universities may be optimized. As noted in chapter three, there are several routes to commercialize knowledge, but most IP is, at least in the initial stage, channeled through the TTO. Given that the TTOs primary objective is to maximize revenue through licensing, there could very well be some form of loss to growth by not allowing scientists to startup on their own invented patent technology. This loss may also ferment what is called the backdoor approach to patenting where scientists do not register their IP with the TTO, furthering the problem of accurately estimating to true rate of return on public R&D. The questions will further help policy makers understand how important knowledge-based scientist entrepreneurship are to regions and economic growth. Whatever the answers may be, it is well worth

noting that scientist entrepreneurship will continue to be an increasingly important field of research for economics and public policy.

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