The Commercialization of University Research Discoveries: Are University Technology Transfer Offices Stimulating the Process?

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Abstract

In this thesis we attempt to estimate the influence of university technology transfer offices in the process of commercializing university discoveries. Using already available data from over one hundred universities and more detailed data we collected directly from eleven universities, we assess how effective technology transfer offices are in facilitating the commercialization process.

The thesis consists of three main analyses. The first two are cross-sectional. We build regression models that use the key determinants (research expenditures, faculty quality rating, and resources provided for technology transfer) to make predictions about the number of licenses, patents, and invention disclosures for each university. We use Data Envelopment Analysis to evaluate the "excellence" score of universities (based on the number of licenses, patents, royalty income, faculty publications, graduate student enrollment, and awarded Ph.D. degrees). We then look at how these scores correlate with the resources universities provide for technology transfer. The results from these cross-sectional analyses suggest that there is a strong positive correlation between investment and success in technology transfer. In the course of this investigation of the technology transfer offices it was necessary to consider the influence of variables not directly related to technology transfer. Our results imply that there are diminishing rates of return for research expenditures, and that "good" faculty perform research more cost effectively than other faculty.

While the cross-sectional analyses show if investment correlates with success, these methods do not tell us about the causal relationship between the two. To shed light on the causal relationship we collected detailed time series data from eleven universities, and analyze the evidence. Our results imply that hiring professionals will lead to an increase in the licensing rate, and that universities respond to an increase in the licensing rate by hiring more support staff for technology transfer.

Our results imply that investing in technology transfer is good for the university, because it may yield a positive return on the investment. It is good for industry, because they can make further use of university discoveries. Last, but not least, it is good for the general public, because it pushes inventions out of the laboratory and into the marketplace.

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Finally, I thank my parents, my brothers, my sister, and all other relatives for their support.

Contents

List of Symbols

$D_{i,t}$	Patent applications filed by university i in year t.
$E_{i,t}$	Patents awarded to university i in year t.
$F_{i,j}$	Average faculty quality rating at university i and department j.
$\Gamma_{i,j,t}$	Idea rate in year t, for university i and department j.
$G_{i,j,t}$	Number of ideas in year t, for university i and department j.
$I_{i,t}$	Invention disclosures received at university i in year t.
i	Index for universities.
j	Index for university departments.
$L_{i,t}$	Licenses executed at university i, in year t.
LF_i	Relative Legal Fee Expenditures at University i.
$\lambda_{i,t}$	Predicted value for D_i, E_i, and I_i.
MP_i	Relative man power of the TTO at university i.
$N_{l,t,i}$	Legal fee expenditures of the TTO at university i.
$N_{p,t,i}$	Number of professionals working on Technology Transfer at university i.
$N_{s,t,i}$	Number of staff working on Technology Transfer at university i.
Q	Measure of fit statistic for cross-sectional regression model.
r, R	Index for inputs.
$R_{i,t}$	Revenue of license number i in its t-th year.
s, S	Index for outputs.
V_g	Number of problem solutions for idea g.
$x_{i,j,t}$	Research expenditures of university i, department j, in year t.
$X_{i,r}$	Input number r for university i.
$Y_{i,s}$	Input number s for university i.

Chapter 1

Introduction

In 1996 expenditures for Research and Development in the United States were $184 billion. About $22 billion of the research was performed at universities and colleges, and, of this, $13.5 billion were federal dollars. There are many benefits resulting from university research, both tangible and intangible. This dissertation focuses on analyzing how new technologies that are invented at universities are disseminated and applied in society.

Most universities operate a Technology Transfer Office (TTO). This office provides the interface between faculty and industry. If many great inventions are being made at universities, they are of little value if they are never put to use, or as President Lyndon Johnson said when he arrived on the NIH campus in 1966: "We must make sure that no life-giving discovery is locked up in the laboratory."[GAO68]

University technology transfer offices are, in principle, very important for drawing maximum benefits from the investment in university research. But theory and practice often diverge. This dissertation addresses questions about the effectiveness of university TTOs. Are TTOs promoting university research outcomes, or are they instead obstacles to the commercialization of new technologies? Are new university-based inventions reaching the market **because** of effective technology transfer, or do the TTOs just manage a process that would exist even without them? Is the investment universities make in technology transfer a good investment?

1.1 What is Technology Transfer?

Clyatt [CLY85] defines *technology transfer* as:

> . . . the process by which science and technology are diffused throughout human activity. Wherever systematic rational knowledge developed by one group or institution is embodied in a way of doing things by other institutions or groups we have technology transfer. This can be either transfer from more basic scientific knowledge into technology, or adaptation of an existing

> technology to a new use. Technology transfer differs from ordinary scientific information transfer in the fact that to be really transferred it must be embodied in an actual operation of some kind.[1]

University technology transfer takes many forms. The most obvious is *technology licensing* in which new technologies are put to practical use. The faculty first secure exclusive rights to use their invention, and then look for industrial parties that may be interested in using the technology. The industrial parties pay the inventor royalties based on sales or other terms of the agreement. Another form of technology transfer occurs when university *graduates* introduce new ideas and knowledge to their employers. Similarly, faculty often engage in *consulting* work with industry. This provides an opportunity for the faculty to apply the state-of-the-art methodology to real problems. Another form of technology transfer has long been practiced through *consortia*. Companies join a consortium, usually involving a substantial membership fee. A team of faculty then receive funds and access to real world data, and in return the members of the consortium have unlimited access to all research outcomes from the work. Historically consortia have been utilized in the petroleum industry but are now becoming more widespread. Finally, when faculty publish *papers* and go to *conferences* it is a medium for sharing their knowledge and get valuable feedback.

1.2 Motivation

This work was originally motivated by a hypothesis about the **negative** impact of university TTOs. A senior Vice President at one of the major pharmaceutical companies recently suggested that university technology transfer specialists were major obstacles to commercializing technologies developed by university faculty. He suggested that everyone would be better off if industry had greater flexibility in working directly with university researchers on commercializing their inventions; industry could take make greater use of university research outcomes, and universities and faculty would benefit from increased royalty income. He is by no means the first person to make this hypothesis. Numerous interviews with TTO specialists have confirmed that many people hold this opinion.

If this hypothesis is correct the commercialization process of university discoveries should be reformed. The primary goal of university technology transfer is to push university research outcomes to the marketplace and help interested users to utilize the technology in return for a moderate compensation. If the current arrangement is not meeting this goal we need to go back to the drawing board.

But what is the other alternative? People who are of the opinion that TTO specialists hinder the commercialization process may prefer working directly with faculty about using their inventions, or they may prefer an entirely different mechanism for marketing

[1] originally from H. Brooks (1966), *National Science Policy and Technology Transfer*.

university research outcomes. In this thesis we look at how the "amount" of resources provided for technology transfer and the success at such transfer relate to each other.

This problem is very relevant from an Operations Research perspective. The techniques of OR are helpful in breaking the problem down to smaller pieces and analyzing the behavior of each piece. We build models—calibrated on empirical data—that suggest what the main determinants of success in commercializing university discoveries are. By looking at the degree of influence of TTOs in the models, we gather evidence about the effectiveness of the current structure of university/industry collaborations.

Most of the analysis focuses on two output measures as evidence of successful technology transfer activities. We look at *patents* that are granted to U.S. universities. Patents are, in some fields of research, the final manifestation that the research was successful. The other measure we focus on is *license agreements.* License agreements are contracts between the licensee (usually a for-profit corporation) and the licensor (in our case the university and faculty). The license agreements are tangible proof that inventions from university research are being used.

It is clear that university priorities vary. Some universities emphasize putting research outcomes to practical use, while others focus on other issues. Low investment in technology transfer may not be a sign of low research quality, but that the emphasis is on other areas of application.

Considering that universities spend over $20 billion on research and receive more than $300 million in royalties per year, it is clear that only a small improvement in the commercialization of university research outcomes would be very valuable.

1.3 Data Sources

In addition to the sources mentioned below, we collected data directly from universities. This was necessary to determine the causal relationship in the licensing process. The data collection effort is outlined in section 5.3.

The Association of University Technology Managers (AUTM) is a nonprofit professional and educational society created to assist administrators of patent and copyright programs at universities to license technologies, encourage the production of inventions, and to make appropriate recommendations to assure the effective transfer of technology to the public. AUTM association has polled its members since 1991 [AUT96], and this is our primary source of data related to technology transfer. This database has information on the following: 1) the number of options and licenses executed (1991-1995), 2) the number of new U.S. patent applications (1991-1995), 3) the number of invention disclosures received (1991-1995), 4) gross royalties received (1991-1995), 5) people providing professional services for technology transfer (1992-1995), 6) people providing staff support for technology transfer (1992-1995), 7) legal fee expenditures for patents and/or copyrights (1991-1995), 8) aggregate research expenditures (1991-1995), and more.

The National Research Council performed a study in 1993 [NRC95]. This study is aimed at gathering information about research-doctorate programs in the United State;

to provide a large, recent database that can be used by scholars who focus their work on characteristics of the national higher learning educational system and its associated research enterprise. We use this database to get 1) the number of faculty publications (1988-1992), 2) the number of full and part time graduate students enrolled (fall 1992), 3) the number of Ph.D.'s produced by university (from academic year 1987-1988 to 1991-1992), and 4) the scholarly quality of program faculty in 1993 (see section 3.4.3).

The National Science Foundation compiles a database each year with the reported research expenditures of American universities, by university and department [SRS95b]. This survey is the primary source of information on separately budgeted research and development expenditures within universities in the United States. These data have been collected from universities for over twenty years.

The U.S. Patent and Trademark Office summarizes patent activity by U.S. colleges and universities between 1969-95 [TAF96]. Separate summaries are provided for those institutions ranked in top 100 by total research and development (R&D) expenditures in fiscal year 1994. Patent data presented in this report were obtained from the Technology Assessment and Forecast database, which is maintained by the Office of Electronic Information Products. We use these data to get longer time series for patents (figure 2-1), and they also have classification information on patents.

1.4 Organization and Conclusions

The dissertation consists of three main analyses. In Chapter 3 we build models that use the most important determinants of research output to make predictions of the number of patents, licenses, and invention disclosures. In Chapter 4 we use Data Envelopment Analysis to evaluate university excellence on a number of dimensions, including the number of patent applications, license agreements, faculty publications, and student enrollment statistics. We first assess the university excellence independent of the TTO resources, but then, in a follow-up investigation, look at the relationship between a school's excellence classification and the resources it provides for technology transfer. Both these analyses look at the cross-sectional data, and analyze the differences among universities. In Chapter 5 we focus on time series analysis to determine the causal relationships between investment in resources and increased output.

1.4.1 Cross-Sectional Regression Models

In Chapter 3 we build nonlinear models that use various determinants of research outputs to predict the number of patents, licenses, and invention disclosures. The most important determinants are: departmental research expenditures, professionals and support staff working on technology transfer, legal fee expenditures for patents and/or copyrights, and the faculty quality rating. Using these variables we build models that fit empirical data to predict the number of patents a university enters in a given year, the number of license agreements made with industry, and the number of invention disclosures received from faculty.

We show that only the Engineering, Physical Sciences, and Life Sciences departments contribute appreciably to the patenting and licensing processes. The results imply that universities which invest more than others in technology transfer are also more successful at such transfer. The models also imply diminishing rates of return for research expenditures. Comparing two universities, one with twice the expenditures of the other, we expect less than 75% more outputs from the larger university.

1.4.2 Data Envelopment Analysis

In Chapter 4 we use Data Envelopment Analysis to evaluate the "success" score of each university. Choosing from six output measures (the number of patent applications, the number of license agreements, gross royalties received, faculty publications, graduate student enrollment, and Ph.D. degrees awarded) each university has the opportunity to put its "best foot forward" when evaluating its "success" score. After evaluating these "success" scores we look the relationship between the score and the resources universities provide for technology transfer.

We reach two main conclusions. We find a strong positive relationship between the resources provided for technology transfer and the "success" score. Universities that invest more in technology transfer have a higher "success" score. Secondly, our results imply that the universities that invest more in technology transfer also derive a higher fraction of their score than others from royalties, patents, and licenses. This outcome suggests that universities which invest in technology transfer look stronger in comparison to others as more emphasis is placed on patents, licenses and royalties. Putting these two conclusion together, we conclude that universities which invest in technology transfer have a higher "success" score **because** of better performance in commercializing university discoveries.

1.4.3 Time Series Analysis

In Chapter 5 we use time series analysis to gather evidence about the causal relationship between hiring more people at the TTOs and increases in technology transfer. We design a survey instrument and collect detailed time series data directly from eleven universities. From these data we try to determine the causal relationship.

We perform a number of analyses on the data. Some of the analyses do not give hints about what the causal relationship is, but they confirm our prior findings in Chapters 3 and 4. The evidence we find about the causal relationship suggests that hiring more people to work on technology transfer will lead to an increase in the number of license agreements entered with industry.

1.4.4 Bringing it all Together

Each of these three analyses on their own explains a "piece of the puzzle", but none gives a complete answer to our question. The results from Chapters 3 and 4 work against the hypothesis that the TTOs hinder the commercialization process of university discoveries; we find a strong **correlation** between the investment in technology transfer and the success in commercializing technologies. These methods do, however, **not** show which way the causal relationship is; does the success lead to the investment, or does the investment lead to success? The time series analysis is aimed at determining the causal relationship, but it does not explain the underlying dynamics of the commercialization process. The evidence we find for determining the causal relationship suggests that hiring more professionals to work on technology transfer will consequently lead to more licenses.

Putting these three pieces together we have a fairly complete understanding of the dynamics involving university technology transfer offices.

Chapter 2

Background

In this chapter we describe the background of this work in some detail. We start by discussing how university discoveries have been utilized in the past, and how universities have gradually placed more and more emphasis on commercializing university inventions. We explain recent changes in legislation that have changed the working environment for technology transfer programs, and we show how the number of patents granted to American universities has increased in the last 20 years. We discuss the role of technology transfer offices today and outline the key resources for those offices. By looking at a hypothetical example we illustrate how a university discovery might be implemented, and we discuss how the technology transfer specialists are involved in this process. Finally, we review previous work related to this dissertation.

2.1 Historical Background

2.1.1 The Wisconsin Alumni Research Foundation

The first documented and most celebrated success story in university licensing is from the university of Wisconsin-Madison. The Wisconsin Alumni Research Foundation (WARF) was formed in 1925 as a nonprofit independent foundation, organized to administer patents and licenses resulting from research discoveries brought to it by the University of Wisconsin faculty members, and to use the income from such licenses to fund further research at the university.

The story of WARF begins in 1924 when Professor Harry Steenbock [STE24] published research demonstrating that vitamin D could be activated by irradiating food. Towards the end of the paper Steenbock mentioned that he was in the process of applying for a patent on the invention on behalf of the University of Wisconsin. This initiative was not well received by fellow academics, as they thought it improper for a faculty member to look for financial gains from research done at a university. After initiating the application, Steenbock received an offer of $900,000 (approximately $7.6M in 1994 dollars) from the Quaker Oats Company for exclusive rights to the patent. Professor Steenbock rejected the offer and assigned his patent rights to WARF without any arrangement for personal compensation. To provide other faculty with an incentive, WARF decided to pay Professor Steenbock 15% of the net income.

2.1.2 The Bayh-Dole Act

Since the twenties, more and more universities have, for one reason or another, taken steps towards protecting and commercializing faculty innovations. The Bayh-Dole Act, P.L. 96-517, passed into law in December 1980. This law forms the cornerstone of university technology transfer programs today. The Bayh-Dole Act provides the universities with the right to own the technology derived from federally sponsored research—it gives universities, nonprofit organizations and small businesses the *"right to retain title to inventions arising under federal funding" (p. 224)*. As a result universities can now protect intellectual property resulting from research sponsored by federal agencies. The university thus holds the property rights, but the faculty usually collects considerable benefit (between 10% to 70% of the net income).

Prior to the act it was not clear if universities could seek financial gains from research sponsored by federal agencies. The Bayh-Dole Act goes even further than just granting the right to the universities, it actually **obliges** the universities to seek opportunities to commercialize invented technologies. If federal agencies believe universities are not sincerely making research outcomes commercially available, they have certain "march-in" rights. They can, under certain circumstances, march in and directly grant corporations, or other interested parties, the right to apply technologies that are otherwise protected by the patent law.

While these "march-in" rights have never been used, there are a few cases where corporations have requested such action. As reported in the June 27, 1997 issue of the *Chronicle of Higher Education* [CHR97], there is a recent and highly publicized case in the courts. In March 1997 CellPro Inc. asked the federal government to exercise its "march-in" rights. They want to use a method invented by a Johns Hopkins professor in the early 1980s. The method identifies and isolates stem cells, the master cells from which all other cells in the blood and immune system develop. This battle, between CellPro Inc. on one hand, and Johns Hopkins University on the other, has been ongoing for many years. It is not until recently that CellPro Inc. asked the NIH to exercise the "march-in" right. In August 1997 the director of the National Institute of Health, Harold E. Varmus, rejected CellPro's request.

2.1.3 Patents Granted to American Universities in the Last 20 Years

University patenting has grown substantially during the past 20 years. In the years before 1981, fewer than 400 U.S. patents were granted each year to American universities. As figure 2-1 shows, this number had risen to more than 1800 in 1995. This exponential growth has averaged an 11% increase each year since 1975.

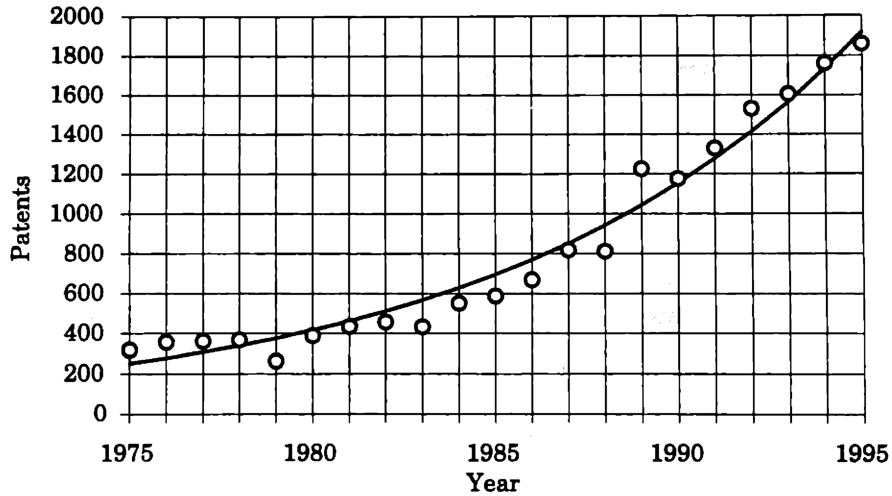

Figure 2-1: Total Patents Granted to U.S. Universities From 1975.

There are many reasons for this growth: Universities have substantially increased the investment in technology transfer programs; faculty have become more and more aware of the commercial potential of their research outcomes; industry has realized better and better the benefits of keeping close working relationships with universities; and, a few success stories have provided faculty with a further desire to get patents.

2.2 The Role of University Technology Transfer Offices

Most universities have started a technology transfer office in the past ten years. The objectives of these offices vary among universities, but include some or all of the following:

1. To help put technologies invented at the university to practical use.
2. To protect the intellectual property generated by research at the university.
3. To protect the university from research-related law suits.
4. To increase direct research support from industry.
5. To generate income for the university.

6. To provide advice and services for faculty.

7. To redistribute the royalty income to faculty and others involved.

In the spirit of the Bayh-Dole Act, most TTOs have the official objective of putting the technologies invented at their university to use. They explicitly emphasize this goal in one form or another. Few TTOs explicitly state their primary objective to be to generate income for the university and faculty. From numerous discussions with TTO professionals it is, however, clear that they think very much in terms of generated income.

Figure 2-2 is a schematic diagram of the communication channels between faculty and industry.

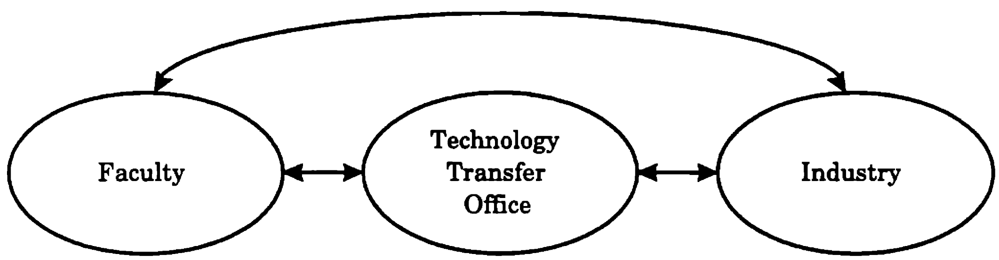

Figure 2-2: The Faculty-Industry Interface.

Several aspects of figure 2-2 are important. Observe that the TTO stands between faculty (the originator of the problem solution) and industry (the potential user of the solution). Observe also that there are ways for industry to communicate directly with faculty. The intensity of these communication channels varies, depending on an institution's practices, funding situation, and other external factors.

When analyzing the operations of TTOs, the first step is to dissect the commercialization process. Figure 2-3 illustrates how good ideas are put to practical use.

When a faculty member has an idea that is potentially of commercial value, the first thing he or she can do is to file an *invention disclosure* with the technology transfer office at the university. In the invention disclosure the faculty member describes his or her invention in general terms. This description needs to be specific enough to help interested parties to understand what it does, but not too specific since the disclosure documents are publicly available. The invention disclosure reveals how the research was funded and identifies any other participants in the research. Here it is important to identify parties that may claim rights to the invention. Often the disclosure also suggests who might be interested in applying the technology.

It is important to realize that it is the faculty who file the invention disclosure with the TTO at their university. If the faculty are not aware of the activity at the TTO, no invention disclosures will be filed. To increase the number and quality of invention disclosures, the staff of the technology transfer offices give seminars for faculty, introducing the technology transfer staff and processes.

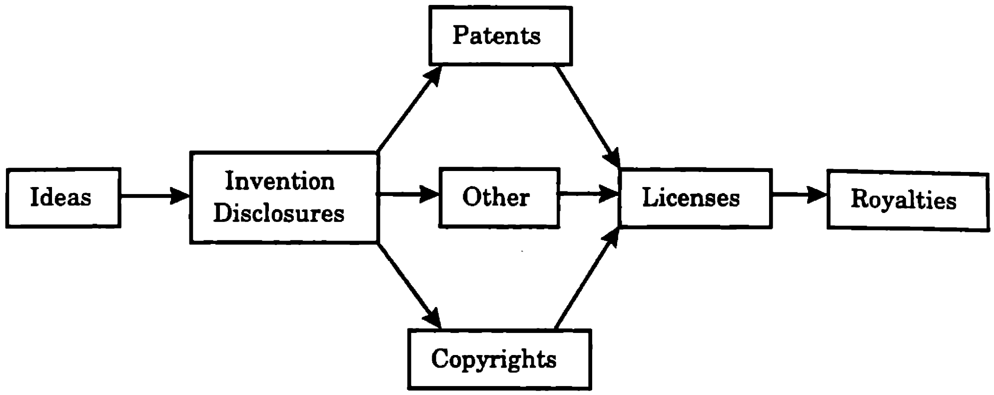

Figure 2-3: The Commercialization Process.

After the invention is disclosed, there are several ways to protect it. In the center of figure 2-3, *patents*, *copyrights*, and *other* refer to various alternatives to protect the intellectual property. The TTO chooses (in cooperation with the faculty) the best way to protect the invention. The key alternatives include:

- Patents. A patent is a grant issued by the United States Patent and Trademark Office, giving an inventor the right to exclude all others from making, using, or selling the invention within the United States, for a period of 17 years from the patent grant. To be patentable, an invention must be **new**, **useful** and **non-obvious**.

- Copyrights. A copyright owner has the exclusive right to reproduce the work, prepare derivative works, distribute by sale or otherwise, and display or perform the work publicly. In contrast to a patent which protects the *idea*, copyright covers the *artistic expression* in the particular work, but does not protect the *idea*.

- Trade and Service Marks. A trade or service mark is a word, name, symbol or device (or any combination) adopted by an organization to identify its goods or services and distinguish them from the goods and services of others.

- Mask Works. A mask work is defined as a series of related images representing a predetermined, three-dimensional pattern of metallic, insulating, or semiconducting layers of a semiconductor chip product.

- Tangible Research Property. The term *tangible research property* refers to those research results which are in a tangible form as distinct from intangible (or intellectual) property. Examples of tangible property include integrated circuit chips, computer software, biological organisms, engineering prototypes, engineering drawings, and other property which can be physically distributed.

- Trade Secret. The law of trade secret may be applied to almost any secret which is used in business and gives the owner of the trade secret a competitive edge over others.

There are primarily two reasons why it is important to protect the intellectual property. Others should not draw unfair financial gains from the invention. The second, and just as important reason, is that when university researchers invent new techniques, methods and processes, these most often do not constitute a product that is immediately marketable. Considerable research and development is needed in order to design a new product that utilizes the invention. If the party that buys the right to the invention cannot trust that it will have exclusive rights to use this technology, the incentive of investing in further research and development is reduced significantly.

When the university TTO has decided how the idea will be protected, it can focus on its **main** objective: to promote the available solution and find someone who is interested in using it. The staff of the TTO gather information on who might be interested in using the idea, contact these parties, and try to reach an agreement with them.

A *license agreement* is a contract between licensor (the holder of intellectual property, here the university and the faculty) and licensee (the party that uses the intellectual property). This contract describes the property the licensee is getting, how it will be used, and what the university gets in return (royalties and more). There are two different types of license agreements. When a company enters an *exclusive* license agreement, it gets exclusive rights to use the invention for its stated purpose. It knows that no one else can—as long as the license is active—use this invention. For an exclusive license agreement, it is therefore in the best interest of both parties that the intellectual property be protected as rigorously as possible. If the company chooses to enter a *non-exclusive* license agreement, the university has the right to license the technology to others that in some cases are in direct competition with the licensee.

The royalties which universities receive from licenses vary greatly. In some cases a large lump sum is paid when the agreement is signed, while in other cases a minor initial fee is paid, but the bulk of the revenue comes when a product reaches the market and sales are generated. When technologies are licensed to small firms, universities sometimes take equity as a form of payment. The benefits universities draw from licensing are not limited to royalties only; research funding is often provided for further research.

When seeking applications for an invention the TTO identifies parties that have the greatest use for it. This is a non-trivial task. We can hypothesize a situation where an established firm in some field is willing to pay a huge sum of money for a new technology. They do this, not to use the technology, but to prevent others from using it. In the true spirit of university technology transfer programs, the technology should—in a case like this—be licensed to someone who uses the idea to increase the public good.

For this and other reasons, licenses often have so-called *milestones*. When entering the contract, the stated objective of the licensee is to develop a specific product. If the product is not developed by, say eight years, the license is automatically cancelled, and the university is free to license the idea to someone else. These milestones also often involve significant payments. Companies that are not using the idea are thus encouraged to officially cancel the agreement as soon as they stop using the licensed technology.

In accordance with the license agreement, the licensee pays the licensor royalties. The licensor is in almost all cases the university, not the faculty. The university TTO redistributes the income from the license. Portions of the revenue are forwarded to the inventor and the technology transfer program. There are no general rules about how much the inventor should receive, it all depends on the practices of each university. Many have installed rules that entitle the faculty to a fixed fraction of the net income. Typically, between 10% and 50% of the net income is forwarded to the faculty, depending on the incentive universities want to provide.

2.2.1 Resources of the TTO and Focus

There are primarily two types of resources at the TTO: people and legal fee expenditures. The staff of the TTO are classified into two categories: people providing professional services for technology transfer (professionals) and people providing staff support for technology transfer (support staff). The professionals work directly with outside parties negotiating license agreements; they educate the faculty of the institution about the practices of the TTO; and they are responsible for redistributing the royalty income. The support staff handles other daily routines.

Legal fee expenditures are incurred when applying for a patent. In most cases the people of the TTO do not have the expertise and resources to administer a patent application, so they hire an outside law firm that specializes in providing such services.

Of the TTO resources, the legal fees are thus mainly used to apply for patents, and the salaried people work on license agreements. A well-run TTO must have the right mix of legal fee expenditures and employees. If there are too many employees and too little is spent on legal fees, the employees do not have a product (patent) to sell; if the balance tips in the other direction, there are too many products (patents) and too few sales (licenses).

2.2.2 A Hypothetical Example

In this section we discuss a hypothetical example of how a license agreement might be entered and royalties received. At the end of the section we discuss the role the TTO played and how that role might have been different.

The time from the start of research until a new product utilizing the new technology is in the market is in some instances short (2-3 years), but in other cases much longer (15-20 years). Many of the new technologies never enter the market, while others are huge commercial successes (for example, Hepatitis B vaccine, a human growth hormone, and the nicotine patch (University of California), Gatorade® (University of Florida), Cardiolite heart imaging agent (Harvard and MIT), the fax algorithm (Iowa State), synthetic penicillin and magnetic core memory (MIT), Cohen-Boyer recombinant

DNA [a process for splicing genes] (University of California and Stanford), CAT scanner (Stanford), ultraviolet irradiation of vitamin D (University of Wisconsin)).

In our specific case, Professor Jennifer Major at London Institute of Technology (LIT) applied for a grant in 1982 to do research on the properties of chemical reactions under high pressure and strong sun light. In September 1983 she was awarded a grant from the NSF and the following spring she started her research. She worked with two of her masters students, who both graduated with honors in May 1984.

In August 1984 Professor Major discovered that under certain circumstances she could accelerate the growth of bacteria considerably. After asking for advice from colleagues at other universities, she filed an *invention disclosure* with the technology transfer people at LIT within two weeks (September 1984). The invention disclosure was the first step in the long process of protecting her invention. It served as a legal document stating what she discovered and when. After filing her invention disclosure, the TTO specialists had one year to file for a patent or protect the idea by other means.

In June 1985 a *patent application* was filed. Before filing, the technology transfer people at LIT had hired lawyers to oversee the patent application process. The lawyers first performed a preliminary search, looking for other patents in the same area. The purpose of this was to make sure the invention was new, and also to cite other patents related to the method.

After filing the patent application the technology transfer administrators at LIT worked with Professor Major on identifying potential users of the invention. They identified four companies and approached all of them. They offered to enter *non-exclusive license agreements* with each company. With this type of an agreement the firms pay royalties in return for a permission to use the invention. After lengthy discussions, none of the companies decided to enter an agreement. They felt it was too risky. In order to use the invention, substantial research had to be performed, and they either did not have the capacity or the specialization to do so at this time. This outreach process took over two years, and it was not until December 1987 that LIT realized they had failed to license this technology.

Concurrent to these negotiations, the U.S. Patent and Trademark Office was working on the patent application. They found some patents they believed intersected with Professors Major's idea, so the patent application had to be revised. Finally in October 1988 the U.S. Patent and Trademark Office *issued two patents* to Professor Major and LIT.[1]

In April 1988 Professor Major and the technology transfer specialists at LIT decided to seek applications for the idea with new industry parties. Glasco was a young firm in the industry. They had grown more than 100% each of the last five years, and analysts on Wall Street predicted they would soon be the major company in the industry. LIT decided to go into one-on-one discussions with Glasco about Professor Major's invention.

[1] It was discovered that a researcher at Pfizer had the rights to a small variation of the idea. It was thus decided to split the patent into two patents, each one for a special variation of the original idea.

After only three weeks of negotiations an *exclusive license agreement* was signed between LIT and Glasco (May 1988). By the terms of the agreement, Glasco agreed to pay LIT \$10,000 each year for the next 17 years (unless they decided to cancel the agreement). Primarily two products were viewed as potential users of the idea, and it was agreed 0.1% of gross sales for the next 17 years would be paid in royalties. Other products would also pay 0.1% unless otherwise negotiated.[2]

Glasco started using Professor Major's idea almost immediately. They had 15 researchers working on the research and Professor Major visited the Glasco research facilities in VA on two occasions to see what was happening. Although she found these visits interesting, she also sensed the researchers were not telling her the whole story. It was clear to her they were making more progress than they were willing to admit. This she found frustrating.

By September 1991 the two projects Glasco started had both failed, but they announced that a new product would be in the market in February 1992, SpeedGrow. This product used Professor Major's invention and after some initial confusion about royalty rights, she was excited to see what would happen to SpeedGrow. Under the general terms of the license, LIT was entitled to 0.1% of gross sales. In February the product was offered for sale.

It is now September 1997. SpeedGrow has earned LIT over \$10,000,000 in net royalties. Professor Major has received over \$3,000,000 for her contribution and is retired. She now spends time with her family in Florida.

This hypothetical example is a success story. It illustrates that the route to success is often long, and there can be many surprises on the way. Since the beginning of university licensing fewer than ten licenses have yielded more royalty income than this example.

The rǫle the TTO played was to take what they received (an idea in the form of an invention disclosure) and try to protect and commercialize it. Although this example is a success story, some questions arise:

- Would it have helped if the TTO had more people working on technology transfer?
  - Could the invention have been commercialized sooner?
  - Did the invention reach its full potential, or did we only get "the tip of the iceberg"?
- What would have happened if LIT did not have a TTO?

If the TTO would have had more resources devoted to this invention, it is uncertain if the technology transfer would have been more or less successful. It is likely that a

[2]In practice, the terms of an agreement vary greatly. In the cases where the licensed technology is the main attribute of the product, the royalties can be as high as 20%. In other cases were multiple licenses are behind a single product the royalties can arbitrarily small.

license agreement had been signed sooner. By the same token, it might have happened that because of this extra effort early on, people in the TTO had shifted their attention to other discoveries when Glasco was ready to enter a license agreement; consequently no agreement would have been made with Glasco and all this income might have been lost. Instead an uncertain income from a different company would have been realized.

Had there not been a TTO at LIT, it is uncertain what Professor Major would have done. Today there are a few alternatives. One can contact some companies directly that might be interested in using the invention. These firms and their experts are in a good position to get exclusive rights to the invention at a reduced cost. Another alternative is to use the services of a company that specializes in commercializing technologies.

2.3 Literature Review

For our specific problem—figuring out the influence of university technology transfer offices in commercializing university discoveries—surprisingly little work has been done. No analysis has been published about the average "contribution" of a TTO employee, or about the causal relationship between hiring a staff member and increase in the TTO outputs.

The Association of University Technology Managers (AUTM) has for the last seven years published a journal. In last year's issue Trune [TRU96] develops measures for assessing the performance of TTOs. This work builds on annual surveys AUTM performs. Universities are spilt into four categories: Medical Schools (14), Technological Institutes (6), Universities with Medical Schools (62), and Universities without Medical Schools (49). For these four categories, linear regression models are built to predict the university output variables: total royalties received, licenses generating royalties, active licenses, licenses executed, invention disclosures received, and grant dollars received. The primary goal of his study is to give universities a "benchmark" to compare their performance with.

Henderson et al. [HEN95] discuss the role universities play as the source of commercial technology. They analyze the trends in university patenting from 1965 to 1988. They show university patenting has grown tremendously in this time period. They claim the reason for this growth is increased attention universities pay to commercial applications of new technologies. Looking at patent citations they also conclude that the average *importance* of university patents increased up until 1980, but has steadily decreased since then. Splitting university patents into two groups, winners and losers, they show that while there is an exponential growth in the number of losers, winners reached an equilibrium around 1980.

Blumenthal et al. [BLU95] discuss policy issues for academic-industry relationships. This study focuses on technology transfer in the Life Sciences. They survey all Fortune 500 companies in the fields of agriculture, chemicals and pharmaceuticals; all international pharmaceutical companies with sales comparable with U.S. Fortune 500 companies; and a random sample of non-Fortune 500 companies. They find that 95% of companies conducting life sciences research in the U.S. had one or more type of relationship with academic institutions, providing an estimated $1.5 billion in research support. Agreements with universities tended to be small and short, implying that most such relationships supported applied research or development. Over 60% of companies supporting life science research in universities had realized patents, products and sales from such relationships. At the same time, companies reported that their relationships with universities often involved agreements to keep research results secret beyond the time required to file a patent. Over the last decade, rates of involvement by companies in academic-industry relationships have increased, but the characteristics of those relationships have remained remarkably stable. Judging from the benefits realized from these relationships, universities seem well positioned to compete for industrial research funds in the future. However, the magnitude of company support for university research is modest compared to federal support, and companies are unlikely to be able to compensate for sizeable federal cutbacks. Finally, the authors point out that academic-industry relationships may pose a greater threat to openness of scientific communication than universities generally admit.

Pressman et al. [PRE95] examine the effectiveness of invention licensing at MIT's TLO in achieving one of the major objective in the Bayh-Dole act: to induce investment by the commercial sector in the development of inventions arising from government-funded research at universities, and by doing so, to enhance economic development. Comparing license income and induced investment, they conclude that while MIT receives substantial financial benefits from research, the induced investment outside MIT is about 24 times as large. They find that over two thousand jobs have been created and/or sustained as a direct result of MIT licenses. Over 70% of the investment and jobs created are associated with start-up companies, while they only account for 35% of the licenses. They extrapolate these MIT figures, and conclude that pre-production investment resulting from university licensing is between $3 and $5 billion per year.

Jaffe [JAF89] and Caballero and Jaffe [CAB93] examine the existence of geographically meditated "spill-overs" from university research to commercial innovation. Two examples are Silicon Valley near San Jose, California and Route 128, Massachusetts. They conclude there is a significant impact of proximity to universities—the impact is strongest in Drugs, and not far behind are Chemicals and Electronics.

Blumenthal et al. [BLU86] take a close look at the experience of the pioneer of university licensing, the Wisconsin Alumni Research Foundation (WARF). They determine that in 1940 WARF provided 18.6% of the university of Wisconsin's research budget. By 1955, that figure had fallen to 11.6%. As research support from other sources, especially the federal government, increased over the next 25 years, WARF's contribution steadily declined as a proportion of the university's total research effort. In 1985 WARF's contribution had fallen to 3.6% of the overall expenditures. They urge caution in assessing the potential financial rewards of university TTOs. From their investigation of WARF they conclude that TTOs are likely to earn less money from the return on patents than administrators and faculty members expect. They also suggest that universities should be prepared to finance and maintain a TTO until earnings, if any, come in. They hypothesize that universities today are unlikely to be able to realize the same return on investments that built WARF's funding capacity and that universities should expect to be involved in lawsuits resulting from patenting.

Mansfield [MAN91] estimates the extent to which technological innovations in various industries are based on recent academic research, and the time lags between the investment in recent academic research projects and the industrial utilization of their findings. He concludes that about one-tenth of the new products and processes commercialized during 1975-85 in the information processing, electrical equipment, chemicals, instruments, drugs, metals, and oil industries could not have been developed (without substantial delay) without recent academic research. The average time lag between the conclusion of the relevant academic research and the first commercial introduction of the innovations based on this research was about seven years (and tended to be longer for large firms than small).

Odza [ODZ96] lists some of the big winners in university licensing. He defines big winners as licenses that have generated more than $5,000,000 in net income to date, and lists most of the universities who have any big winners.

To understand the changes that have occurred in the field of university technology transfer and licensing consult Blumenthal et al. [BLU86], Caballero and Jaffe [CAB93], Feiwel [FEI87], David et al. [DAV92], Jaffe et al. [JAF92], Mansfield [MAN91] or Pavitt [PAV91].

Chapter 3

Cross-Sectional Regression Models

This is the first of the three methodologies we use to determine what impact TTOs have on the licensing process at universities. We build models that aim at predicting the research output from a university given a set of relevant inputs. The resources universities commit to technology transfer are imbedded in those models; and from the functional relationship of how the resources influence the predictions, we draw inferences about the impact they have.

We first build a conceptual model for the research process leading to licencing activities. We then quantify the conceptual model and estimate the parameters of the model from empirical data.

We conclude that there is a positive relationship between investment in technology transfer and the number of patents and licenses a university gets. We further conclude that there are diminishing rates of return for research expenditures.

3.1 The Research Process

Since the first universities were formed they have primarily served two purposes. They have served as an establishment where learned people pass on their knowledge to younger generations in order to help them lead better lives and ensure that the wisdom of scholars lives and is enhanced after they pass away. The second purpose is to provide a shelter for thinkers to work on pending problems in their field and expand the overall universe of knowledge.

Quantifying the impact a certain piece of university research has in society is difficult. When Einstein put forward his *General Theory of Relativity* it was not well received. In hindsight it is doubtful whether any single piece of research has had greater influence on our lives today. His theory should be rated as one of the most important contributions to the expansion of our base of knowledge. This example illustrates that it is not easy to come up with a method for evaluating the importance and value of research.

Let us start by describing the research that is performed at a university. In return for receiving shelter, necessary equipment, and money, the researcher trains students and performs investigations. The researcher "brainstorms" ideas and works out the necessary details to solve a problem. In doing this he or she usually interacts with a number of other people—students, fellow academics, and others—who provide the researcher with critical feedback on the idea, and help finalize details.

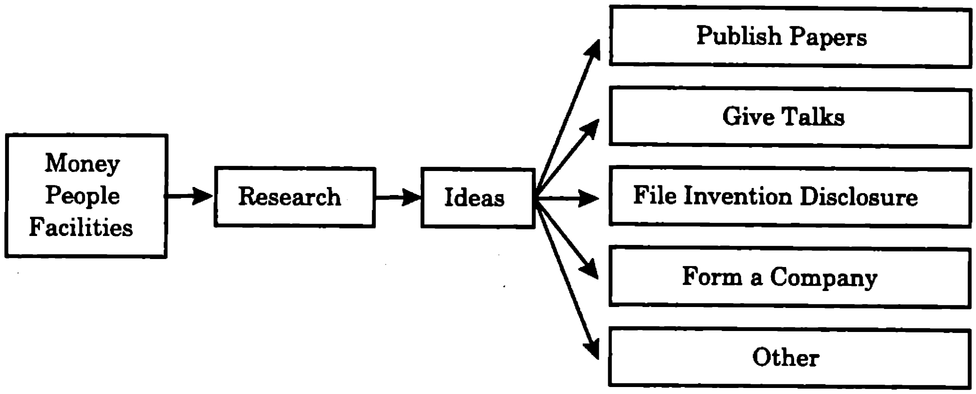

Figure 3-1: The University Research Process.

The researcher may deliver a partly or fully developed idea in several different forms. First of all, the researcher may write a paper explaining the idea. Publishing a paper is one way to let interested parties in the field know about the finding. Another way of delivering the idea is to give talks at conferences or in public places. If the idea has commercial value, the researcher may either start his or her own company or seek ways to protect and sell the idea. The first step in protecting the idea is to file an invention disclosure with a Technology Transfer Office or an agency that specializes in protecting intellectual property. For a detailed discussion about what happens after the invention disclosure is filed, consult section 2.2.

This dissertation focuses on analyzing the role of TTOs. Of the five ways to deliver an idea in figure 3-1, the TTO is involved only if an invention disclosure is filed. As discussed in section 2.2, filing an invention disclosure marks the first step in protecting the idea. After filing the invention disclosure, a patent application is often filed and the university tries to sell the idea by entering a license agreement.

3.2 The Model Components

In this section we introduce the building blocks of the cross-sectional model. We start by building a conceptual model for the number of patents and licenses a university gets. We introduce the assumptions we make about each component of the model, and then integrate them all to get an expression for the expected number of patents and licenses.

3.2.1 Building Blocks

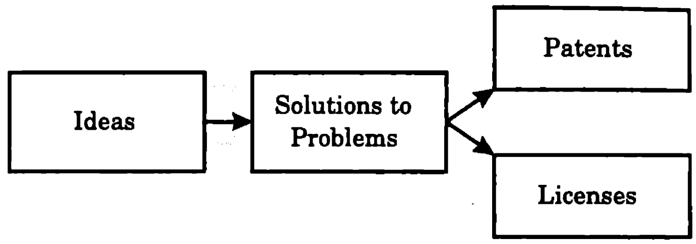

Figure 3-2: The Basic Building Blocks of Commertialized Research.

Figure 3-2 shows the core building blocks of putting research outcomes to commercial use. *Ideas* are born when faculty do research and some of these ideas provide *solutions* to practical problems. Solutions that may have commercial value can be protected by filing a *patent* application and when selling the right to use an invention the, owner enters a *license* agreement.

Ideas

When faculty perform research, they get ideas of how they might solve a particular problem. Let us define a variable g as number of ideas that may be of commercial value. We index the universities by i and the departments by j. The number of ideas resulting from research in department j of university i (in one particular year) is $g_{i,j}$.

Let us define the set of all departments at university i as $J(i)$. The total number of ideas at university i is,

$$g_i = \sum_{j \in J(i)} g_{i,j}. \tag{3.1}$$

Problem Solutions

Each idea may provide a solution to one or more problems. As an example, the wheel solved many problems. The first and most immediate use was to put it under carriages for transportation, but since then it has been used in many different situations.

Let us define $v_{i,j,g}$ as the number of problems idea g from department j in university i solves. The total number of problems solved at university i is thus,

$$v_i = \sum_{j \in J(i)} \sum_{g=1}^{g_{i,j}} v_{i,j,g}. \tag{3.2}$$

Patents & Licenses

Ultimately, we are interested in patents and licenses. We denote the number of patents that are granted based on solution v using idea g in department j of university i by $d_{i,j,g,v}$. Similarly, the number of license agreements is $l_{i,j,g,v}$. The total number of patents and licenses is thus,

$$d_i = \sum_{j \in J(i)} \sum_{g=1}^{g_{i,j}} \sum_{v=1}^{v_{i,j,g}} d_{i,j,g,v} \tag{3.3}$$

$$l_i = \sum_{j \in J(i)} \sum_{g=1}^{g_{i,j}} \sum_{v=1}^{v_{i,j,g}} l_{i,j,g,v}. \tag{3.4}$$

3.2.2 Assumptions

A Note on Notation: In general we use the convention for random variables to note the random variable by capital letters and the observed values by small cap letters. For example: The random variable D is used for the number of patents. If in a particular year seven patents are granted, then $d = 7$.

Ideas

University departments spend money on research. This expenditure can be viewed as the starting point of the research. Each dollar spent can be thought of as an attempt to generate an idea of how to solve a problem in the field of the department.

We denote the number of ideas that may be of commercial value by G, so $G_{i,j}$ is the number of ideas at university i and department j. We postulate that the number of ideas that come out of a university department follow a Poisson process. The rate of this process is a function of two variables. The research expenditures are positively related to the rate—the more we spend on research, the more ideas we get. The second variable is the faculty quality rating (see section 3.3.2 for the details of this variable). Other things even, we anticipate that "good" faculty get more ideas per research dollar than others.

We use Γ for the *idea rate*, so $\Gamma_{i,j}$ is the idea rate for department j at university i. We postulate that the idea rate for department j at university i is,

$$\Gamma_{i,j} = \alpha_j \left(1 + \delta_j F_{i,j}\right) x_{i,j}^{\beta_j}, \tag{3.5}$$

where $F_{i,j}$ is the faculty rating of university i and department j, $x_{i,j}$ are the research expenditures, and α, β, and δ are parameters to be estimated from data. The model is flexible enough to capture both diminishing ($\beta_j < 1$) and increasing ($\beta_j > 1$) rates of return for research expenditures. The model also accounts for the fact that faculty are not all equally productive. Highly competent faculty can probably perform research—or research that generates many ideas—more "cost effectively" than other faculty.

Summing over all departments at the university, we get the university idea rate,

$$\Gamma_i = \sum_{j \in J(i)} \alpha_j \left(1 + \delta_j F_{i,j}\right) x_{i,j}^{\beta_j} \ . \tag{3.6}$$

Problem Solutions and Patents & Licenses

In figure 3-2 we showed how ideas lead to problem solutions, and then to patents and licenses. Now that we have postulated that the number of ideas follows a Poisson process, we establish that the number of patents and licenses may follow a compound Poisson process.

The number of problems an idea solves is a random variable that we denote by V. For each solution to a problem v lets call the number of resulting licenses L_v and the number of resulting patents D_v.

We assume that the number of licenses and patents per idea ($L_{i,j,g,v}$ and $D_{i,j,g,v}$) are independent of the idea rate. This does not suggest that the total number of licenses ($L_{i,j}$) is independent of the number of ideas ($G_{i,j}$); it merely assumes that for a single idea the number of patents and licenses resulting from **that** idea is independent of the underlying idea rate.

We also assume that the number of problems each idea solves ($V_{i,j,g}$) is independent of the number of ideas at that department ($G_{i,j}$). We have thus assumed that,

$$D_{i,j,g,v} \quad \text{is independent of} \quad G_{i,j} \tag{3.7}$$

$$L_{i,j,g,v} \quad \text{is independent of} \quad G_{i,j} \tag{3.8}$$

$$V_{i,j,g} \quad \text{is independent of} \quad G_{i,j} \tag{3.9}$$

Under these assumptions the number of patents (and licenses) is a *compound Poisson random variable* of rate Γ_i (see equation 3.6) and with compounding determined by the convolution of D_v and V (L_v and V).

The primary function of the university TTOs is to take faculty solutions to problems and to protect and sell the solution by getting patents and enter license agreements. The number of problems a given idea solves and the number of resulting patents is assumed independent of the faculty idea rate; this number may however, depend on the resources available at the TTO. There are two primary resources that may be important: 1) The number of people a TTO employs (the more people working on technology transfer the more attention they can give to each invention); 2) the flexibility the TTO has to pay legal fees. The professionals in the TTO can rarely pursue patent applications themselves so they hire a firm that specializes in providing such services. If the TTO does not have the financial resources to pay the necessary fees, it is less able to apply for patents.

We denote these two resource variables as,

$$LF = \frac{\text{legal fee expenditures for patents and/or copyrights}}{\text{research expenditures}} \tag{3.10}$$

$$MP = \frac{\$100{,}000 \ \times \ \text{professionals} + \$50{,}000 \ \times \ \text{staff working on TT}}{\text{research expenditures}}. \tag{3.11}$$

The first variable is the ratio of legal fee to research expenditures. This measures the "force" of legal attention per research activity. A university with large research expenditures clearly needs to pay more than a smaller university in legal fees in order to give the same legal attention to each research effort. The second variable is the ratio of professionals and staff (weighted by an approximation of the variable cost of employment), to research expenditures. This variable is aimed at capturing the technology transfer expertise per research effort. A university with a high MP is thus providing more attention to each inventor than a university with a low MP.

We postulate that the mean of the random variable for the number of patents resulting from each idea ($D_{i,j,g} = \sum_{v=1}^{v_{i,j,g}} D_{i,j,g,v}$) is a function of the TTO resources, and that it has the following form,

$$E\left[D_{i,j,g}\right] = E\left[\sum_{v=1}^{v_{i,j,g}} D_{i,j,g,v}\right] = \left(\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2}\right), \tag{3.12}$$

where MP_i and LF_i are the variables defined above, and γ_1, γ_2, and γ_3 are parameters to be estimated from data. Equation 3.12 is very flexible, it allows for both a positive ($\gamma_2 > 0$) and negative ($\gamma_2 < 0$) impact of increasing the TTO resources. It allows diminishing and increasing rates of return, and does not restrict the relative importance of them: If $\gamma_3 = 0$ then the people working on technology transfer are not important, but only the legal fee expenditures; if $\gamma_3 \to \infty$ then the legal fees are not important, but only the employees of the TTO.

In order for the patents and licenses to be a compound Poisson processes we also need to assume that the variance be proportional to the mean,

$$\sigma^2_{D_{i,j,g}} = \Phi E\left[D_{i,j,g}\right] = \Phi \ \left(\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2}\right), \tag{3.13}$$

where Φ is an unknown parameter. We test this assumption in section 3.2.4.

Bringing it All Together

In figure 3-3 we have put it all together. For each department, j, we have the idea rate, $\Gamma_{i,j}$, and the number of ideas, $G_{i,j}$ (in this case $g_{i,j} = 7$). Each idea, g, yields a random number of solutions, $V_{i,j,g}$ (here $v_{i,j,3} = 5$), and a solution to a problem, v, yields a random number of licenses, $L_{i,j,g,v}$, and a random number of patents, $D_{i,j,g,v}$ (here $d_{i,j,3,4} + l_{i,j,3,4} = 4$).

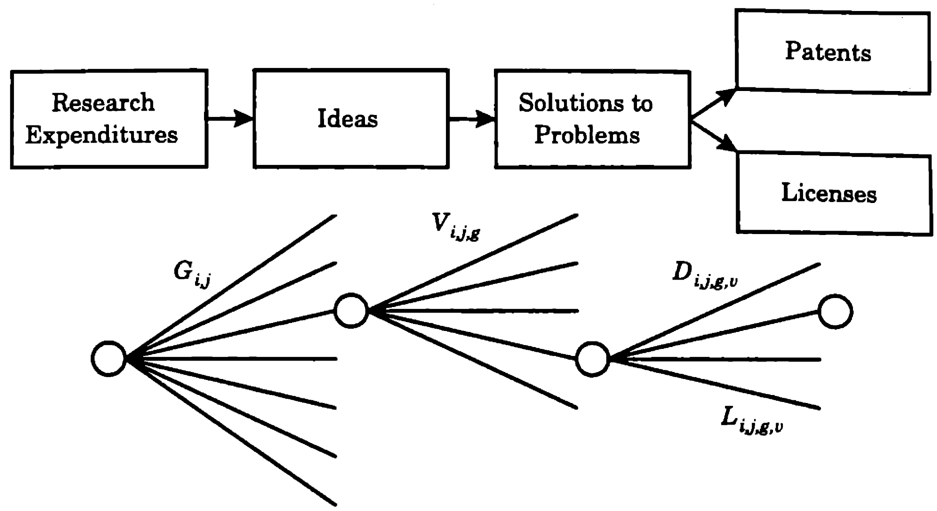

Figure 3-3: The Random Variables for the Entire Research Process from Research Expenditures to Patents and Licenses.

The Issue of Time

The process in figure 3-3 is not instantaneous. When research expenditures are incurred we do not simultaneously get the ideas, solutions to problems, patents, and licenses. It has been estimated that the last step in the process from the problem solution to license alone takes on average seven years.

In the analysis of this chapter we do not make an attempt at capturing this time lag. We assume that the research expenditures have not changed significantly in the last few years, and we use the research expenditures in the same year as the patent and/or licenses was granted to estimate the idea rate. We will, however, assess the issue of time lags in Chapter 5.

3.2.3 The Expected Number of Patents and Compounding

Under our various assumptions, the expected number of new patents at university i is,

$$E[D_i] = E\left[\sum_{j\in J(i)}\sum_{g=1}^{g_{i,j}}\sum_{v=1}^{v_{i,j,g}} D_{i,j,g,v}\right] \quad (3.14)$$

$$= E\left[\sum_{j\in J(i)}\sum_{g=1}^{g_{i,j}} E[D_{i,j,g}]\right] \quad (3.15)$$

$$= E\left[\sum_{j\in J(i)}\sum_{g=1}^{g_{i,j}} (\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2})\right] \quad (3.16)$$

$$= (\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2})\, E\left[\sum_{j\in J(i)} \sum_{g=1}^{g_{i,j}} 1\right] \tag{3.17}$$

$$= (\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2}) \sum_{j\in J(i)} \alpha_j \left(1 + \delta_j F_{i,j}\right) x_{i,j}^{\beta_j} \tag{3.18}$$

where,

- $E[D_i]$ is the expected number of new patents for university i.
- LF_i are the legal fee expenditures divided by the research expenditures, see equation 3.10.
- MP_i is a measure of the relative man-power of the TTO; defined as $100,000 times the number of professionals working on technology transfer plus $50,000 times the number of support staff working on technology transfer, all divided by the research expenditures, see equation 3.11.
- $x_{i,j}$ are the annual expenditures on R&D at university i and department j; measured in million-1994-dollars.
- $F_{i,j}$ is the average rating of the faculty at university i and department j; on a scale from -1 (worst) to 0 (best). We define this variable at the end of section 3.4.3 on page 3.3.2.
- $\gamma, \alpha, \beta, \delta$ are parameters we want to estimate from data.

To calculate the variance of D_i under our various assumptions, it is useful to view it as a random sum of random variables. We have already postulated what the variance and mean of the number of patents per idea ($D_{i,j,g}$) are (see equations 3.12 and 3.13), and it only remains to figure out how many ideas ($G_{i,j}$) we need to sum up. The ideas follow a Poisson process of rate $\Gamma_{i,j}$, see equation 3.5. We arrive at,

$$\sigma^2_{D_{i,j}} = \sigma^2_{D_{i,j,g}}\, E[G_{i,j}] + E[D_{i,j,g}]^2\, \sigma^2_{G_{i,j}} \tag{3.19}$$

$$= \sigma^2_{D_{i,j,g}}\, \alpha_j (1 + \delta_j F_{i,j})\, x_{i,j}^{\beta_j} + E[D_{i,j,g}]^2\, \alpha_j (1 + \delta_j F_{i,j})\, x_{i,j}^{\beta_j} \tag{3.20}$$

$$= E\left[D^2_{i,j,g}\right]\, \alpha_j (1 + \delta_j F_{i,j})\, x_{i,j}^{\beta_j} \tag{3.21}$$

$$\sigma^2_{D_i} = \sum_{j\in J(i)} \sigma^2_{D_{i,j}} \tag{3.22}$$

$$= \sum_{j\in J(i)} E\left[D^2_{i,j,g}\right]\, \alpha_j (1 + \delta_j F_{i,j})\, x_{i,j}^{\beta_j}\,. \tag{3.23}$$

Let us define a statistic based on the ratio of the variance to the mean of the number of patents university i gets per year (D_i),

$$
\begin{aligned}
Q &\equiv \frac{\sigma_{D_i}^2}{E[D_i]} & (3.24)\\
&= \frac{\sum_{j\in J(i)} E\left[D_{i,j,g}^2\right]\ \alpha_j\left(1+\delta_j F_{i,j}\right) x_{i,j}^{\beta_j}}{\sum_{j\in J(i)} E\left[D_{i,j,g}\right]\ \alpha_j\left(1+\delta_j F_{i,j}\right) x_{i,j}^{\beta_j}} & (3.25)\\
&= \frac{E\left[D_{i,j,g}^2\right]}{E\left[D_{i,j,g}\right]}. & (3.26)
\end{aligned}
$$

Note that $E\left[D_{i,j,g}^2\right]$ and $E\left[D_{i,j,g}\right]$ are independent of j, thus the last equal sign holds. If the process is a pure Poisson process, we get one patent for every idea and $E\left[D_{i,j,g}\right] = E\left[D_{i,j,g}^2\right] = 1$, and thus $Q = 1$. To estimate the amount of compounding in our processes we have calculated empirical values for the Q-statistic defined above. In Appendix B we introduce two statistics (Q^{1*} and Q^{2*}) to estimate the compounding for patents, licenses, and invention disclosures. The results are summarized in table 3.1.

Output Measure	Q^{1*}-statistic	Q^{2*}-statistic
New U.S. Patent Applications	1.4	1.6
Licenses and Options Executed	1.2	1.2
New Invention Disclosures	1.9	1.4

Table 3.1: The Poisson Compounding for Patents, Licenses, and Invention Disclosures.

3.2.4 Test of Variance-to-Mean Ratio Assumption

We have assumed that the variance in the number of patents per idea ($D_{i,j,g}$) is proportional to the mean; see equation 3.13. If this assumption holds, the variance in the number of patents a university gets (D_i) should also be proportional to the mean. In this section we test this.

From the Association of University Technology Managers [AUT96] we have data on the number of new patent applications by year for 74 universities between 1991 and 1995. In figure 3-4 we have plotted the variance of the five yearly outcomes against the mean for each university. Regressing the logarithm of the mean on the logarithm of the variance we get,

$$\sum_t \left(d_{i,t} - \overline{d_i}\right)^2 \sim \overline{d_i}^{1.18}. \tag{3.27}$$

This finding suggests that the variance is almost linear in the mean. The 95% confidence interval for the exponent (under the ordinary least squares assumptions) is $[0.93; 1.44]$. This suggests that it is reasonable to assume that the variance is linear in the mean.

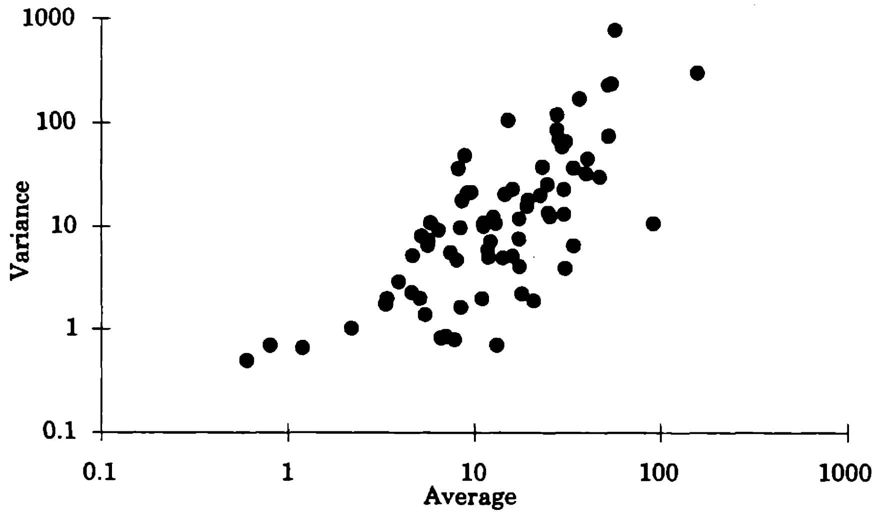

Figure 3-4: Number of New U.S. Patents Applications; University Variance versus Average.

3.3 Estimation

In this section we estimate the parameters of the model introduced in section 3.2. We first discuss the estimation procedure and the data we use. We then present the parameter estimates and discuss them briefly; a more detailed discussion of the parameter values and implications is in section 3.4. Finally, we introduce the methodology we use to develop confidence intervals and test hypotheses in section 3.3.5.

3.3.1 Objective Function and Parameter Constraints

In equation 3.18 we have an expression for the expected number of patents. The predicted number of patents is,

$$\lambda_i = (\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2}) \sum_{j \in J(i)} \alpha_j (1 + \delta_j F_{i,j}) x_{i,j}^{\beta_j}. \quad (3.28)$$

It is a non-trivial task to estimate the parameters for this nonlinear model. The easiest penalty function to use is the traditional sum-of-squared-errors,

$$f(\alpha, \beta, \gamma, \delta) = \sum_i (\lambda_i (\alpha, \beta, \gamma, \delta) - d_i)^2 . \quad (3.29)$$

Using this penalty function, let us compare how two different universities affect the estimation: MIT and the University of South Alabama. In 1994 MIT filed 98 new patent applications in the U.S. and the research expenditures were about \$360 million, while the University of South Alabama filed for 1 new patent and the research expenditures were \$9.4 million. The penalty-function of equation 3.29 penalizes us equally for each patent so if the prediction is 108 patents for MIT and 11 for the University of South Alabama, both contribute equally to the objective function. It is a much more serious error to predict the University of South Alabama applies for 11 patents than MIT for 108. We thus want to weigh our penalty function.

As discussed in section 3.2.2 we assume that the underlying process is a compound Poisson process. The variance is thus proportional to the mean. With this in mind we change the objective function to,

$$f(\alpha,\beta,\gamma,\delta) = \sum_i \frac{(\lambda_i(\alpha,\beta,\gamma,\delta) - d_i)^2}{\lambda_i(\alpha,\beta,\gamma,\delta)}. \tag{3.30}$$

With this new objective function an over-prediction of 10 patents for MIT is equally important as a 1.5 patent over-prediction for the University of South Alabama.[1]

The estimation with the objective function of equation 3.30 can be formulated as the following mathematical program:

$$\begin{array}{ll} \min & \sum_i \frac{\left[(\gamma_1+(\gamma_3 MP_i+LF_i)^{\gamma_2})\sum_j \alpha_j(1+\delta_j F_{i,j})x_{i,j}^{\beta_j}-d_i\right]^2}{(\gamma_1+(\gamma_3 MP_i+LF_i)^{\gamma_2})\sum_j \alpha_j(1+\delta_j F_{i,j})x_{i,j}^{\beta_j}} \\ \text{subject to:} & \\ & \begin{array}{lll} \alpha_j & \geq 0 & \forall j \\ \delta_j & \leq 1 & \forall j \\ \gamma_1 & \geq 0 & \end{array} \end{array} \tag{3.31}$$

The constraints are:

- The idea rate for all departments is non-negative. We thus impose the constraint that $\alpha \geq 0$.
- We must also ensure that $(1+\delta_{i,j}F_{i,j}) \geq 0$. The faculty quality rating ($F_{i,j}$) is between -1 and 0, and we require that $\delta \leq 1$. Note that we have not assumed that highly rated quality faculty perform as well or better than lower rated faculty. If we want to impose this restriction, we should also require $\delta \geq 0$.
- From equation 3.28 we have that the average number of patents per idea is proportional to $(\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2})$. If there are no resources for technology transfer ($LF_i = MP_i = 0$) and $\gamma_2 > 0$, this quantity must still be non-negative and we require $\gamma_1 \geq 0$.

[1] $\frac{(108-98)^2}{108} \approx \frac{(2.5-1)^2}{2.5}$

3.3.2 Data

From the Association of University Technology Managers [AUT96] we have information on: 1) New patent applications (1991-1995); 2) licenses and options executed (1991-1995); 3) invention disclosures received (1991-1995); 4) professionals and staff working on technology transfer (1992-1995); and 5) legal fee expenditures for patents and/or copyrights (1991-1995). These data are reported by the people working on technology transfer at the universities.

The National Science Foundation compiles a database each year with the reported research expenditures of American universities, by university and department [SRS95b].

The National Research Council performed a study of American graduate programs in 1993 [NRC95]. This database has a variable called "scholarly quality of program faculty". To estimate this variable they asked faculty to rate faculty in their discipline at other universities. The respondents should therefore be very well qualified to assess the value of this variable. We have aggregated this "program quality" measure into one "department quality" measure.

3.3.3 Results

In order to solve the mathematical program we used a stylized Newton-Raphson method. We did not impose the constraints from the start, but did so iteratively. We started with a unconstrained problem and if any of the parameters was outside the feasible region we projected it onto the feasible set and re-ran the optimization with the constrained incorporated.

Each university may represent up to four observations, one for each of the years from 1992 to 1995. While the faculty quality rating is the same, and the research expenditures do not change much, the resources available for technology change from year to year. It is thus more appropriate to use each year as a separate data point, than using averages.

The first conclusion is that not all departments contribute appreciably to the patenting process. The departments we used are listed in table 3.2.

Of these departments only Engineering, Physical Sciences, and Life Sciences contribute to increasing the number of patents and licenses.[2] (Industry experts told the author that this assessment is accurate, and the fact that the model predicts this behavior increases their comfort with the model.)

When estimating the model parameters from now on, we impose the restrictions that the Engineering and Physical Sciences departments observe the same returns to scale

[2] We use a bootstrap methodology (see section 3.3.5) to approximate the confidence intervals for the model parameters. The p-value estimates for the hypothesis that the nine departments in table 3.2 do no contribute to the patenting process are approximated to be (from 6,000 simulation runs): 0%, 0%, 48%, 99%, 15%, 0%, 79%, 88%, and 84%.

Department
Engineering
Physical Sciences
Environmental Sciences
Mathematical Sciences
Computer Sciences
Life Sciences
Psychology
Social Sciences
Other Sciences

Table 3.2: The Departments in the Database.

for research expenditures ($\beta_{\text{Eng}} = \beta_{\text{Phy}}$), and that the impact of the faculty quality rating is also the same ($\delta_{\text{Eng}} = \delta_{\text{Phy}}$). The reason for doing this is that there is a high degree of multicolinearity in the data, and consequently we may get unrealistic parameter estimates for those parameters. Imposing these restrictions only reduces the model fit by a small amount; if we estimate the model parameters of the relaxed model and test the hypothesis that these parameters values are the same, we accept the hypothesis. For a full discussion of this issue consult Appendix B.

In table 3.3 we have presented the parameter estimates for the models. We use the Q^{1*} and Q^{2*}-statistics as our measures of fit. We discuss their definition in section 3.3.4. We discuss the confidence intervals for the parameter estimates in section 3.3.5.

Let us take a quick look at the implications of the parameter estimates.

The γ_2 parameter determines the impact of the TTO resources. If $\gamma_2 < 0$ then increasing the resources results in a lower prediction for the outputs, but if $\gamma_2 > 0$ then increasing the resources makes the prediction higher. In general a higher value of γ_2 implies higher returns on investment in technology transfer for that output measure.

The γ_3 parameter determines the **relative** weight of the man power of the TTO (MP_i) and the legal fee expenditures (LF_i). For patent applications the parameter value implies that the impact of adding one full time professional to the staff working on technology transfer is the same as increasing the legal expenditures about ($0.29 \times \$100,000 =$) \$29,000. If γ_3 is low it implies that the legal fee expenditures are more important in determining the output than staff, but if γ_3 is high the staff is more important than the legal fee expenditures. We see that the value of γ_3 is lowest for patent applications, and highest for license agreements. This is as expected, the people of the technology transfer office primarily focus on selling the technologies and thereby entering license agreements, while the legal fees go primarily towards paying legal fees for patent applications. We discuss the impact of the TTO resources further in section 3.4.1.

The elasticities for the research expenditures are determined by β. If $\beta < 1$ there are diminishing rates of return, but if $\beta > 1$ there are increasing rates of return. The best way to interpret this parameter is to look at what happens to the prediction when we double

Parameter	New Patent Applications	Licenses Executed	Invention Disclosures
α_{Eng}	37.6	82.7	28.1
α_{Phy}	24.1	4.12	41.9
α_{Lif}	11.3	40.0	7.62
β_{Eng}	0.61	0.62	0.67
β_{Phy}	0.61	0.62	0.67
β_{Lif}	0.76	0.64	0.79
γ_1	0.014	0.015	0.038
γ_2	0.64	1.13	0.46
γ_3	0.29	5.64	0.78
1-δ_{Eng}	0.29	0.12	0.24
1-δ_{Phy}	0.29	0.12	0.24
1-δ_{Lif}	0.63	0.00	0.97
$2^{\beta_{\text{Eng}}}-1$	52%	54%	59%
$2^{\beta_{\text{Phy}}}-1$	52%	54%	59%
$2^{\beta_{\text{Lif}}}-1$	70%	56%	72%
Q^{1*}-statistic	1.64	2.27	3.58
Q^{2*}-statistic	4.70	7.10	12.9

Table 3.3: Model Parameter Estimates For Patents, Licenses, and Invention Disclosures.

the research expenditures. Doubling the research expenditures we get 2^β times as much output, and $2^\beta - 1$ is thus the predicted increase in the output when the expenditures are doubled. We see that doubling the research expenditures in Engineering and Physical Sciences, we would get between 50% and 60% more output, but doubling the expenditures in the Life Sciences the increase is a little higher. In all cases the increase is less than 75%. We discuss this further in section 3.4.2.

The δ parameters tell us what the impact of the faculty quality rating is on the predictions. The parameter estimates imply that in Engineering and Physical Sciences the lowest rated faculty get between 12% and 29% of what the highest rated faculty get. The impact of the faculty rating in the Life Sciences varies significantly depending on what we are predicting. This is further discussed in section 3.4.3.

3.3.4 Measure of Fit

We use two measures of fit statistics. The first is based on Q^{1*} in equation B.2. We take the median across universities of the squared errors normalized by the prediction,

$$Q^{1*}\text{-statistic} = \operatorname*{median}_i \left[\frac{(\lambda_i - d_i)^2}{\lambda_i}\right]. \tag{3.32}$$

The other measure is based on Q^{2*} in equation B.3. The empirical statistic is defined as the weighted squared error,

$$Q^{2*}\text{-statistic} = \frac{\sum_i (\lambda_i - d_i)^2}{\sum_i \lambda_i}. \tag{3.33}$$

As we discuss in section 3.3.6 there are a few large deviations from the model predictions. While these observations may just represent the stochastic nature of the processes, it is more likely that something else is creating this diversion. For this reason we focus on the first measure of fit because it is less sensitive to large deviations.

3.3.5 Sensitivity Analysis

With the model parameters in hand we want to evaluate how robust they are. This is important as we want to test hypotheses about the parameters. We are, for example, interested in testing if there are significant economies of scale, both for the research expenditures and the TTO resources.

For traditional least squares linear regression models we (under some general assumptions) have closed form expressions for the confidence intervals of our model parameters. These expressions provide us with the statistics to evaluate most hypotheses we want to test.

In our case the nonlinearity of the model forces us to use more sophisticated methods. We use re-sampling methods to develop confidence intervals for the model parameters.

Re-sampling Methods

In the last few years re-sampling methods have become the technique of choice to develop confidence sets and to test hypotheses. The computer technology has made it feasible to use these methods to arrive at numerical answers to previously unsolvable problems.

We work with two re-sampling methods. The Jackknife dates back to Quenouille [QUE49]. The method was introduced to estimate the bias of an estimator by deleting one datum each time from the original data set and recalculating the estimator based on the rest of the data. Let $X_1, \ldots, X_n$ be n vectors of data, and $T_n = T_n(X_1, \ldots, X_n)$ be an estimator of an unknown parameter θ. The bias of T_n is defined as,

$$\text{bias}(T_n) = E[T_n] - \theta. \tag{3.34}$$

Letting $T_{n-1,i} = T_{n-1}(X_1, \ldots, X_{i-1}, X_{i+1}, \ldots, X_n)$ be the given statistic based on only $n-1$ observations, the *Quenouille's jackknife bias estimator* is,

$$b_{\text{JACK}} = (n-1)\left(\overline{T_n} - T_n\right), \tag{3.35}$$

where $\overline{T_n} = n^{-1}\sum_{i=1}^{n} T_{n-1,i}$. From this we get the *bias-reduced jackknife estimator* of θ,

$$T_{\mathrm{JACK}} = T_n - b_{\mathrm{JACK}} = nT_n - (n-1)\,\overline{T_n}. \tag{3.36}$$

An estimate of the variance of the estimator has also been developed, see Tukey [TUK58]. The (delete-1) *jackknife variance estimator* for T_n is,

$$v_{\mathrm{JACK}} = \frac{n-1}{n}\sum_{i=1}^{n}\left(T_{n-1,i} - \frac{1}{n}\sum_{i=1}^{n} T_{n-1,i}\right)^2. \tag{3.37}$$

Calculating these estimators requires running the estimation procedure n times. For our problem this is easy as we have already developed efficient procedures to estimate the model parameters.

With n data points, there are $2^n - 1$ non-empty subsets. The jackknife utilizes only n of those but Hartigan [HAR69] discusses methods for using more than these n subsets. The *bootstrap* is introduced by Efron [EFR79].

The central idea of the bootstrap is to **randomly** choose a subset of the observations and calculate the parameter estimate. Let us draw $\{X^*_{1b}, \ldots, X^*_{nb}\}$, $b = 1, \ldots, B$ independently from $\{X_1, \ldots, X_n\}$. Now define $T^*_{n,b} = T_n\left(X^*_{1b}, \ldots, X^*_{nb}\right)$. The *bootstrap parameter estimator* is,

$$T^{(B)}_{\mathrm{BOOT}} = \frac{1}{B}\sum_{b=1}^{B} T_n\left(X^*_{1b}, \ldots, X^*_{nb}\right). \tag{3.38}$$

The variance can be approximated by,

$$v^{(B)}_{\mathrm{BOOT}} = \frac{1}{B}\sum_{b=1}^{B}\left(T^*_{n,b} - \frac{1}{B}\sum_{b=1}^{B} T^*_{n,b}\right)^2. \tag{3.39}$$

We use the simulated distribution of $T^*_{n,b}$ to make inferences about our estimator. We test hypotheses and develop confidence intervals using this simulated statistic. For further discussion about the jackknife and bootstrap consult Shao and Tu [SHA95].

Jackknife and Bootstrap Results

To get the Jackknife estimators, we first estimate the model parameters when the first data point is missing, we then estimate the model when the second data point is missing, etc. There are in all 416 observations, so we need to estimate the model parameters 416 times in order to get the Jackknife estimates. In order to get the bootstrap estimates we randomly choose 416 observations with replacement, and then estimate the model parameters for these observations. We repeat this 10,000 times and the detailed distribution functions for the runs are plotted in figures C-14 to C-24 in Appendix C.

The summary statistics for the Jackknife and bootstrap estimates for the patent applications model are listed in table 3.4.

In table 3.4 the first two columns have the Jackknife statistics. In the first column we have the bias-reduced jackknife estimator values (equation 3.36), and in the second

	Jackknife		Bootstrap				New Patent Applications
Parameter	T_{JACK}	$\sqrt{v_{\text{JACK}}}$	$T_{\text{BOOT}}^{(B)}$	med[]	%	$\sqrt{v_{\text{BOOT}}^{(B)}}$	T_n
α_{Eng}	12.6	42.7	75.87	37.6	50.0%	148	37.6
α_{Phy}	12.4	21.8	39.85	24.1	50.1%	57.3	24.1
α_{Lif}	4.28	9.62	22.5	13.2	41.4%	38.7	11.3
β_{Eng}	0.59	0.10	0.62	0.62	44.7%	0.10	0.61
β_{Phy}	0.59	0.10	0.62	0.62	44.7%	0.10	0.61
β_{Lif}	0.77	0.07	0.76	0.76	50.7%	0.07	0.76
γ_1	0.017	0.006	0.011	0.011	68.6%	0.005	0.014
γ_2	0.58	0.17	0.69	0.65	46.3%	0.17	0.64
γ_3	0.28	0.16	0.29	0.27	54.5%	0.16	0.29
1-δ_{Eng}	0.24	0.16	0.33	0.28	50.6%	0.18	0.29
1-δ_{Phy}	0.24	0.16	0.33	0.28	50.6%	0.18	0.29
1-δ_{Lif}	0.61	0.26	0.65	0.61	53.5%	0.26	0.63
$2^{\beta_{\text{Eng}}} - 1$	52%		54%	54%			52%
$2^{\beta_{\text{Phy}}} - 1$	52%		54%	54%			52%
$2^{\beta_{\text{Lif}}} - 1$	70%		69%	70%			70%
Q^{1*}-statistic	2.54	0.30					1.64
Q^{2*}-statistic	4.86	0.67	4.48	4.52			4.70

Table 3.4: Jackknife and Bootstrap Parameter Estimates for the New Patent Applications Model.

column we have the standard deviation estimates (equation 3.37). In the next four columns we have the bootstrap statistics. In the first column we have the bootstrap estimates of the parameters (equation 3.38). The second column (marked "med[]") has the median parameter value for the bootstrap runs. The third column (marked "%") lists the percentage of the 10,000 runs that resulted in a parameter value lower than the value estimated on the entire data set. The fourth column relating to the bootstrap results lists the estimates for the standard deviation (see equation 3.39). Finally, in the last column of table 3.4 we present the "regular" parameter estimates (T_n) from table 3.3.

The re-sampling estimates for α are not good. The reason is that the α's are very nonlinear in β and rigorously bound away from zero; when α moves upward, it can move a long distance, but when going down it is rigorously bound away from zero. Consequently the average of the simulated values is too high.

If we compare the parameter estimates of the Jackknife (T_{JACK}), the bootstrap (T_{BOOT}), and the regular method (T_n), we see that apart from the estimates for α they are very similar. We also notice that the regular parameter estimates are always between the two re-sampling method estimates ($T_{\text{JACK}} \geq T_n \geq T_{\text{BOOT}}$ or $T_{\text{JACK}} \leq T_n \leq T_{\text{BOOT}}$). We use the regular parameter estimates as our preferred values.

If we look at the variance estimates for the parameters (v_{JACK} and v_{BOOT}), we see that the Jackknife and the bootstrap methods yield very similar values (except for α). While the Jackknife provides us only with a variance estimate, the bootstrap method approximates the entire distribution function for the parameter. With the bootstrap we can thus easily test various hypotheses **without** assuming that the estimation errors have a normal distribution. We thus adopt the bootstrap as our preferred method to develop confidence intervals and test hypotheses.

3.3.6 Data Outliers

As in most regression problems we have observations that deviate much more than most others from the model predictions. The University of Pennsylvania did, for example, apply for 40, 50, 54, 107, and 36 new patents in 1991-1995 respectively. The large jump in 1994 cannot be explained by a huge increase in the research performed or resources made available for technology transfer. Our models consistently predict about 50 new patent applications for the period from 1991 to 1995. This one outlying observation causes our Q^{2*}-statistic to jump from 4.30 to 4.70 (using the parameter estimates of table 3.3 in both cases.

Another "outlier" is Cornell University. In 1992 and 1993 they applied for 92 and 97 new U.S. patents according to the AUTM data. Data are not available for the other years. The prediction for Cornell is consistently around 50 new patents each year. Recalculating the Q^{2*}-statistic when these two observations are also excluded we get 3.92. These three observations increase the penalty measured by the Q^{2*}-statistic from 3.92 to 4.70 or about 20%.

The patent data we used for the estimation are from the Association of University Technology Managers [AUT96]. For some of the universities in that database we have the number of patent **grants** from a database provided by the U.S. Patent and Trademark Office [TAF96]. Looking up the number of patents awarded to University of Pennsylvania and Cornell in the years from 1991 to 1995 we find that University of Pennsylvania was granted between 18 and 37 patents each year, and Cornell between 35 and 41. The ratio of patent grants to patent applications at other universities is between 0.8 and 1.0. This suggests that there is something fishy with these observations for Cornell and the University of Pennsylvania.

We do not eject these observations from our database, but we should keep in mind that these "outliers" throw our Q^{2*}-statistic of the mark.

3.4 Implications of Model Parameters

In this section we discuss the implications of the parameter estimates of the cross-sectional regression models. We use the bootstrap method to develop approximate 95% confidence intervals for the parameters of the three output models. In each case 10,000 runs were made to approximate the distribution, and in table 3.5 we have listed the results.

Parameter	New Patent Applications		Licenses Executed		Invention Disclosures	
α_{Eng}	37.6	[9.5; 444]	82.7	[0.56; 441]	28.1	[10.5; 88]
α_{Phy}	24.1	[7.9; 192]	4.12	[0; 60]	41.9	[18.9; 70]
α_{Lif}	11.3	[3.7; 102]	40.0	[0.3; 186]	7.62	[1.93; 33]
β_{Eng}	0.61	[0.44; 0.81]	0.62	[0.50; 0.77]	0.67	[0.56; 0.81]
β_{Phy}	0.61	[0.44; 0.81]	0.62	[0.50; 0.77]	0.67	[0.56; 0.81]
β_{Lif}	0.76	[0.60; 0.89]	0.64	[0.57; 0.76]	0.79	[0.52; 0.96]
γ_1	0.014	[0; 0.023]	0.015	[0.004; 1.94]	0.038	[0; 0.061]
γ_2	0.64	[0.46; 1.16]	1.13	[0.72; 1.50]	0.46	[0.31; 0.70]
γ_3	0.29	[0.05; 0.66]	5.64	[2.1; 627]	0.783	[0.26; 2.54]
$1\text{-}\delta_{\text{Eng}}$	0.29	[0.11; 0.78]	0.12	[0.04; 0.20]	0.24	[0.13; 0.42]
$1\text{-}\delta_{\text{Phy}}$	0.29	[0.11; 0.78]	0.12	[0.04; 0.20]	0.24	[0.13; 0.42]
$1\text{-}\delta_{\text{Lif}}$	0.63	[0.24; 1.25]	0	[0; 0.17]	0.97	[0.28; 2.77]
$2^{\beta_{\text{Eng}}} - 1$	52%	[35%; 75%]	54%	[41%; 71%]	59%	[48%; 75%]
$2^{\beta_{\text{Phy}}} - 1$	52%	[35%; 75%]	54%	[41%; 71%]	59%	[48%; 75%]
$2^{\beta_{\text{Lif}}} - 1$	70%	[52%; 85%]	56%	[49%; 70%]	72%	[44%; 94%]
Q^{1*}-statistic	1.64		2.27		3.58	
Q^{2*}-statistic	4.70	[3.38; 5.88]	7.10	[5.01; 8.82]	12.9	[7.39; 17.5]

Table 3.5: Model Parameters and Confidence Intervals for Patents, Licenses, and Invention Disclosures. Confidence interval is based on 2.5 and 97.5 percentiles.

3.4.1 The Technology Transfer Office Resources

Lets look closer at the influence of the TTO resources. From equation 3.28 we have that the influence is multiplicative of the form,

$$(\gamma_1 + (\gamma_3 MP_i + LF_i)^{\gamma_2})\,. \tag{3.40}$$

Comparing the number of new patent applications for a university with a TTO that has 70% of the median resources to one that has 140% of the median resources (the median is $MP = 0.003236$ and $LF = 0.002627$), we get,

$$\frac{\gamma_1 + (\gamma_3 * 1.4 * 0.0032 + 1.4 * 0.0026)^{\gamma_2}}{\gamma_1 + (\gamma_3 * 0.7 * 0.0032 + 0.7 * 0.0026)^{\gamma_2}}. \tag{3.41}$$

Using the parameter estimates for the three output measures we find that we expect 34% more patents, 44% more licenses, and 25% more invention disclosures from the university that invests 140% of the median in technology transfer than the one that only invests 70% of the median.

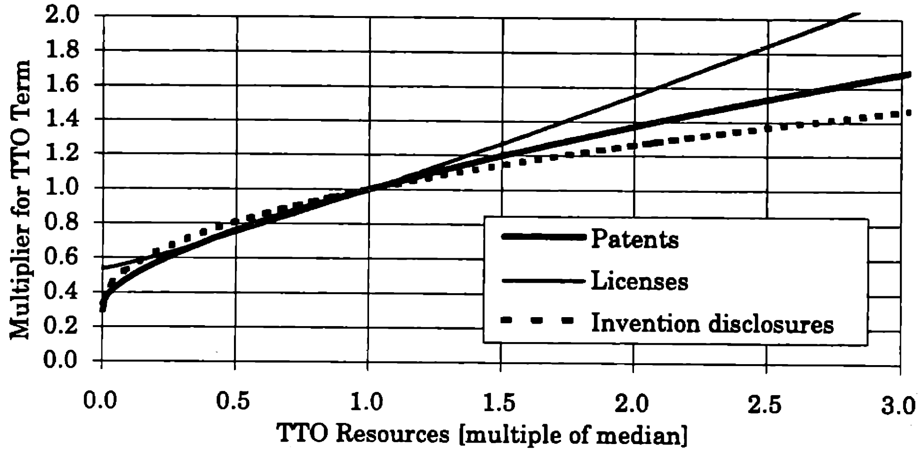

Figure 3-5: The Impact of TTO Resources on each of the Three Output Measures.

In figure 3-5 we have a continuous plot of the TTO multiplier for all the output variables discussed above. We first observe that all the functions are increasing—the more resources available for technology transfer, the higher the predicted number of outputs. If the hypothesis that the TTOs are hindering the process of commercializing university discoveries was true, these functions should not be increasing but decreasing.

When comparing the difference in how the TTO resources impact the output measures, we observe that the impact is smallest on the number of invention disclosures. This is as expected; the only role the TTO plays in getting invention disclosures is to educate the faculty about what these are and encourage them to file. We also see that the impact on the number of patents is larger but still smaller than the impact on licenses. This again is consistent with what we expect. The TTO is active in applying for patents but the primary focus of the TTO is to find applications for invented technologies outside the universities. A license manifests that the university has successfully entered an agreement with an outside party about using the invention.

From equation 3.28 we see that γ_3 is the factor that determines the relative importance of legal fee expenditures and people resources at the TTOs. If γ_3 is high it gives a large weight to the professionals and staff. This means that the people working on technology transfer are much more important for the prediction of the corresponding measure than legal fees. When γ_3 is close to zero it means that the people are much less important than legal fee expenditures in determining the output. When γ_3 is close to one the balance is about equal, assuming that the variable cost of hiring one professional is \$100,000 the impact of hiring one more professional for technology transfer when $\gamma_3 \approx 1$ is the same as if we would not hire the person but increase the legal expenditures about \$100,000.

The people of the TTO are much more influential than legal fee expenditures in the prediction of the number of license agreements ($\gamma_3 = 5.64$). This is not surprising because the primary role of the technology transfer professionals is to look for applications for university discoveries, and negotiate license agreements. The staff of the TTO does not play a major role in filing patent applications ($\gamma_3 = 0.29$). Instead they hire a legal firm that specializes in administering the patent prosecution process.

It is interesting to compare the prediction of the nonlinear model in two cases. We first use the model to make predictions using the current amount of TTO resources and then make another prediction when we have increased the TTO resources. We have done this for licenses and patents. In table 3.6 on page 48 we have the difference in the predictions when we add one professional or increase the legal fee expenditures about \$100,000.

The universities where the prediction of the number of licenses goes up by three or more from hiring an additional professional to work on technology transfer, are listed in table 3.6. We see that the greatest increase is at Drexel University. When comparing the predictions with the current resources and the resources after adding one professional, the increase is 6.7 licenses (per year). If the number of professionals working on technology transfer is increased by one at Drexel, notice that we are more than doubling the current resources. If we add one professional to the resources at MIT or Stanford, the proportional increase is much smaller, but there is still an increase in the prediction of license agreements of more than three.

The median increase in the number of licenses (patents) when adding one professional to the TTO staff is 2.2 (0.6). The median increase when adding \$100,000 to the legal fees is 0.4 (1.9).

	Increase in Number of Licenses		Increase in Number of Patents		Current Resources	
University	Add One More Prof.	Inc. Legal Fees $100K	Add One More Prof.	Inc. Legal Fees $100K	Man Power	Legal Fees (1994-M$)
Drexel University	6.7	1.1	1.0	3.4	0.63	0.093
Brigham Young	5.8	1.0	0.7	2.3	3.00	0.137
Carnegie Mellon	5.4	1.0	0.7	2.6	3.00	0.334
Illinois Inst. of Tech.	5.0	0.8	1.1	3.5	0.30	0.036
Stevens	5.0	0.9	0.7	2.3	1.55	0.049
Syracuse	4.8	0.8	0.8	2.7	2.50	0.072
Rice	4.8	0.8	1.0	3.4	0.50	0.085
Michigan Tech.	4.3	0.7	0.8	2.6	1.50	0.065
Princeton	4.1	0.7	1.0	3.3	1.50	0.189
Northeastern	4.0	0.7	0.6	2.1	0.63	0.250
U. of Delaware	4.0	0.7	0.8	2.8	1.50	0.133
Brown	4.0	0.7	0.9	3.1	1.50	0.094
Illinois State	3.8	0.7	0.4	1.3	2.50	0.000
Brandeis	3.6	0.6	0.7	2.2	1.50	0.039
Arizona State	3.6	0.6	0.6	2.0	2.75	0.413
Louisiana State	3.5	0.6	0.6	2.0	2.00	0.190
NJ Institute of Tech.	3.5	0.6	0.6	1.9	2.00	0.052
U. of Oregon	3.3	0.6	0.8	2.4	1.32	0.033
Ohio University	3.2	0.5	0.7	2.3	0.75	0.079
U. of Illinois, Urbana	3.2	0.6	0.8	2.6	4.63	0.304
MIT	3.2	0.6	0.4	1.4	14.00	3.033
U. of Utah	3.2	0.6	0.6	2.0	5.00	0.395
Stanford	3.1	0.6	0.4	1.6	14.50	1.847
U. of Tulsa	3.1	0.5	0.9	2.6	0.55	0.000
U. of Central Florida	3.1	0.5	0.7	2.4	1.13	0.076
Dartmouth	3.0	0.5	0.7	2.3	1.50	0.150
Median of all 130 U.	2.2	0.4	0.6	1.9	2.48	0.216

Table 3.6: Change in Prediction Induced by Increasing Resources. "Man Power" is defined as professionals plus 0.5 times support staff working on technology transfer.

3.4.2 Diminishing Rates of Return for Research Expenditures

Our estimates suggest that there are diminishing rates of return. From the confidence interval estimates in table 3.5 we see that we can in all cases reject the hypothesis that there are constant returns to scale ($\beta = 1$ is never in the 95% confidence interval). The economies of scale parameter for research expenditures is usually between 0.6 and 0.8, implying that a university with twice the research expenditures should expect between 50% and 75% more outputs. Government agencies that award research grants should, however, be careful in interpreting this finding. Taken out of context, this might suggest that more funds should be awarded to the smaller institutions at the expense of the larger ones.

One explanation of the diminishing rates of return is that some ideas are more expensive to elicit than others. In the Physical Sciences for example, small university programs may not be equipped to do experiments on colliding particles performed with a linear accelerator. In order to do research in this area the university has to invest in expensive equipment before it can start doing experiments in the field. The cost of research in the Physical Sciences, can thus vary widely among universities.

Another possible explanation is that as the departments get larger, faculty projects tend to be less differentiated. The younger faculty members may gravitate towards the research priorities of the more experienced faculty.

One hypothesis of why the model parameters always imply diminishing rates of return is that maybe there are a few small universities that are doing exceptionally well, and thereby pushing the predictions for small entities upwards. To test this hypothesis we split the universities into two categories based on aggregate research expenditures in the three departments. We estimate the model parameters separately on the smaller and larger universities. We find that in both cases the model parameters imply diminishing rates of return for research expenditures. We must thus conclude that the diminishing rates of return are not caused by a few small universities.

3.4.3 The Faculty Quality Rating

Our estimates imply that the faculty quality rating has a significant impact on the predicted number of licenses, patents, and invention disclosures. The δ parameters tell us what the influence of the faculty quality rating is on the predictions. The highest rated faculty have $F_{i,j} = 0$ and the lowest $F_{i,j} = -1$. Comparing the influence of the lowest rated faculty to the highest rated faculty in equation 3.18, we see that the lowest get $(1 - \delta)$ of the output the highest get. From table 3.5 we see that in Engineering and Physical Sciences the lowest rated faculty get between 12% and 29% of what the highest rated faculty receive. The impact of the faculty rating in the Life Sciences varies significantly depending on what we are predicting.

It is interesting to notice that of the three output measures the faculty rating influences the number of license agreements the most. This implies that while all faculty file invention disclosures and patent applications, highly rated faculty are more successful in applying their inventions outside the university.

This finding is quite significant; it implies that "good" faculty perform research that leads to applications outside the university more **cost effectively** than other faculty. The models correct for the fact that some universities have more money to spend on research than others. Taking this finding to its extreme, one can claim that the additional rewards from hiring "good" faculty outweigh the additional costs.

We should be careful not to read too much into the diminishing rates of returns and faculty quality importance because there is a strong correlation between these two variables (about +0.55). If we estimate models where we have set $\delta = 0$, the resulting β's are closer to one than the values presented in table 3.5.

3.5 Testing the Model

We test the model in two ways. The patent data we use to estimate the model parameters do not differentiate by department. In other words, we do not know the number of patents applications for research in the Life Sciences, Engineering, or Physical Science. When we calculate the predictions for each university, we can project the number of patent applications by department. We can thus use the model to approximate the portion of patents that come from each department. From another source we have classification data about patents. From these data we estimate the number of patents that are most likely based on research in the 1) Life Sciences, and 2) Engineering and Physical Sciences. By comparing this ratio to the ratio predicted by our model, we can test if the model is estimating the balance between the Life Sciences and the other departments correctly.

The other method we use is to keep a hold-out sample. We estimate the model on one set of data and use the resulting parameters to make predictions for the remaining data. We have data for four years from 1992 to 1995. We estimate the model parameters on data from three years and make predictions for the fourth.

3.5.1 Fraction of Patents in the Life Sciences

We use the data from the U.S. Patent and Trademark Office [TAF96] and split patents into two categories: 1) patents that are most likely based on research in the Life Sciences, and 2) patents that are most likely based on research in Engineering or Physical Science. In figure 3-6 we show how the number of patents in each category has changed since 1975.

The average annual growth in Engineering and Physical Sciences is 11.0% and 11.6% in the Life Sciences. The fraction of patents that are most likely based on research in the Life Sciences varies between 47% and 56%, but the average for all patents granted to American universities since 1975 is 51%.

When we calculate the contribution from each department using equation 3.28 and the parameter estimates for patents (table 3.5), we get the following:

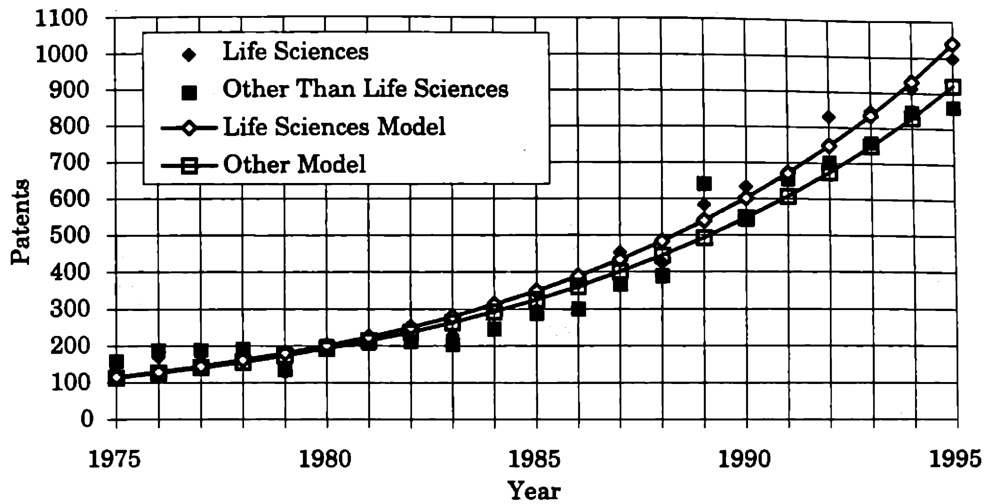

Figure 3-6: Patents Granted to American Universities by Research Field.

$$\sum_i \left(0.014 + (0.288MP_i + LF_i)^{0.64}\right) \times 37.6\,(1 + 0.71F_{i,\mathrm{Eng}})\,x_{i,\mathrm{Eng}}^{0.61} = 2473 \quad (3.42)$$

$$\sum_i \left(0.014 + (0.288MP_i + LF_i)^{0.64}\right) \times 24.1\,(1 + 0.71F_{i,\mathrm{Phy}})\,x_{i,\mathrm{Phy}}^{0.61} = 1425 \quad (3.43)$$

$$\sum_i \left(0.014 + (0.288MP_i + LF_i)^{0.64}\right) \times 11.3\,(1 + 0.37F_{i,\mathrm{Lif}})\,x_{i,\mathrm{Lif}}^{0.76} = 4659 \quad (3.44)$$

We see that the nonlinear model predicts that 29% of all patents result from research in Engineering, 17% from Physical Sciences, and 54% from Life Sciences.

The difference between 51% and 54% is small and can be explained by ambiguity in the classification of some patents. This shows that the nonlinear model not only fits the data quite well, but also predicts the ratio of all patents that result from research in the Life Sciences quite accurately.

3.5.2 Hold-Out Sample

The model parameters should be robust enough to be consistent over time. In looking into this issue we estimate the model parameters on three years of data and use the resulting parameters to predict the number of patents each university applies for in the forth year. The parameter estimates for each case are listed in table 3.7.

The last five rows of table 3.7 list the measure of fit statistics evaluated on only some of the data. The bold face statistics are for the data that are not used in the estimation.

Parameter	All Four Years	FY 1993 FY 1994 FY 1995	FY 1992 FY 1994 FY 1995	FY 1992 FY 1993 FY 1995	FY 1992 FY 1993 FY 1994
α_{Eng}	37.6	38.1	32.7	26.7	66.0
α_{Phy}	24.1	18.5	25.3	22.3	38.0
α_{Lif}	11.3	8.67	18.8	12.7	11.7
β_{Eng}	0.61	0.61	0.70	0.64	0.50
β_{Phy}	0.61	0.61	0.70	0.64	0.50
β_{Lif}	0.76	0.79	0.76	0.73	0.76
γ_1	0.014	0.011	0.012	0.016	0.013
γ_2	0.64	0.60	0.75	0.63	0.65
γ_3	0.29	0.30	0.23	0.26	0.37
$1\text{-}\delta_{\text{Eng}}$	0.29	0.24	0.53	0.39	0.11
$1\text{-}\delta_{\text{Phy}}$	0.29	0.24	0.53	0.39	0.11
$1\text{-}\delta_{\text{Lif}}$	0.63	0.71	0.63	0.53	0.59
$2^{\beta_{\text{Eng}}} - 1$	52%	53%	62%	56%	41%
$2^{\beta_{\text{Phy}}} - 1$	52%	53%	62%	56%	41%
$2^{\beta_{\text{Lif}}} - 1$	70%	73%	69%	66%	69%
Q^{2*} / Q^{1*} (all data)	4.70/1.64	4.76/1.60	4.87/1.71	4.72/1.68	4.82/1.51
Q^{2*} / Q^{1*} (1992 data)	5.33/1.71	**5.86/1.77**	5.49/1.93	5.14/1.82	4.91/1.73
Q^{2*} / Q^{1*} (1993 data)	4.82/1.44	4.94/1.39	**5.42/1.45**	4.78/1.63	4.65/1.27
Q^{2*} / Q^{1*} (1994 data)	4.92/1.57	4.83/1.51	5.10/1.71	**5.05/1.67**	5.18/1.62
Q^{2*} / Q^{1*} (1995 data)	3.93/1.68	3.74/1.61	3.70/1.73	4.05/1.70	**4.60/1.58**

Table 3.7: Parameter Estimates When Using Data From Three Years at a Time.

When looking at the measure of fit statistics for data from a single year, we see that, as expected, the Q^{2*}-statistics are largest when the corresponding year is not used in the estimation. From figure C-24 in Appendix C we see that the probability that the overall Q^{2*}-statistic is greater than 5.65 is 5%. The largest value for the entire data is 4.87.

When looking at the Q^{1*}-statistic (which is not based on a summed penalty but rather the median error) we see that in none of the four cases is the statistic at a maximum when that year's data are not used for the estimation. This is encouraging as it suggests that the model fit is consistent through time.

We see that all the parameters are fairly stable. The largest changes are in the faculty quality rating variables for Engineering and Physical Sciences. When excluding the 1993 data the coefficient is 0.53 but when excluding 1995 it is 0.11. When looking at figure C-22 in Appendix C we see that the probability that this parameter for the full data set is lower than 0.47 is 11.7% and the probability it is greater than 0.89 is 2.8%, so although the variation is substantial, we still stay within the 95% confidence interval.

3.6 Limitations of Cross-Sectional Regression Models

It is important to realize what the limitations of these models are. We built a conceptual model and made various assumptions about the processes leading to patent applications and licenses. The model is limited by how reasonable these assumptions are.

There are two key assumptions. We assume that the number of ideas in each department that may lead to patent applications and licenses follows a Poisson process. We further assume that the rate of this process is a function of the research expenditures and the average faculty quality rating. This is clearly a very simple model for the idea process. Other variables, not included in our model, may also influence the rate of this process.

We also assume that the number of patent and licenses per idea is a random variable with a mean that depends only on the resources provided for technology transfer. We postulate that two measures of the TTO resources are relevant: the number of professionals and staff working on technology transfer, and legal fee expenditures for patents and/or copyrights. These two measures are clearly imperfect. If one person leaves the TTO and a new person is hired, the gross number of full-time employees stays unchanged, but the new person is most likely less experienced than the person who left. We also assume that a staff member contributes one-half of what a professional contributes. There are clearly other factors about the TTO that are also relevant. Is the director of the office an enthusiastic person with many personal contacts with faculty and industry? Is the focus of the office on stimulating technology licensing, or merely to do what has to be done? Does the university reward the TTO and faculty for successfully transferred technologies?

We also assume that the variance in the number of patents and licenses per year is proportional to the mean. We test this assumption on data, and it appears to be a reasonable assumption.

The model of this chapter are cross-sectional; they predict the number of outputs from a university in one given year, but are not tailored towards tracking changes over time. The models do not tell us anything about causal relationships; they can only tell us how different variables may be dependent upon each other.

We used empirical data from more than 100 universities in the United States to estimate the parameters of the model. The model fits the "best curve" through the "center" of the data. The model is thus based on average performances, unlike the model in Chapter 4 which is based on best practices.

3.7 Conclusions from Cross-Sectional Regression Models

We started this chapter by building a conceptual model for the commercialization process of university discoveries. We then quantified this model and tested some of our assumptions. In these models the number of license agreements and patent applications for each university is approximated by compound Poisson processes.

We used empirical data to estimate the parameters of our model, and we used resampling methods to approximate the distribution functions for the parameters.

Our first conclusion is that only three departments—Engineering, Physical Sciences and Life Sciences—contribute significantly to the licensing process. This is not surprising as we do not expect successful research in all departments to lead to patent applications and license agreements. This finding is consistent with what industry experts expect.

The resources that are available for technology transfer are imbedded in our models. By looking at how the predictions vary as we vary the resources, we can draw conclusions about the apparent impact of providing more or less resources. All of our results show a **positive** relationship between the investment in technology transfer and the licensing activities (measured by patents and/or licenses). This result contradicts the hypothesis that the people at TTOs hinder the effective utilization of university discoveries. Rather, universities that commit more resources for technology transfer are also more successful at such transfer.

Our models suggest that the rewards from adding to the TTO resources vary among universities. In table 3.6 we listed the change in the predicted number of license agreements when comparing the current resource level to the situation when one more professional has been hired. The greatest expected increase in the number of license agreements occurs at Drexel University (6.7), but 25 other institutions have an expected increase higher than 3.0. The median increase for all universities is 2.2 licenses.

Our parameter estimates imply diminishing rates of return for research expenditures. Comparing the predictions for two universities, one with twice the research expenditures of the other, we expect 52% more patents, 54% more licenses, and 59% more invention disclosures in Engineering and Physical Sciences. In the Life Sciences we expect 70% more patents, 56% more licenses, and 72% more invention disclosures from the university with twice the research expenditures of the other. Our findings also suggest that the faculty quality rating has a significant association with the expected number of licenses, patents, and invention disclosures. On a per dollar basis, highly rated faculty perform research more cost effectively than others. Of the three output measures we consider, the relationship is strongest for license agreements. This implies that while all faculty file invention disclosures and get patents, the inventions of highly rated faculty are more successful commercially.

Chapter 4

Data Envelopment Analysis

Data Envelopment Analysis is the second of the three methodologies we use to evaluate the influence of university technology transfer offices in commercializing university research discoveries.

In Chapter 3 the influence of the TTO was imbedded into our models. Here our approach is different. We first develop a performance measure independent of the TTO. This performance measure not only considers variables related to technology transfer, it also includes faculty publications and student enrollment statistics. After evaluating the excellence of the universities, we analyze how it relates to the resources provided for technology transfer. Do "excellent" universities provide more resources for technology transfer than others? Are universities that invest more in technology transfer judged more "excellent" based on their performance in technology transfer, or is it based on other performance measures?

We conclude that there is a positive correlation between the university excellence and the resources provided for technology transfer. Furthermore, we show that the reason for the greater excellence of the universities that provide more resources for technology transfer is a better performance in commercializing university discoveries.

4.1 Introduction

Data Envelopment Analysis (DEA) was introduced by Charnes et al. [CHA78] as a method for evaluating the efficiency of decision making units (DMUs). Since the method was first introduced in 1978 substantial work has been done on both extending the theory and applying it to a wide class of problems. For a summary of recent developments and applications consult Charnes et al. [CHA94].

This section briefly introduces the DEA methodology. We define the *contribution* of output variables; it is a dimension-less measure that aims at showing which outputs are contributing to the efficiency score of the DMU. We also extend the definition of the efficiency score of the DMUs on the efficient frontier.

4.1.1 DEA Background

As in Chapter 3 the universities are indexed by $i = 1, 2, \ldots, n$. Each university has input measures denoted by $X_{i,r}$, $r = 1, 2, \ldots R$, and output measures denoted by $Y_{i,s}$, $s = 1, 2, \ldots, S$.

When calculating any kind of an efficiency score, these inputs and outputs need to be scaled (priced). Lets call the input weights v_r and the output weights w_s. Using these, the efficiency score of university i is defined as,

$$e_i = \frac{\sum_{s=1}^{S} w_s Y_{i,s}}{\sum_{r=1}^{R} v_r X_{i,r}}. \tag{4.1}$$

For some efficiency problems there are universally accepted weights for the inputs and outputs. This is for example the case when both the inputs and outputs are traded in an open market. Letting the weights equal the prices in the market, the numerator of equation 4.1 is the aggregate revenue, and the denominator is the cost. The efficiency score thus measures the return on the production.

In many cases it is difficult to determine the weights (prices). At universities, for example, what is the relative worth of publishing a paper versus entering a license agreement? Is one paper equally valuable as one license, or is it ten papers for one license.

Data Envelopment Analysis deals with this ambiguity problem by providing each university with the opportunity to put its "best foot forward." When determining the efficiency of a university, DEA chooses the weights that result in the best possible efficiency for that university. For example, if royalties are one of the output variables in the model, and a university is very successful in generating royalty, this university will do well if all of its weight (w_s) is placed on royalties. By using these weights, the university may have a higher efficiency as defined in equation 4.1 than all the other universities.

DEA constructs the *efficient frontier* by a convex combination of the best DMUs.[1] As an example, in figure 4-1 on page 58 we have plotted the efficient frontier for a hypothetical problem with two output variables. A DMU is on the efficient frontier if and only if $e_i = 1$, and we call the DMUs that are on the frontier *efficient.*

When the DEA algorithm finds the optimal weights for university i^*, it solves the following mathematical program:

$$\max e_{i^*} = \frac{\sum_{s=1}^{S} w_{i^*,s} Y_{i^*,s}}{\sum_{r=1}^{R} v_{i^*,r} X_{i^*,r}} \tag{4.2}$$

subject to:

$$\frac{\sum_{s=1}^{S} w_{i^*,s} Y_{i,s}}{\sum_{r=1}^{R} v_{i^*,r} X_{i,r}} \leq 1 \qquad i = 1, 2, \ldots, n \tag{4.3}$$

[1] A vector $\overrightarrow{z}$ is a convex combination of a set of vectors $\overrightarrow{x_i}$ if $\overrightarrow{z} = \sum_i \alpha_i \overrightarrow{x_i}$, where $\sum_i \alpha_i = 1$ and $\alpha_i \geq 0$ for all i.

$$w_{i^*,s} \geq 0 \qquad s = 1, 2, \ldots, S \tag{4.4}$$
$$v_{i^*,r} \geq 0 \qquad r = 1, 2, \ldots, R \tag{4.5}$$

The constraint 4.3 makes sure the scale is right—all the efficiency scores must be between zero and one. The positivity constraints 4.4 and 4.5 ensure that negative weights are not given to any of the outputs or inputs.

Observe that if $(w_{i^*,\cdot}, v_{i^*,\cdot})$ is an optimal solution to the nonlinear program above, then $(\alpha w_{i^*,\cdot}, \alpha v_{i^*,\cdot})$ is also optimal for $0 < \alpha < \infty$. By constraining the denominator of 4.2 to equal one, the nonlinear program above can be replaced by a equivalent linear program. While it is difficult to solve the nonlinear program, it is easy to solve the linear program.

4.1.2 Output Contribution

When DEA has determined the optimal weights $(w_{i,\cdot}, v_{i,\cdot})$ for university i, the *contribution* of each output measure towards the university's excellence can be evaluated. This concept has not been explicitly defined in the literature, but it is very intuitive. Define the contribution of output measure s for university i as,

$$W_{i,s} = \frac{w_{i,s} Y_{i,s}}{\sum_{s=1}^{S} w_{i,s} Y_{i,s}}. \tag{4.6}$$

Observe that for each university the contributions sum to one , i.e. $\sum_{s=1}^{S} W_{i,s} = 1$. If "royalties received" has a 80% contribution, it means that for this university, 80% of its efficiency score is derived from royalties received. This does not say that if the university had no royalties, the resulting efficiency score would be only 20% of the current score, because in the absence of royalties the algorithm would have chosen other weights.

4.1.3 The Extended Efficiency Measure

We have extended the definition of the DEA efficiency for the universities on the efficient frontier. Using traditional DEA, the efficiency of the DMUs on the efficient frontier is 100%. This evaluation is based on the performance relative to the best practices, but when a university is on the efficient frontier, itself is the best practice. It is more insightful to compare the DMU to all the **other** DMUs excluding itself. We thus exclude the case $i = i^*$ in the constraint 4.3. This does not alter the efficiency score for the universities that are not on the frontier, but the ones on the frontier have efficiency score of 100% or higher. An efficiency score of 300% means that if this unit was not included in the analysis, a hypothetical unit with these outputs would be on the efficient frontier although it had to use 300% of the inputs our unit uses.

4.1.4 A Simple DEA Example

To further illustrate these concepts, lets look at a simple example. Suppose there are only two relevant outputs (licenses and published papers), and assume that all universities have equal inputs. There are five hypothetical universities in the database, all listed in table 4.1.

University	Licenses	Papers
A	31	250
B	25	390
C	52	70
D	35	180
E	5	420

Table 4.1: DEA Example; The Data.

It is not immediately obvious which universities are efficient. Going back to the basis of DEA we see that university C is efficient—by placing all the weight on licenses, no other university performs better. University E is similarly efficient by placing all the weight on papers. The remaining question is, which of the other universities (if any) are also efficient, and if they are not efficient, what is their efficiency score? Figure 4-1 plots the two output measures against each other for all five universities.

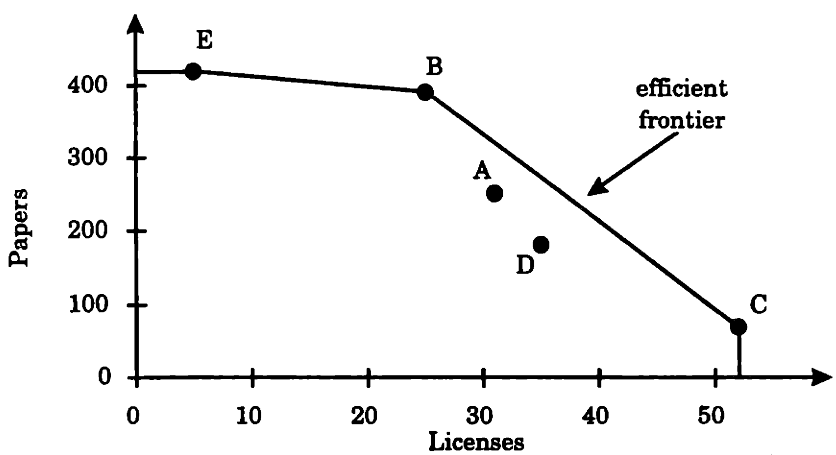

Figure 4-1: DEA Example; Data and the Efficient Frontier.

The *efficient frontier* is a convex combination of the best performing universities. DEA assumes that any convex combination of the observed points is feasible. Figure 4-1 shows that by choosing the right weights for licenses and papers, university B is efficient, but no matter how the weights are, A and D will never be evaluated as efficient. The reason is that they are **dominated** by a convex combination of B and C. Table 4.2 shows the numerical results from the DEA of this example.

			Contribution	
University	Efficiency	Extended Efficiency	Licenses	Papers
A	90.0%	90.0%	60%	40%
B	100.0%	122.3%	30%	70%
C	100.0%	148.6%	100%	0%
D	86.7%	86.7%	70%	30%
E	100.0%	107.7%	0%	100%

Table 4.2: DEA Example; The Numerical Results.

The efficiency score of university A is 90%, and 60% of its performance comes from licenses and 40% from papers. Lets create a hypothetical university A' that has the same ratio of outputs as A, but is on the efficient frontier. By blending 65% of B and 35% of C, we get that A' should have $(0.65 \times 25 + 0.35 \times 52 =)$ 34.45 licenses and $(0.65 \times 390 + 0.35 \times 70 =)$ 278 papers. Since $\frac{31}{34.45} \approx 90\%$ and $\frac{250}{278} \approx 90\%$, the efficiency of A is 90%. We say that A is dominated by this convex combination of B and C. Figure 4-2 shows where the hypothetical university A' would be on the two-dimensional outputs plot. The efficiency score is the length of the dotted line from zero to A divided by the length of the dotted line from zero to A'.

When calculating the extended efficiency of university B, B is not included in constraint 4.3. This means that the efficiency of B is evaluated relative to A, C, D, and E, but not B itself. The extended efficiency score can thus be higher than 100%. Figure 4-3 plots the hypothetical efficient frontier for the data set when B is not included. In this hypothetical situation, E and C stay on the efficient frontier, A is now also on it, but D is not. The intersection of a line from zero to B and this hypothetical efficient frontier is B'. The length of the dotted line from B' to B is the amount that B could reduce its outputs, but still stay on the hypothetical efficient frontier. The extended efficiency score is defined as the ratio of the length from zero to B to the length from zero to B'.

Letting B' be 81.8% of B, B' has $(0.818 \times 25 =)$ 20.45 licenses and $(0.818 \times 390 =)$ 319 papers. By blending together 59.4% of A and the remaining 40.6% of E, there are $(0.594 \times 31 + 0.406 \times 5 =)$ 20. 45 licenses and $(0.594 \times 250 + 0.406 \times 420 =)$ 319 papers. This blend of A and E produces 81.8% of what B does, so the extended efficiency of B is $(\frac{1}{0.818} =)$ 122.3%.

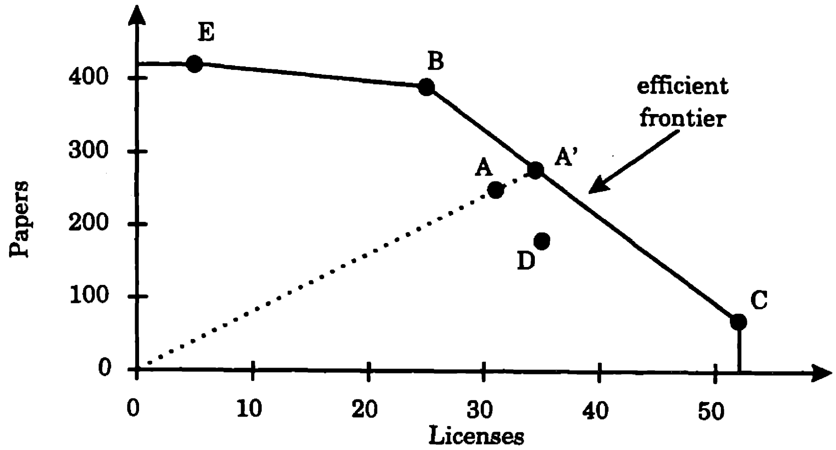

Figure 4-2: DEA Example; The Hypothetical University A' is a Convex Combination of B and C.

4.1.5 Variable Returns to Scale

The traditional DEA assumes constant returns to scale; if the inputs are doubled, the outputs should also double. In this section we illustrate how the method can be changed in order to account for variable returns to scale.

Norman and Stoker [NOR91] introduce the two most widely accepted methods to capture variable returns to scale. The first alternative is usually referred to as *input minimization*. It answers the question: "Given the outputs the university has, how much lower should the inputs be in order for the university to reach the efficient frontier." The mathematical program to solve is:

$$\max e_{i^*} = \frac{\sum_{s=1}^{S} w_{i^*,s} Y_{i^*,s} + c_{i^*}}{\sum_{r=1}^{R} v_{i^*,r} X_{i^*,r}} \tag{4.7}$$

subject to:

$$\frac{\sum_{s=1}^{S} w_{i^*,s} Y_{i,s} + c_{i^*}}{\sum_{r=1}^{R} v_{i^*,r} X_{i,r}} \leq 1 \qquad i = 1, 2, \ldots, n \tag{4.8}$$

$$w_{i^*,s} \geq 0 \qquad s = 1, 2, \ldots, S \tag{4.9}$$

$$v_{i^*,r} \geq 0 \qquad r = 1, 2, \ldots, R \tag{4.10}$$

The only change from the original mathematical program is the constant c_{i^*} that is added to the numerator of the efficiency measure 4.7 and the constraint 4.8.

The way to think about this, is that a synthetical output is created and an equal amount of it given to every university. If the algorithm gives every other university a

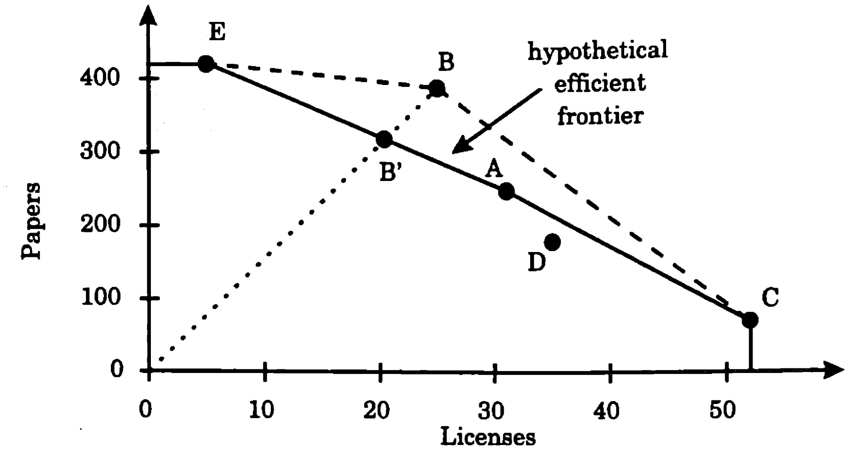

Figure 4-3: DEA Example; The New Hypothetical Efficient Frontier Used to Evaluate the Extended Efficiency Score of University B.

positive amount, it implies diminishing rates of return. If it subtracts a constant value from everyone, it implies increasing rates of return.

The other alternative for incorporating variable returns to scale is called *output maximization*. Output maximization answers the question: "Given the set of inputs, by how much do the university outputs need to increase for it to reach the efficient frontier." The following nonlinear program should be solved:

$$\max e_{i^\bullet} = \frac{\sum_{s=1}^{S} w_{i^\bullet,s} Y_{i^\bullet,s}}{\sum_{r=1}^{R} v_{i^\bullet,r} X_{i^\bullet,r} - c_{i^\bullet}} \tag{4.11}$$

subject to:

$$\frac{\sum_{s=1}^{S} w_{i^\bullet,s} Y_{i,s}}{\sum_{r=1}^{R} v_{i^\bullet,r} X_{i,r} - c_{i^\bullet}} \leq 1 \qquad i = 1, 2, \ldots, n \tag{4.12}$$

$$w_{i^\bullet,s} \geq 0 \qquad s = 1, 2, \ldots, S \tag{4.13}$$

$$v_{i^\bullet,r} \geq 0 \qquad r = 1, 2, \ldots, R \tag{4.14}$$

Here a similar constant as before is used, except it is subtracted from the denominator of the efficiency ratio and the constraint. For a more detailed discussion of variable returns to scale consult Norman and Stoker [NOR91].

4.2 Analysis

In this section we first introduce the variables we use as input and output measures of our model. We then discuss the data we use in the analysis, and the method we use to capture diminishing rates of return for research expenditures. Finally, we briefly list the efficiency scores for some of the universities.

4.2.1 Measures

The output measures for our analysis must meet two criteria. First of all we need a proxy for each type of excellence; we want to judge universities based on their performance in 1) performing applied research, 2) performing theoretical research, and 3) training new researchers. Secondly we must use measures that we can gather data on.

We use six output measures for the analysis:

1. Number of new U.S. patent applications, median of 1991-1995.
2. Number of options and license agreements entered, median of 1991-1995.
3. Gross royalties received, median of 1991-1995 (1994 dollars).
4. Number of faculty publications, total 1986-1992.
5. Number of enrolled graduate students, fall 1992.
6. Number of Ph.D. graduates, 1987-1988 academic year to 1991-1992 academic year.

Universities that focus on theoretical work will put most of their weight on faculty publications. Universities that focus on training new researchers will be compensated by placing a large weight on the number of enrolled graduate students and awarded Ph.D. degrees. Finally, universities that emphasize applied research will do well by placing high weights on the number of patent applications, licenses executed, or royalties received.

These measures are imperfect, but they are a reasonable approximation. When a researcher works on applied research, the ultimate goal is to **use** the results. Transferred technologies represent a fair proxy for the amount and quality of applied research outcomes. Theoretical work is most often brought to the public by publishing the results in a journal. Simple publication counts serve as a fair proxy for the volume of theoretical research findings. Training new researchers is one of the key objectives of universities. The number of graduate students and Ph.D. degrees awarded is the most tangible measure of performance in this regard. We have not attempted to evaluate the **quality** of any of those outputs; we assume that one publication is just as valuable as another, and that one patent is just valuable as another.

One of the most important input variables for university research is research expenditures. With money at hand a university is in a strong position to maintain strong research programs; it can attract faculty and students of the highest caliber and invest in necessary equipment. Other input variables are less important and the DEA only considers this one input measure:

1. Total research expenditures of all departments of table 3.2, median of 1991-1995, (1994 dollars).

4.2.2 Data

The aggregate research expenditures are published by the National Science Foundation [SRS95a]. These data are compiled each year after collecting the numbers from all American universities.

Data about the number of new patent applications, license agreements, gross royalties, and the TTO resources are from the survey the Association of University Technology Managers has compiled for the last five years [AUT96]. Universities report these numbers directly to AUTM, and the reliability is limited only by how truthfully the numbers are reported and how unambiguous the definitions are.

Finally, the number of faculty publications, student enrollment, and Ph.D. graduates is compiled from the study the National Research Council performed in 1993 [NRC95].

4.2.3 Returns to Scale

The models in Chapter 3 imply that there are diminishing rates of return for research expenditures—a university that has twice the research expenditures of another, does not receive twice as many patents or licenses. The DEA should be flexible enough to capture this behavior; but not too rigid to impose it on our data.

Of the two alternatives for modeling diminishing rates of return, input minimization is more appropriate for our purpose[2]. The nonlinear mathematical program for input minimization is equivalent to the following linear program:

$$\max e_{i^*} = \sum_{s=1}^{S} w_{i^*,s} Y_{i^*,s} + c_{i^*} \tag{4.15}$$

subject to: (4.16)

$$\sum_{r=1}^{R} v_{i^*,r} X_{i^*,r} = 1 \tag{4.17}$$

$$\sum_{r=1}^{R} v_{i^*,r} X_{i,r} - \sum_{s=1}^{S} w_{i^*,s} Y_{i,s} - c_{i^*} \geq 0 \qquad i = 1, 2, \ldots, i^* - 1, i^* + 1, \ldots, n \tag{4.18}$$

[2]Our results are not dependent on using input minimization as opposed to output maximization. We also performed the analysis using the other method, and while there are some minor differences, the key results are all the same.

$$\sum_{r=1}^{R} v_{i^\bullet,r} X_{i^\bullet,r} = 1 \qquad (4.19)$$

$$w_{i^\bullet,s} \geq 0 \qquad s = 1, 2, \ldots, S \qquad (4.20)$$

$$v_{i^\bullet,r} \geq 0 \qquad r = 1, 2, \ldots, R \qquad (4.21)$$

$$c_{i^\bullet} \geq 0 \qquad (4.22)$$

This linear program is easy to solve (and it is actually even easier to solve the dual), and we used a standard MATLAB®package to do the arithmetic. It has to be solved 122 times—once for each university in the database.

4.2.4 Results

In Appendix D we have the detailed results from the DEA. Of the 122 universities in the database, 20 are on the efficient frontier. The universities that have a higher efficiency score than 80%, and the contribution of the output variables, are listed in table 4.3.

The University of California has the largest aggregate number on all the output dimensions. Because of the way the DEA algorithm models diminishing rates of return, the University of California will therefore always be on the efficient frontier (and the efficiency score infinite). Stanford has been very successful in entering new license agreements. The median of 1991-1995 is 122 licenses (research base of 319 million), while MIT only entered 71 new license agreements (research base 364 million). Bringham Young is very effective in graduating Ph.D. students, but also derives some of its score from executing licenses. University of Akron is a small university that has many graduate students enrolled and has also filed many patent applications.

Looking at the contribution values, observe that the universities on the efficient frontier that place a high weight on patent applications are: Cal Tech, Northeastern, University of North Carolina in Charlotte, MIT, and Thomas Jefferson. Universities that place a high weight on licenses executed are: Stanford, Marquette, and Iowa State. Universities that place a the highest weight on royalties are: Columbia and Michigan State, but neither derived more than 50% of its performance from this measure. Universities that perform on publications are: Vanderbilt, UPenn, University of Massachusetts at Amherst, and Michigan State. Universities that place a high weight on the number of graduate students are: SUNY, University of Akron, Columbia, and Illinois Institute of Technology. Finally, universities that derive their performance from graduating Ph.D.'s are Bringham Young, and University of Chicago.

University	Extended Efficiency	Contribution					
		Patent Appl.	Lic. Exe.	Roy. Rec.	Fac. Pub.	Grad. Stud. Enr.	Ph.D. Stud. Grad.
U. California	∞	n/a	n/a	n/a	n/a	n/a	n/a
Stanford	403%		100%				
Brigham Young	332%		23%				77%
U. Akron	219%	30%				70%	
Cal. Tech.	173%	100%					
MIT	172%	89%	11%				
Iowa State	171%	40%	60%				
Marquette	148%	17%	83%				
U. NC, Charlotte	138%	95%	5%				
U. Chicago	136%	15%				26%	59%
U. Penn.	132%	14%			86%		
IL Inst. of Tech.	127%					51%	49%
U. Mass., Amh.	124%				79%	6%	15%
Columbia	122%			49%		51%	
SUNY	117%					100%	
Northeastern	116%	100%					
U. IL, Urbana	112%		15%		40%	36%	9%
Thomas Jefferson	111%	88%	12%				
Michigan State	110%			41%	59%		
Vanderbilt	104%		10%		90%		
U. TX, Houston	98%			3%	97%		
Rutgers	97%		3%	5%	70%	22%	
U. Florida	91%	2%	7%	14%	74%		4%
Purdue	90%	7%	15%				78%
Arizona State	90%	6%		3%	91%		
Washington U.	85%		24%		72%	4%	
Syracuse	85%			1%	99%		
Northern IL U.	84%				100%		
Ohio State	83%		8%	1%	67%		24%
U. NC, Chap. H.	82%		8%		73%	19%	
Princeton	82%						100%
U. Alabama	82%	13%	12%		75%		
U. WI, Madison	81%	24%		8%	26%	42%	
Northwestern	81%			1%	75%		24%

Table 4.3: The Extended Efficiency Scores and Output Contributions for the Universities with Higher Extended Efficiency Scores than 80%.

4.3 Implications about TTOs

The efficiency scores in the previous section are only based on the six outputs and the research expenditures. We have so far not used the resources universities commit to technology transfer in our analysis.

If the TTOs stimulate the licensing process at universities, we expect universities that invest more than others in technology transfer to make more license agreements, apply for more patents, and receive more royalties than others. Consequently, universities that invest more in technology transfer should, other things even, get a higher efficiency score and place higher weights on patents, licenses, and royalties. In other words, we think there should be a positive correlation between the amount of resources universities invest in technology transfer and the efficiency score, and there should also be a positive correlation between the TTO resources and the contribution (W_s) of the three dimensions related to technology transfer.

In this section we show that this is in fact the case. We do so by showing that we can reject the following two hypotheses:

1. There is no correlation between the efficiency score and the resources provided for technology transfer.

2. There is no correlation between the weights universities place on the three TTO related outputs (licenses, patents, and royalties) and the resources provided for technology transfer.

We use four measures for the TTO resources:

1. Number of professionals working on technology transfer per million dollars invested in research.

2. Number of support staff working on technology transfer per million dollars invested in research.

3. Gross legal fee expenditures for patents and/or copyrights per million dollars invested in research.

4. A weighted average of the above. $\$100,000\times$ the number of professionals plus $\$50,000\times$ the number of support staff plus legal fee expenditures, all divided by million dollars invested in research.

The last measure is aimed at capturing the variable cost of operating a technology transfer office. It assumes that the average cost of a professional is \$100,000 and the average cost of employing a staff member is \$50,000.

The reason we normalize the resources by the total research expenditures is that we want to capture how much TTO resources are provided per research activity. One person at Ohio State can obviously do more per research dollar, than one person at MIT.

4.3.1 Does a Strong Efficiency Score Correlate with TTO Resources?

Lets test the hypothesis that there is no correlation between the efficiency score and the resources provided for technology transfer. To test this hypothesis we use the Spearman Rank Correlation test. For details about the test consult Conover [CON80]. Table 4.4 shows the p-values of the hypothesis for each of the four resource measures.

TTO Resources	p-value
Number of Professionals	2.6%
Number of Staff	0.09%
Total Legal Expenditures	0.002%
Weighted Measure	0.002%

Table 4.4: The p-value for a Spearman Rank Correlation Test of the Hypothesis: "TTO Resources are Independent of the Extended Efficiency Score."

As table 4.4 shows, all the p-values are well below 5%. To further illustrate the point, we have in table 4.5 split the universities into four groups based on the number of professionals working on technology transfer and the extended efficiency score. The cut-off points are at the median (55%) efficiency score, and at 20 professionals working on technology transfer per billion dollars invested in research.

		Number of Professionals working on TT < 20 per billion spent on research	Number of Professionals working on TT > 20 per billion spent on research
Extended Efficiency Score	$< 55\%$	25	36
Extended Efficiency Score	$> 55\%$	13	48

Table 4.5: Head Counts for TTO Resources versus Extended Efficiency Score.

We see there is a strong positive relationship between the two variables. Of the 61 universities with extended efficiency above the median, only 13 have fewer than 20 professionals working on technology transfer per billion dollars spent on research, while 25 of the 61 universities below the median efficiency score do. The p-value for the hypothesis that the two dimensions are independent is 1.9% using a χ^2-test.

We can confidently reject the hypothesis that there is no correlation between the resources provided for technology transfer and the efficiency score of the university. This is consistent with the conclusion from Chapter 3 that the resources are positively correlated with university performance.

4.3.2 Do the Contributions from the TTO Related Outputs Correlate with TTO Resources?

The contribution of the TTO related measures is the combined contribution of patent applications, license agreements executed, and royalties received:

$$W_{\mathrm{TTO}} = W_{\mathrm{Pat}} + W_{\mathrm{Lic}} + W_{\mathrm{Roy}}, \tag{4.23}$$

where the contributions are defined as in equation 4.6. If the university is truly excellent in technology transfer, these add to 100%, but if the university is better in getting faculty publications, enrolling graduate students, or graduating Ph.D.'s, they add to 0%.

Out of the six output dimensions of the DEA, three are related to technology transfer. For a university at random, we therefore expect that on average about 50% of the contribution comes from the TTO related outputs, and the rest from the other outputs.

We now want to show that we can reject the hypothesis that the contribution for the TTO related outputs is independent of the TTO resources. In table 4.6 we have the p-values for this hypothesis.

TTO Resources	p-value
Number of Professionals	4.5%
Number of Staff	0.64%
Total Legal Expenditures	0.37%
Weighted Measure	0.55%

Table 4.6: The p-value for a Spearman Rank Correlation Test of the Hypothesis: "TTO Resources are independent of the TTO related Output Contributions."

Observe that the p-value is below 5% for all the TTO resource measures. As before we have also created a 2-by-2 table, splitting the universities into four groups based on the number of professionals working on technology transfer, and the sum of the contributions.

		Number of Professionals working on TT < 20 per billion spent on research	Number of Professionals working on TT > 20 per billion spent on research
Combined Contribution	< 50%	35	62
Combined Contribution	> 50%	3	22

Table 4.7: Head Counts for TTO Resources versus Combined TTO Related Output Contributions.

The first thing to notice about table 4.7 is that of the 122 universities only 25 derive more than 50% of their extended efficiency score from patents, licenses and royalties. Considering that these three measures are positively correlated—a university with many patents and licenses is also likely to receive large royalties—this is not surprising. Table 4.7 also shows that there is a strong correlation between the combined contribution and professionals working on technology transfer. The p-value for the hypothesis that the two are independent is 2.0% using a χ^2-test.

We can therefore confidently reject the hypothesis that the investment in technology transfer is independent of the weights universities put on patents, licenses, and royalties.

4.4 Limitations of DEA

There are two major objections to the technique. DEA is very sensitive to outliers. If there is one freakish observation, the entire analysis may be cast into doubt. Say, for example, that the output of one DMU was accidentally recorded ten-fold. This may deem many other DMUs very inefficient, as they cannot compete with this one super performer.

In an effort to diagnose a problem like this, we extend the method in one way. When performing the optimization for university i^*, $i = i^*$ is not included in the constraint of equation 4.3. Intuitively, this means that the efficiency score of the university is evaluated relative to all other universities, excluding itself. An extended efficiency score of 300% means that in the absence of this unit, a hypothetical unit with these inputs and outputs would be on the efficient frontier with as little as one-third of the outputs. If the extended efficiency scores are much greater than 100%, the data should be verified and the presence of that single DMU in the analysis should be confirmed. If we accidentally recorded one of the outputs ten-fold, the extended efficiency might be about 1000%. Since this efficiency score is so high, we will verify the data and catch the error.

The second objection is that the method does not deal effectively with non-convex spaces. It assumes that all convex combinations of the DMUs are feasible. Say, for example, that plants that make nuts and bolts are being analyzed. Lets assume that all the plants use the same amount of resources, and plant A produces 1,000 nuts and no bolts, and plant B 1,000 bolts but no nuts. For plant C that produces one bolt for every nut, DEA assumes that it should at least be able to produce 500 pairs, otherwise plant C is dominated by a 50-50 mix of A and B. In cases where specialization is of great value this convexity assumption is problematic, but in most cases the assumption is reasonable.

Like the analysis in Chapter 3, the DEA is cross-sectional, we build models that explain differences among universities, but we cannot use these models to determine causal relationships. In Chapter 5 we gather evidence about the causal relationship between investment and success in technology transfer.

The DEA does not quantify the influence of the TTO. We can only say that universities that invest more have a higher efficiency score, and they draw a higher proportion of their score from the TTO related measures. We cannot approximate the return from hiring one more professional to work on technology transfer.

Unlike the cross-sectional models in Chapter 3 that focus on explaining the "average" performance, DEA compares each university to the "best practices" of similar universities.

4.5 Conclusions from Data Envelopment Analysis

We use Data Envelopment Analysis to evaluate university excellence. Using six output measures the universities are given the opportunity to put their "best foot forward" in measuring their excellence. Only **after** we have evaluated the excellence of the universities do we look at the resources they provide for technology transfer. The approach is therefore both methodologically and conceptually different from the approach in Chapter 3.

The results of Chapter 3 suggest there are diminishing rate of returns for research expenditures. We have therefore chosen a variation of DEA that is flexible enough to capture such effects without imposing diminishing rates of returns on our results. Another alternative would be to assume constant rates of return.

An extension to the DEA methodology is introduced. We define the extended efficiency score. This extension does not alter the efficiency score for the universities that are not on the efficient frontier, but gives an estimate of the degree of excellence of the universities on the frontier. A contribution measure is also defined and shows for each university what portion of the overall efficiency score is drawn from each of the outputs.

The first conclusion from the analysis is that there is a strong positive relationship between the resources that are made available for technology transfer and the extended efficiency score. This suggests that universities that invest more than others in technology transfer are also more efficient. As in the results of Chapter 3, this is inconsistent with the hypothesis that the TTOs are hindering the process of commercializing university discoveries.

The second conclusion is that universities that employ many people for technology transfer and spend more on legal fees place higher weights on the TTO related output measures than others. This shows that when looking across universities, the universities that invest more than others in technology transfer are performing better in commercializing technologies.

Putting these two conclusions together, we can say that universities that invest more than others in technology transfer **are** more efficient because of their success in commercializing discoveries. On the other hand, we **cannot** say that these universities are more efficient because of the investment in technology transfer.

The analyses in both this and Chapter 3 draw inferences from the observed differences among universities. They do not determine what drives the changes at a single university: Does the investment lead to success, or does the success lead to the investment? In Chapter 5 we present two contradictory hypotheses that both give possible explanations for the results above (see page 73). In order to determine the causal relationship, we look at what has happened at a few universities in the last ten years. By analyzing the time series for these universities we shed light on the causal relationships.

Chapter 5

Time Series Analysis

In Chapters 3 and 4 we concluded that there is a strong correlation between the resources universities provide for technology transfer and the success at such transfer. The methods we used there do not, however, reveal the causal relationships. Are the TTOs driving the universities toward excellence in achieving patents and licenses, or do universities with strong performance decide that they should commit vast resources to technology transfer? In the latter case, these resources may have no stimulatory effect in themselves.

In this chapter we try to answer the question about causality. We first look at the AUTM data. We only have five years of data from AUTM, and it is impossible to rigorously reach a conclusion about the causal relationships from such a short time series. We therefore went out in the field and collected longer time series data directly from eleven universities. We first analyze the patterns at each of these eleven universities, and then perform various other analyses on the aggregated data.

Analyzing the universities one by one, we find no consistent patterns—what seems to be the causal relationship at one university, is contradicted by other universities. When combining the data some of our analyses do not give any hints about the causal relationships, but the evidence we find suggests that if a university hires more professionals, it will consequently enter more license agreements. This implies that professionals are stimulating the commercialization of university discoveries.

5.1 Introduction

Our results from the analyses in Chapters 3 and 4 suggest there is a strong correlation between the resources and success in technology transfer. We need to be careful to note that correlation does not mean causality. George Bernard Shaw provides an excellent example of this in his book *The Doctor's Dilemma*[SHA11]:

> Comparisons which are really comparisons between two social classes with different standards of nutrition and education are palmed off as comparisons between the results of a certain medical treatment and its neglect. Thus it

> is easy to prove that the wearing of tall hats and the carrying of umbrellas enlarges the chest, prolongs life, and confers comparative immunity from disease; for the statistics show that the classes which use these articles are bigger, healthier, and live longer than the class which never dreams of possessing such things. It does not take much perspicacity to see that what really makes this difference is not the tall hat and the umbrella, but the wealth and nourishment of which they are evidence, and that a gold watch or membership of a club in Pall Mall might be proved in the same way to have the like sovereign virtues. A university degree, a daily bath, the owning of thirty pairs of trousers, a knowledge of Wagner's music, a pew in church, anything, in short, that implies more means and better nurture than the mass of labors enjoy, can be statistically palmed off as a magic-spell conferring all sorts of privileges.

In this chapter we try to answer the question about causality. Two contradicting hypotheses that both give a possible explanation of the correlation results we got in Chapters 3 and 4 are:

1. The university technology transfer employees are effective in promoting university inventions. By hiring people to work on technology transfer (and making funds available for paying legal fees), a university can substantially increase the commercial success of faculty discoveries.

2. The university technology transfer employees provide service for transferring technologies. Universities that have had success in licensing inventions to industry have retrospectively hired people to administer the process. These people primarily focus on managing the process, but do not stimulate the commercialization of university discoveries.

Our primary goal in this chapter is to determine the causal relationship between **professionals** and **licenses**. We know that professionals primarily focus on marketing university discoveries (and thereby entering licenses agreements). In addition to this relationship, we also analyze the evidence for the causal relationships between support staff and licenses, and legal fee expenditures and patent applications.

5.1.1 Overview

In this chapter we assume that all licenses are equally valuable. This is clearly a key assumption for our analysis, and we discuss this and some of our methodologies in section 5.2. In section 5.3 we introduce the data. The AUTM data does not provide us with long enough time series and we therefore collected a longer time series from eleven universities. In section 5.4 we introduce the findings from the data collection and perform some basic correlation calculations for single universities. In section 5.5 we introduce methods to test hypotheses based on data from the eleven universities. We do not merge the data, but work out statistics for each university, and then combine the statistics. In section 5.6 we present probability models for technology transfer outputs. Based on changes in TTO inputs we build models for the probability that the outputs go up in the same and subsequent years. In section 5.7 we build simple regression models to estimate the effect on licenses from hiring professionals. Finally, we present our conclusions for the time series analysis in section 5.9.

5.2 Assumptions and Methodologies

In this section we introduce the key assumptions and methodologies we use to reveal what the causal relationships are between investment and success in university technology transfer.

We first argue that using license counts is a reasonable way to evaluate how much technology is transferred. We then discuss a hypothetical time series, and how one can look for evidence about causal relationships in such data.

5.2.1 Are All Licenses Equal?

We use a license agreement as the unit of measure for technology transfer. But are all license agreements equal? The impact of license agreements varies significantly. Some do not have any significant impact—there is no induced research, no development of products using the licensed technology, there are no sales generated by the invention, and the general public will never realize any benefits from the agreement. Other agreements are very important—the licensed technology induces a lot of research and product development, many products using the technology are put to market, and the lives of many people are made better in one way or another by products based on this invention. We must conclude that not all licenses are equal.

Ideally, when measuring how much technology is transferred, we would use a measure that captures most of the effects mentioned above. The problem is that it is not possible to get a good and **timely** estimate of the impact a license agreement has. Technology transfer specialists may sometimes know that a license will be a success, but in most cases it is a lottery—the licensed technology may or may not be successfully used. In most cases it is impossible to determine the success of a licenses until several years after the agreement is first signed. If we had chosen to do this for our analysis, we could not use data from the last several years.

As a first approximation, however, we must reluctantly treat all license agreements as equal. In Appendix F we argue that this first approximation works reasonably well. We build models that estimate that the average "quality" of licenses has not deteriorated in the last ten years.

There are two primary resources of the TTOs: salaried personnel and legal fee expenditures. From the results in Chapter 3 and what industry experts tell us, the people working at university TTOs primarily focus on marketing inventions and thereby entering license agreements with industry, while legal fees go primarily towards paying patent prosecution costs. Our main focus in this chapter is to reveal the causal relationships between licenses and the staffing of the TTO, but we also analyze briefly the causal relationship between patent applications and legal fee expenditures. In table 5.1 we have listed all the input and output variables.

Input Variables:	• People Providing Professional Services for Technology Transfer • People Providing Staff Support for Technology Transfer • Legal Fee Expenditures for Patents and/or Copyrights
Output Variables:	• Options and Licenses Executed • New U.S. Patent Applications

Table 5.1: The Input and Output Variables for Technology Transfer Offices.

5.2.2 Causal Relationships

When changes in one variable cause changes in another, we call the first variable the independent variable, and the other the dependent variable. Lets suppose we have time series for two variables: the independent variable z_t, and the dependent variable x_t. We have one measurement for each variable per year. Suppose a change in z causes an immediate change in x, then a model for x as a function of z may be,

$$\Delta x_t = 0.3\Delta z_t + \varepsilon_t, \tag{5.1}$$

where ε_t is a random noise component and the Δ is the one-year differential operator, $\Delta x_t = x_t - x_{t-1}$. Since the induced change in x is immediate, there is no information about the current change in x in any of the past changes in z. There will be a positive correlation between Δz_t and Δx_t, but Δz_{t+T} and Δx_t will not be strongly correlated for $T \neq 0$. If, on the other hand, some of the change is immediate, and some of it does not occur until the following year, we may have a model like,

$$\Delta x_t = 0.2\Delta z_t + 0.3\Delta z_{t-1} + \varepsilon_t. \tag{5.2}$$

If this model is accurate, a one unit change in z at time t causes an expected change of 0.2 units in x at time t and 0.3 unit change at time $t+1$. As before, there will be a positive correlation between Δz_t and Δx_t. There will also be a positive (and stronger) correlation between Δz_{t-1} and Δx_t, but for other time shifts, $T \notin \{0, -1\}$, there should not be a significant correlation between Δz_{t+T} and Δx_t.

If we do not know what the relationship between Δx and Δz is, one way is to first look at the correlation between the two. If there is no correlation even when we shift one variable several time units, we may conclude that Δx and Δz are independent. If, on the other hand, there is a strong correlation between Δx_t and Δz_t, we conclude that they are related. In order to assess the causal relationship, we calculate the correlations when shifting one variable a few years back and a few years forward. If there is a strong correlation between the two variables when one of them is delayed one or more years, we infer—all other factors being equal—that the changes in the delayed variable are caused by the changes in the other variable. The delayed variables is thus the dependent variable, and the other the independent variable.

5.2.3 Example

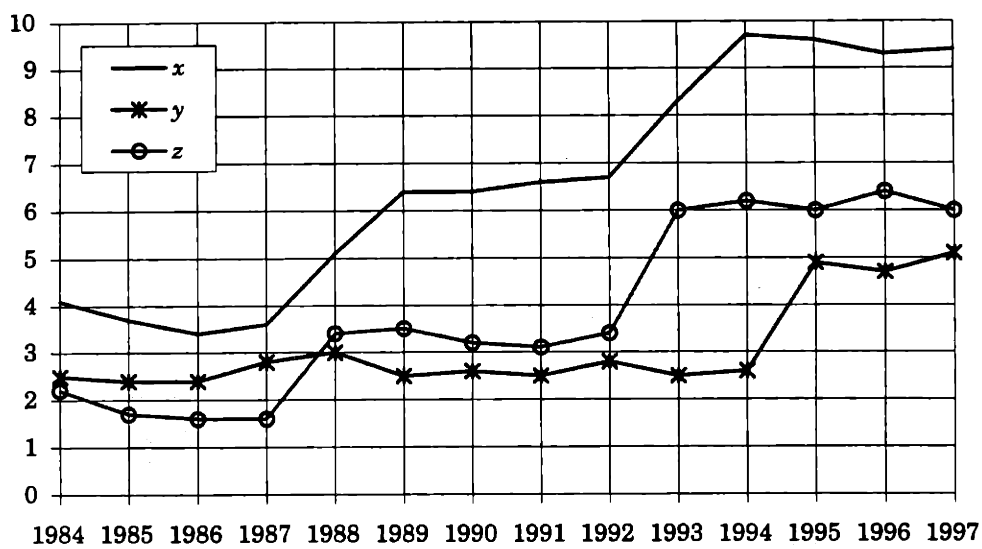

Figure 5-1: Time Series Data for Hypothetical Example.

Suppose we have the time series shown in figure 5-1. There are three variables labelled x, y, and z. Variable x is fairly stable from 1984 until 1987. In 1988 there is an increase from 3.6 up to 5.1, and then again in 1989 from 5.1 to 6.4. From 1989 until 1993 x is stable between 6 and 7. In 1993 and 1994 there are jumps, first to 8.3 and then to 9.7. Variable y is stable except for a jump-increase in 1995. The z variable is similarly fairly stable except for jump-increases in 1988 and 1993.

What is the relationship between x and the other variables? From figure 5-1 we see that the jump-increases in z occur in 1988 and 1993, and there are jump-increases in x in 1988-1989 and 1993-1994. This suggests that there is a positive correlation between Δx_t and Δz_t. Looking at the relationship between x and y we see that the only jump-increase in y is in 1995. We conclude that the observed univariate relationship between y and x is much weaker than that between z and x.

Now that we have reasoned that there is a positive correlation between Δz and Δx, what can we say about the causal relationship. From figure 5-1 we see that there is both an increase in x in 1988 and 1989, while there is only an increase in z in 1988. This suggests that an increase in z causes an increase in x. Some of the increase in x is in the same year, but some of it is postponed until the following year. We observe the same pattern for the increases in 1993-1994. We infer that changes in z may cause changes in x and that there is some time lag.

So far we have reached our conclusions by visual inspection. In section 5.4 we use simple correlation measures to evaluate the strength of the relationship between two variables. The time series of our example goes from 1984 to 1997, and we thus have valid one-year differential measurements for 1985-1997.

The correlation between the one-year differentials with time shift T is the same as the covariance between Δx_{t+T} and Δz_t divided by the standard deviations of Δx_t and Δz_t.

$$Corr\left(\Delta x_{t+T}, \Delta z_t\right) = \frac{\frac{1}{13-T}\sum_{t=1985}^{1997-T}\left(\Delta x_{t+T} - \overline{\Delta x}\right)\left(\Delta z_t - \overline{\Delta z}\right)}{\sqrt{\frac{1}{12}\sum_{t=1985}^{1997}\left(\Delta x_t - \overline{\Delta x}\right)^2} \times \sqrt{\frac{1}{12}\sum_{t=1985}^{1997}\left(\Delta z_t - \overline{\Delta z}\right)^2}}. \tag{5.3}$$

In the first two columns of table 5.2 we have listed the correlation coefficient between Δx and Δz, and the one-tailed p-value for the hypothesis that the correlation is zero. These p-values assume that Δx and Δz are normally distributed. For the data we work with in this chapter the normal assumption is violated. We have thus adopted another approach to evaluate the correlation between two variables. We use the nonparametric Spearman Rank Correlation coefficient. In section 5.5 we give the formula for the correlation coefficient and the p-value. In the last two columns of table 5.2 we have listed the Spearman Rank Correlation Coefficient and the p-value for the hypothesis that the two variables are not correlated.

Time Shift	$Corr\left(\Delta x_{t+T}, \Delta z_t\right)$	p-value	Spearman Rank Correlation	p-value
$T = -2$	-0.34	15%	-0.25	23%
$T = -1$	-0.16	31%	0.12	35%
$T = 0$	0.72	0.3%	0.64	1.0%
$T = +1$	0.62	1.6%	0.51	4.6%
$T = +2$	-0.34	15%	-0.38	12%

Table 5.2: Correlation Between Δx and Δz for Various Time Shifts.

We find that Δz_t is positively correlated with Δx_t and Δx_{t+1}. This is exactly what we had reasoned earlier by inspection. We also observe that there is a negative but insignificant correlation between Δz_t and Δx_{t+T} for $T \notin \{0, -1\}$.

We also observe that the Spearman Rank Correlation coefficient is close to the traditional correlation coefficient defined in equation 5.3.

Now that we have evidence implying that changes in z cause changes in x, we want to quantify the relationship between the two variables. We could use regular least squares regression to estimate the parameters of the model,

$$\Delta x_t = 0.09 + 0.58\Delta z_t + 0.52\Delta z_{t-1}. \tag{5.4}$$

The p-values for the two parameters are both below 0.02%. We estimate that 53% of the impact Δz has on Δx is immediate, and the remaining 47% is in the following year.

We have used three methods to show that Δz is the independent variable and Δx is the dependent variable. First by inspection of figure 5-1, then by calculating the correlation coefficient between the two measures with various time shifts, and finally by building a simple regression model.

Suppose that x represents the number of license agreements a university enters each fiscal year (measured in 10's), and z represents the number of people (full-time equivalences) working on technology transfer. If the empirical evidence is as in figure 5-1 we conclude that of the two hypotheses on page 73, hypothesis 1—TTOs are pushing university discoveries to the marketplace, and they proactively increase the number of license agreements— is closer to the truth. In this case the number of licenses is the dependent variable and the number of people is the independent variable.

If, on the other hand, x is the number of people and z the number of agreements we must conclude that hypothesis 2—TTOs are not pushing new technologies to the marketplace, but rather institutional reactions to processes that they do not stimulate—holds. In this case the dependent variable is the number of people working on technology transfer and the independent variable is the number of licenses.

In sections 5.6 and 5.7 we build models that use the independent variable to predict the dependent variable. When analyzing evidence in support of hypothesis 1—hiring people to work on technology transfer leads to increases in licensed technologies— we build models where we use the number of people to predict the number of licenses. Similarly, when we build models to test hypothesis 2—the universities respond to increases in the number of licenses by hiring people—we use the number of licenses to predict the number of people working on technology transfer.

5.2.4 Long Term Trends

The time series in figure 5-1 are somewhat representative for the time series we work with in this chapter in that there is an increase in all the measures. If we calculate the correlation between the absolute values instead of the differentials, we almost always find a positive correlation between any two variables. The reason is the positive trend—at the beginning of the time window the variables are close to a minimum, but towards the end they are usually close to the maximum. In order to correct for this trend, we work with the one-year differentials in the measures. By doing so we filter out a linear trend in the data.

5.2.5 Notation

Throughout this chapter we note the number of people providing professional services for technology transfer in year t by $N_{p,t}$ and support staff by $N_{s,t}$. Legal fee expenditures for patents and/or copyrights—as all monetary units in this thesis given in constant 1994 dollars—is denoted by $N_{l,t}$. The number of options and license agreements entered in year t is denoted by L_t and the number of patent applications by D_t.

5.3 Data Sources

5.3.1 The AUTM Data

To answer the question about the causal relationship we need time series data. The Associations of University Technology Managers has collected data since 1991 [AUT96]. These data, while fairly detailed, do not provide us with long enough time series to determine the causal relationships. We therefore designed a survey instrument and collected data directly from eleven universities.

From AUTM we have data for fiscal years 1991 to 1995. These data have the aggregate numbers of licenses, patents, invention disclosures, royalties, people working on technology transfer, legal fee expenditures and reimbursements from corporations, and research expenditures. Some of the summary statistics are listed in table 5.3 for the 68 universities that have provided data for all five fiscal years.

Fiscal Year	People Providing Prof. Services for Tech. Transfer	People Providing Staff Support for Tech. Transfer	Legal Fee Expendit. ($M 1994)	Legal Fee Reimb.	Licenses and Options Executed	New U.S. Patent Appl.
1991	n/a	n/a	$26.5	33%	928	1,157
1992	239	197	$30.4	36%	1,225	1,296
1993	255	193	$35.3	46%	1,264	1,478
1994	273	201	$38.4	49%	1,513	1,580
1995	265	215	$43.8	47%	1,549	1,757

Table 5.3: Summary of AUTM Data for FY1991-FY1995.

We see there was about a ten percent increase in the number of people working on technology transfer from FY1992 to FY1995. This is an underestimate of the overall increase because universities that have just recently started TTOs are not included in the numbers. There has been a substantial increase in the legal fee expenditures since FY1991. In FY1995 the 68 universities spent about $43.8 million on legal fees, while in FY1991 it was about $26.5 million. This is an average annual increase of 13.4%.

The legal fee reimbursements have increased from about a third of the total legal fee expenditures in FY1991 to one-half in FY1995. The number of licenses has increased on average about 13.7% each year since FY1991, and the number of new U.S. patent applications has increased about 11.0% each year. The total research expenditures have on average increased about 3.7% each year (in constant dollars).

These number show that there has been a growth in technology transfer in the last few years. The numbers only include universities that have participated in the AUTM survey in all years since FY1991. In the last few years more and more universities have started a TTO, and the estimates of the technology transfer activities above are thus surely underestimates. In the first AUTM survey 98 American universities participated, but for FY1995 this number had risen to 127.

The AUTM data does not provide us with long enough time series to analyze what is happening at each university. We need a longer time series to determine the causal relationship between investment and success in technology transfer. We collected data from eleven universities and in section 5.4 we introduce some of the results from the data collection.

5.3.2 The Survey Instrument

The goal of the data collection was to gather the necessary data to decide which of the two hypotheses on page 73 is closer to the truth. For each fiscal year going back to FY1986, we asked for:

1. The number of professionals and staff working on technology transfer, as well as the gross legal fee expenditures for patents and/or copyrights.
2. The number of license agreements.
3. The number of new U.S. patent applications.
4. The income profiles for each license executed since the start of fiscal year 1986.

We use the data from items 1 through 3 to build models that assess the causal relationships between TTO outputs and inputs. The data in item 4 are valuable in estimating the impact of single licenses. The income profiles are the most tangible proof of how successful each license is.

It was not easy to collect these data. Many universities do not have electronic databases with this information, and for universities with many licenses, it is a formidable task to dig up all the required information. Consequently, there are some gaps in the data for the fourth item for some of the eleven universities.

More data are in most instances better than less, but when collecting the data we need to be careful not to ask for too much. Asking for too much data, or data that is difficult to report, will result in lower cooperation from the survey participants. Asking for too little data we risk not being able to answer the questions we are trying to answer.

In designing the survey instrument every precaution was made to make it as easy to understand as possible. Before sending the survey instrument to the participants, it was tested with several TTO specialists. A copy of the survey and the accompanying cover letter is in Appendix E.

5.3.3 The Sample Design

In designing the sample we tried to get as close a representation of the university population as possible. In trying to cover the entire spectrum of universities, we considered the following dimensions:

- Research expenditures; gross research expenditures of all departments.
- Technology transfer resources; \$100,000 times the number of people providing professional services for technology transfer, plus \$50,000 times the number of people providing staff support for technology transfer, plus legal fee expenditures for patents and/or copyrights, all per gross research expenditures.
- Trend in technology transfer resources; the proportional change in technology transfer resources between 1992 and 1995.
- Emphasis on research in Engineering and Physical Sciences; proportion of total research budget dedicated to these two departments.
- Emphasis on research in the Life Sciences; proportion of total research budget dedicated to Life Sciences research.

In all we have the background information for 130 universities. We ranked the universities on all these variables, and then tried to make our sample as uniformly distributed as possible with respect to the dimensions above. In table 5.4 we list the eleven universities in our sample, and rank them among the full set of universities in the AUTM database.

Ideally the ranks in table 5.4 should average 60.5, and be as evenly distributed between 1 and 130 as possible. In all there is a small bias towards universities that have not increased the investment in technology transfer, and do not emphasize research in the Life Sciences (the average ranking in table 5.4 is 68 and 69), but overall the sample is a good representation of the university population.

We have shown above that the selection bias is small on the dimensions listed, but there is always some response bias. It is more difficult to get universities that are not well staffed to respond. This was confirmed in the selection process as we had to contact many universities that are running small technology transfer programs.

	Rank of Variable over 130 Universities				
	Research Expend.	Tech. Transfer Resources	Trend In Tech. Transfer Resources	Emphasis on Research in Eng. and Physical Sciences	Emphasis on Research in the Life Sciences
Harvard	10	26	28	93	56
MIT	7	13	94	7	121
Ohio State	28	100	122	47	75
Syracuse	103	23	97	25	115
U. of Arkansas	101	35	123	63	54
U. of Missouri	72	71	19	53	59
U. of Notre Dame	108	126	42	3	114
U. of Rhode Island	93	32	58	91	106
U. of Texas MB	88	42	63	123	6
Vanderbilt	48	104	39	80	29
Yale	16	119	68	96	26

Table 5.4: The Surveyed Universities and Their Ranking Among All Universities in the AUTM Database.

5.3.4 Data Collection Process & Selection Bias

We first chose ten universities that represented an unbiased extract from the population. A cover letter and the survey was faxed to the directors of the TTOs, or the person responsible for technology transfer at these institutions. A few days after faxing the survey, the author followed up with a phone call. This phone call focused on answering any questions the respondent might have about the survey and evaluate the chances of getting the data. In the cases where the respondent rejected our request, or it was determined that the chances of getting the data were slim, a new university was added to the sample. In no case was the university's status left indeterminate—if the chance of getting a complete answer was estimated as being low, the author worked with that university until they either declined the request or provided the data. In choosing universities to add to the sample, we tried to keep the sample as unbiased as possible.

In all 42 universities were approached and we have eleven completed surveys. The reasons for rejecting our request varied; some did simply not have the data available; some did not have the resources (people) to compile the data; and some were simply tired of the requests for data they were getting from various sources.

We cannot exclude the possibility that some of the universities rejected our request because they were concerned with their performance in technology transfer. But, by continually replacing universities that did not comply with our request with the most similar representatives, we have tried to minimize the influence of such bias.

5.4 Survey Results

In this section we introduce the survey results for each of the eleven universities we collected data from. For each university we list the aggregate statistics about technology transfer and calculate some basic correlation coefficients. In order to understand the environment for the universities, we also plot the research expenditures in Engineering, Physical Sciences, and the Life Sciences since 1980. These are data from the National Science Foundation [SRS95a].

When comparing the results for the eleven universities we find that there are no consistent patterns. Evidence we find about causal relationships at one university, is invariably contradicted by evidence from a few of the other universities. In section 5.4.12 we build a model for how the universities would "vote" for one of the two hypotheses on page 73. In section 5.4.13 we summarize our findings from analyzing the universities in the section. In sections 5.5, 5.6, and 5.7 we use various methods to work with the aggregated data.

For each university we calculate the rank correlation coefficient of the change in the number of licenses and 15 output measures (professionals, staff, and legal fee expenditures; each with time shift from -2 to +2 years). Similarly we calculate 15 correlation coefficients for the change in the number of patent applications. After calculating these coefficients, we discuss those that are significantly different from zero at the 95% level. Since we are testing 30 coefficients, it is quite likely that some insignificant relationships, will incorrectly be called significant because of the vast number of relationships we test. When we have 30 correlation estimates between independent variables and use a 95% confidence interval, the probability we will not call any of the correlation estimates significant is only 21%. The probability we will make one error is 34%, two errors 26%, three errors 13%, and four or more errors 6%. We should thus stay alert that relationships may be called significant purely by chance.

5.4.1 Harvard University

Figure 5-2 shows that in 1995 Harvard spent about $170 million on research in the Life Sciences, $30 million in Physical Sciences, and $5 million in Engineering. Looking at the last 15 years, the research expenditures in the Life Sciences have increased substantially. This increase was primarily realized in the last ten years.

Table 5.5 lists the aggregate survey results for Harvard University. The number of people working of technology transfer at Harvard increased steadily from 1986 until 1990. In this time period people were hired both to provide professional services for technology transfer and staff support. Since 1990 the number people working on technology transfer has been stable; about ten people providing professional services for technology transfer, and seven providing staff support.

Legal fee expenditures have increased substantially in the last ten years. In 1986 less than $330,000 were paid in legal fees, but in both 1995 and 1996 this figure was

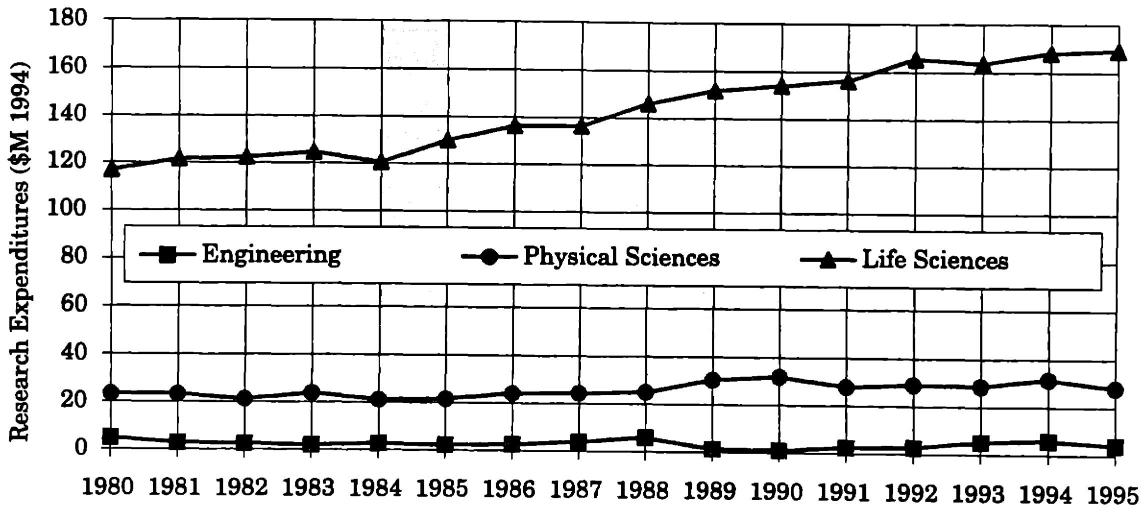

Figure 5-2: Harvard University Research Expenditures Since 1980.

above $2,000,000. This does not suggest that the net legal expenditures at Harvard are over $2 million because corporations reimburse a substantial part of these expenditures. Subtracting the reimbursements, the net legal expenditures at Harvard in 1995 and 1996 average about $500,000.

The number of options and licenses executed has increased. From 1987 until 1991 between 35 and 48 agreements were entered each year. In 1992 the number of licenses suddenly jumps to 89. This year, however, was anomalous because of the 89 agreements, 64 were non-exclusive[1]. Since 1993 between 55 and 70 agreements have been entered each year.

The number of new U.S. patent applications has jumped up and down for the past ten years, but overall there was an increase. We can split the last ten years into two periods. In the former period, between 1986 and 1992, the number of new U.S. patent applications was between 25 and 31 (aside from 1987 when only 18 applications were filed) for an average of 28 patent applications per year. In the latter period, between 1993 and 1996, the number of applications ranged from 41 to 55 for an average of 48.

Licenses & Patents

Looking at the rank correlation between the change in the number of licenses and the inputs, we find a strong positive correlation with:

[1]In the preceeding year 17 non-exclusive agreements were entered and in the following year that number was 31. We thus see that the majority of the spike in 1992 is caused by many non-exclusive agreements.

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	7.0	2.0	329,812	n/a	25
1987	7.5	3.0	419,327	35	18
1988	9.5	3.5	695,642	46	35
1989	10.5	4.0	844,384	36	30
1990	10.5	6.0	1,124,165	48	31
1991	9.0	6.0	1,192,554	38	25
1992	10.0	8.0	1,274,796	89	31
1993	9.0	6.8	1,434,482	69	41
1994	9.5	6.8	1,700,000	61	43
1995	9.5	6.8	2,293,826	55	55
1996	9.5	6.8	2,066,135	57	53

Table 5.5: Harvard University Survey Data.

1. Legal fee expenditures two years earlier (p-value 0.11%).

2. The number of support staff in the same year (p-value 0.9%).

3. The number of professionals two years later (p-value 3.3%).

The second finding is as expected: when Harvard hires more people, it has more resources to work on license agreements. A possible explanation for the first finding is that legal fee expenditures are strongly correlated with patent applications. Viewing patents as the products and licenses as sold products, this suggests that two years after getting the product (patent), Harvard finds an application for the new technology and sells it to a corporation (license). It is hard to come up with a reasonable explanation for the third relationship. One explanation is that Harvard responds to success in licensing by hiring more professionals two years later. Another likely explanation is that this significance may just happen by chance alone.

When looking at the rank correlation between the change in the number of patents and the inputs, we find two significant relationships:

1. There is negative correlation with the legal expenditures in the previous year (p-value 2.7%).

2. There is positive correlation with the legal fee expenditures in the same year (p-value 3.2%).

The second relationship is as expected—we know there are significant costs associated with filing a patent application. The first relationship is not as intuitive. One explanation is that there is "bounce-back". If many patent applications are filed, substantial legal expenditures are also paid. When faced with the legal fee expenditures, the TTO may decide to file for fewer patents in the following year, and thereby reduces the legal expenditures. The auto-correlation in the number of patent applications supports this explanation. The auto-correlation coefficient is -0.48 (p-value 9%).

Conclusions for Harvard University

There has been a substantial increase in the inputs of the TTO at Harvard. The gross legal fee expenditures have grown six-fold since 1986, and the people resources have approximately doubled. At the same time the number of license agreements has gone up approximately 50% and patent applications have doubled. This growth is substantially faster than the growth in research expenditures in the corresponding years (31%).

The evidence we find in support of the two hypotheses on page 73 is vague. The only relevant relationship is between licenses and professionals two years later. This evidence supports hypothesis 2—Harvard responds to increased licensing activity by hiring professionals—but another explanation is that this may just be statistical noise.

5.4.2 Massachusetts Institute of Technology

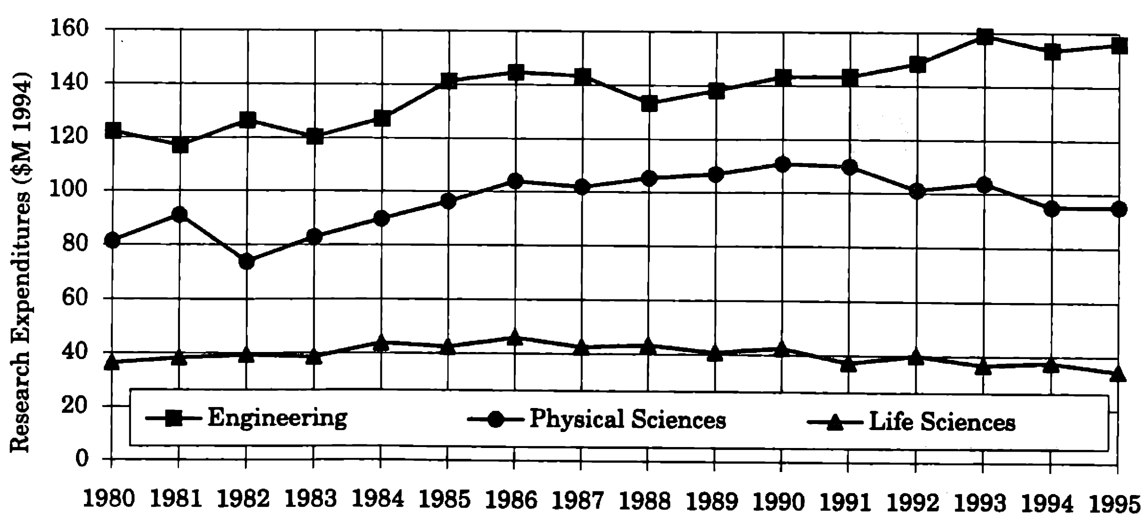

Figure 5-3: MIT Research Expenditures Since 1980.

From figure 5-3 we see that in 1995 MIT spent almost $160 million on research in Engineering, $95 million in Physical Sciences, and $35 million in the Life Sciences. The

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	4.8	3.6	858,048	22	65
1987	6.0	4.4	1,553,064	41	94
1988	6.8	4.4	1,617,772	64	97
1989	6.0	4.8	2,375,200	39	106
1990	6.8	6.0	2,821,700	47	100
1991	8.4	5.2	2,948,861	47	91
1992	10.4	8.0	3,034,224	53	88
1993	11.2	8.0	3,381,279	73	89
1994	12.0	8.8	3,208,000	86	98
1995	8.4	11.2	2,947,469	58	93
1996	11.6	8.0	3,206,234	54	72

Table 5.6: MIT Survey Data.

research expenditures in Engineering have increased since the early eighties when about $120 million was spent on this research. Research expenditures in Physical Sciences increased quite rapidly from 1982 until 1986. Life Sciences research expenditures have stayed around $40 million for the last fifteen years.

As table 5.6 shows the number of people working on technology transfer has increased significantly since 1986. The increase is more than two-fold, and takes place between 1986 and 1994. Since 1994 the number of people working on technology transfer has been stable.

There has been a steady increase in the legal fee expenditures at MIT's Technology Licensing Office. In 1986 about $850,000 were paid in legal fees. This number increased year-by-year until 1993 when it peaked at over $3.3 million. Since 1993 about three million have been paid in legal fees each year. Companies that license technologies from MIT pay a substantial part of these legal fees. The net expenditures for MIT in the last couple of years are about $1.8 million.

The number of options and license agreements has also increased. In 1986 only 22 agreements were made, but in 1994 this figure was 86. In the last two years we have data for, the number of license agreements dropped back to about 55.

The number of new U.S. patent applications has fluctuated between 65 and 106 since 1986. There is a peak in 1989, but the two least active years in filing patent applications are 1986 and 1996. This drop in 1996 catches the eye, but it remains to be seen if this is a permanent change or just statistical noise.

Licenses & Patents

Calculating the rank correlation between the change in the number of licenses and the inputs reveals a positive correlation with the legal expenditures in the previous year (p-value 3.1%). This is the only significant relationship. We also find a positive correlation between licenses and patents in the previous year (p-value 0.5%). The most likely explanation for these relationships is that when patents are granted to MIT (positively correlated with legal fee expenditures), the TTO finds applications for the new technology and enters a license agreement in the following year.

When calculating the rank correlation coefficients for the patents we find two significant relationships:

1. A negative correlation with the number of people providing professional services for technology transfer in the following year (p-value 2.5%).

2. A positive correlation with the number of professionals two years prior to the patent application (p-value 3.5%).

Although both relationships could well be statistical noise, we can hypothesize reasons why this might occur. A possible explanation for the first finding is that when filing many patent applications (and thereby incurring legal fee expenditures), the TTO has to cut down on personnel (1994) for budgetary reasons. Consequently the number of professionals in the following year is likely to go down (1995). One way to explain the second finding is that two years after new people start working on technology transfer, their work leads to an increase in the number of patent applications.

Conclusions for MIT

The inputs for technology transfer at MIT increased substantially in the last ten years. The number of people working on technology transfer more than doubled, while legal fee expenditures almost quadrupled. At the same time, the total research expenditures in the three departments have not changed appreciably (+2% in the last ten tears).

When looking for correlations between the outputs and the inputs we do not find many meaningful relationships. Licenses seem to be correlated with the legal expenditures in the previous year, while patent applications are correlated with professionals working on technology transfer. A likely explanation for the latter two relationships is that they are just statistical noise.

5.4.3 Ohio State University

Figure 5-4 shows the research expenditures for Ohio State University. All three departments have increased their research expenditures fairly evenly since 1980. The increase was most rapid in the Life Sciences between 1984 and 1989. In 1995 the Life

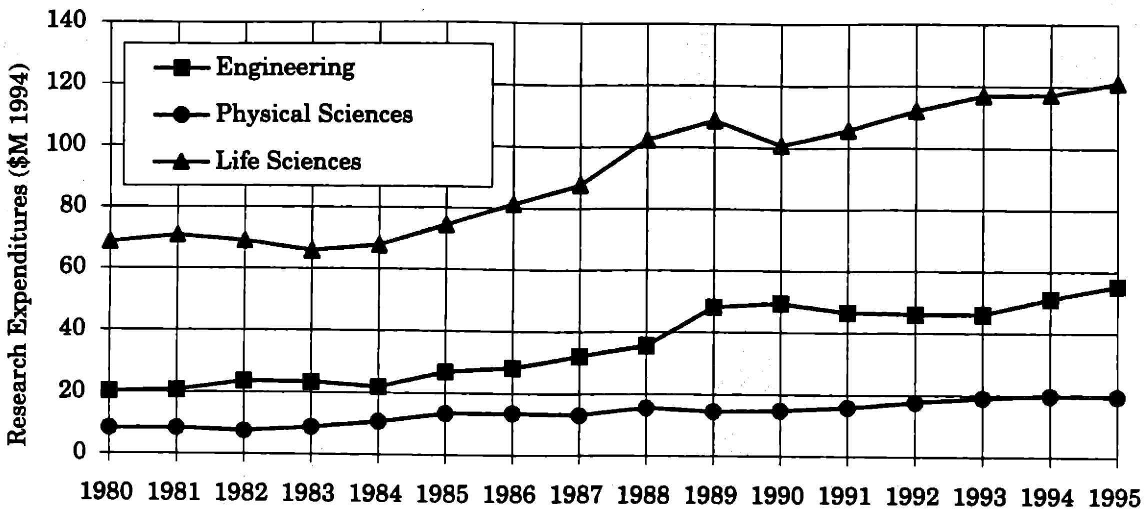

Figure 5-4: Ohio State University Research Expenditures Since 1980.

Sciences research expenditures for the first time reached $120 million, while Engineering totalled $55 million and Physical Sciences approached $20 million.

We do not have data about the technology transfer activities prior to 1990 at Ohio State University. In 1990 two professionals were working with two staff members on technology transfer. A new professional was added in 1991, but in 1993 one departs and in 1994 the number of professionals working on technology transfer went down to 1.5. There have always been two staff members working on technology transfer, except in 1994 when only one staff member supported the technology transfer activities.

Legal fee expenditures have jumped up and down since 1990, but there does not seem to be any long term trend. Each year the expenditures have stayed between $270,000 and $385,000. Subtracting expenditures that companies reimburse, the average net expenditures for the last two years were about $190,000.

The number of options and license agreements entered has fluctuated between 10 and 32 since 1990. Fewest agreements were made in 1990, but over the next two years this number increased up to 30. Between 1992 and 1995 the annual number of new agreements was between 20 and 32, but in 1996 only 12 new agreements were made. It is too soon to tell if this drop in 1996 is only temporary or permanent. Considering how the research expenditures have increased in the last ten years, we expect the number of licenses to jump back up in 1997.

In 1990 28 new patent applications were filed, but the next four years fewer than 20 applications were filed each year. Starting in 1994 we see a strong increase in the number of patent applications, starting at 12 and reaching 49 in 1996.

The reason for this recent growth in the number of patent applications is most likely

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	n/a	n/a	n/a	n/a	n/a
1987	n/a	n/a	n/a	n/a	n/a
1988	n/a	n/a	n/a	n/a	n/a
1989	n/a	n/a	n/a	n/a	n/a
1990	2.0	2.0	328,833	10	28
1991	3.0	2.0	279,708	16	16
1992	3.0	2.0	342,404	30	18
1993	2.0	2.0	296,272	20	12
1994	1.5	1.0	362,028	21	25
1995	1.5	2.0	269,420	32	30
1996	1.5	2.0	384,600	12	49

Table 5.7: Ohio State University Survey Data.

that Ohio State has over the last few years focused on building a portfolio of patents and marketable technologies. If this hypothesis is true, and the necessary resources are made available, the next ten years should be exciting. Many more license agreements should be made, and subsequently we should see an increase in the royalty income.

We also observe that the growth in the research expenditures in the last ten years is about 70% for the three departments combined. Despite this growth, Ohio State has not increased their investment in technology transfer.

Conclusions for Ohio State University

We only have seven years of data from Ohio State. The resources did not increase over those seven years, while the research expenditures have grown 70% in the last ten years. The number of license agreements has been on the rise aside from a big drop in 1996. The number of patent applications was steady for the first few years, but has risen significantly in the last four years.

5.4.4 Syracuse University

Figure 5-5 shows the annual research expenditures for Engineering, Physical Sciences and Life Sciences at Syracuse University. We see that all programs are rather small. Engineering jumped up and down from year to year, but stayed between $6 million and $14 million. Physical Sciences expenditures ranged from $3.5 to $9.5 million, and Life Sciences between $4.4 and $7.9 million.

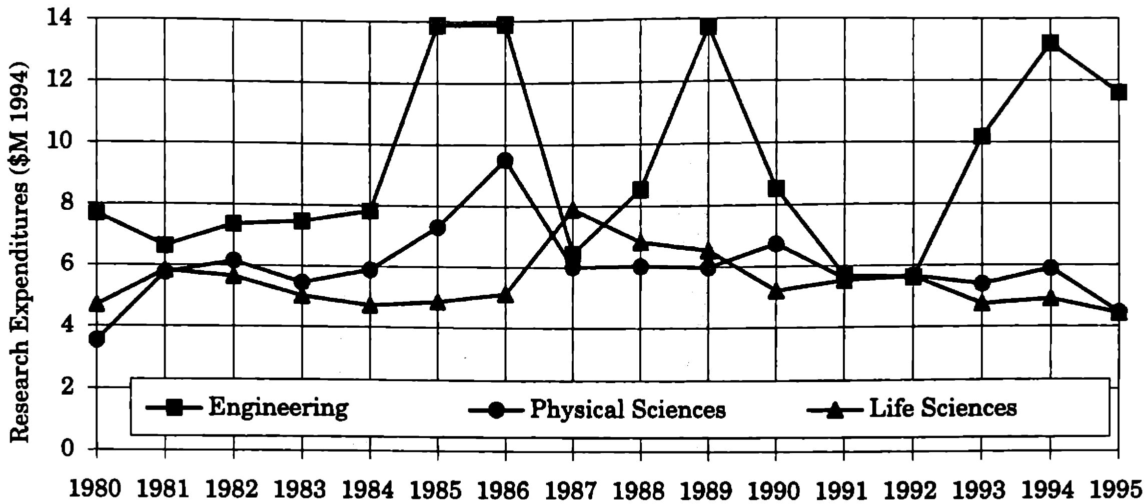

Figure 5-5: Syracuse University Research Expenditures Since 1980.

In table 5.8 we have the aggregate data on technology transfer for the last six years. Data prior to 1991 are not available. The same number of people have worked on technology transfer since 1991, two professionals and one staff member.

Legal fee expenditures were at a peek at the beginning of the period when $167,000 was paid. Since then, the expenditures have been much lower, between $72,000 and $92,000. After subtracting the part that corporations reimburse Syracuse University, the net expenditures in the last couple of years average about $50,000.

The number of options and licenses peaks has been between zero and three since 1991, except for two years; in 1993 Syracuse made 14 license agreements, and in 1994 they made 8 agreements. This is a substantial difference from the other years. We do not see any changes in the resources of the TTO that explain these jumps. In 1991 Syracuse University applied for seven new U.S. patents, but since then the number of patent applications has decreased year by year and in 1996 they only filed one new patent application.

Conclusions for Syracuse University

Data are only available for six years at Syracuse University. In those six years the number of people working on technology transfer has not changed, and the legal expenditures were at a maximum at the beginning of the period. The research expenditures in the three departments have decreased about 20% in the last ten years. The number of licenses peaked in 1993 and 1994, but has dropped significantly since then. The number of patent applications was at a maximum in 1991, but has steadily decreased since then. This evidence shows that Syracuse is not improving its performance in technology transfer

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	n/a	n/a	n/a	n/a	n/a
1987	n/a	n/a	n/a	n/a	n/a
1988	n/a	n/a	n/a	n/a	n/a
1989	n/a	n/a	n/a	n/a	n/a
1990	n/a	n/a	n/a	n/a	n/a
1991	2.0	1.0	167,003	2	7
1992	2.0	1.0	84,153	3	2
1993	2.0	1.0	91,850	14	3
1994	2.0	1.0	79,644	8	3
1995	2.0	1.0	71,560	1	2
1996	2.0	1.0	84,851	0	1

Table 5.8: Syracuse University Survey Data.

and that the performance in the last two years is well below par.

Due to the limited data, no significant correlation relationships were found between any of the inputs and outputs.

5.4.5 University of Arkansas

Figure 5-6 shows that in 1995 the University of Arkansas invested $36 million in Life Sciences research, $10 million in Engineering research, and $3.8 in Physical Sciences research. There has been a very significant increase in research in the Life Sciences. There were two jump-increases in the research expenditures, one in 1982 when the increase was about $12 million. The other increase was $10 million in 1993 (the same year as President Clinton was inaugurated). Research in Physical Sciences has been between $5 and $10 million, and research in Engineering at about $5 million since 1980.

From table 5.9 we see that no people were working on technology transfer until 1990 when one person was hired to provide professional services for technology transfer and 25% staff support was also provided. These numbers were then fairly stable until 1996 when the full time professional went half-time.

No legal fees were incurred in 1986 and 1987. In 1988 $24,000 were paid for external legal services, and in the next four years it increased up to $260,000. Since 1992 the legal fees have fluctuated between $70,000 and $200,000.

No license agreements were entered until 1989 when one agreement was made. Since then between one and three agreements have been entered each year. Three agreements were entered in 1992, the same year as the number of people working on technology

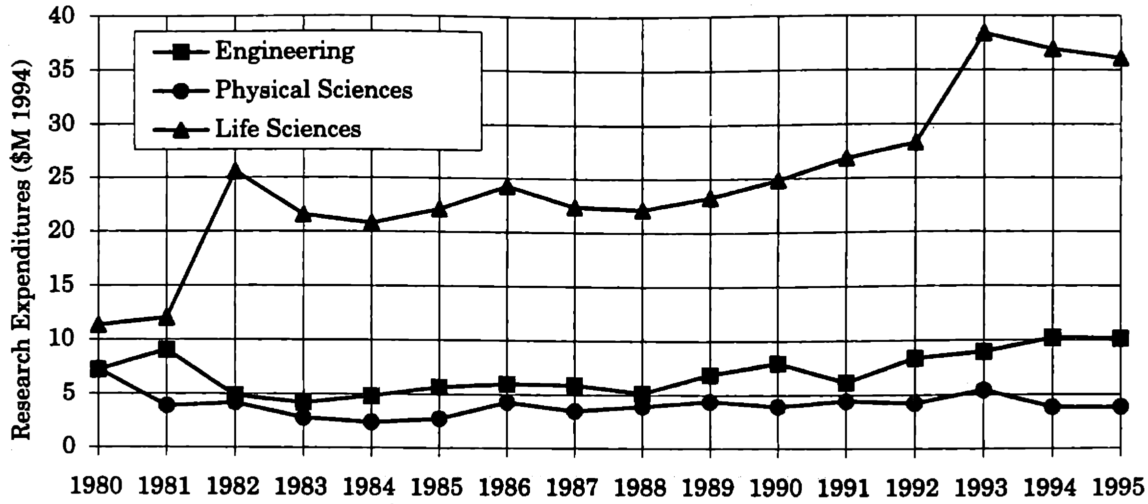

Figure 5-6: University of Arkansas Research Expenditures Since 1980.

transfer was at a maximum.

One patent application was filed in 1986 and none in 1987. The next four years the number of patent applications surges up to 17 and 15. In 1992 the number of new U.S. patent applications dropped back to seven, and since then between five and ten applications have been filed each year.

The research expenditures at the University of Arkansas have grown about approximately 65% in the last ten years. From the rough estimates about the average investment in technology transfer in section E.2 they should employ one-and-a-half full-time equivalences professionals, one staff member, and spend about $250.000 on legal fees. From table 5.9 we see that since 1991 they have invested less than this average, and recently they have reduced their investment in technology transfer even further.

Licenses & Patents

When analyzing the correlation relationships between inputs and outputs, we find a triangle:

1. There is a positive correlation between the change in the number of licenses and the change in legal fees in the same year (p-value 3.7%).

2. There is a positive correlation between the change in the number of licenses and the change in the number of patent applications in the previous year (p-value 3.3%).

3. There is a positive correlation between the change in legal expenditures and the number of patent applications in the previous year (p-value 2.5%).

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	0.00	0.00	0	0	1
1987	0.00	0.00	0	0	0
1988	0.00	0.00	23,980	0	6
1989	0.00	0.00	184,969	1	12
1990	1.00	0.25	176,458	1	17
1991	1.00	0.25	259,744	3	15
1992	1.50	0.25	202,057	3	7
1993	1.00	0.50	131,643	1	8
1994	1.50	0.25	128,480	1	9
1995	1.00	0.25	73,959	2	10
1996	0.50	0.25	142,142	2	5

Table 5.9: University of Arkansas Survey Data.

If the University of Arkansas paid substantial part of the legal fees in the year after they applied for a patent, it explains the third finding. If we view a patent as the key to an opportunity to sell an invention, patent applications can lead to licenses in the following year, hence the second relationship. The third finding is likely caused by the linkage between the other two.

Conclusions for the University of Arkansas

We found that no people were dedicated to technology transfer until 1990 when one person was hired along with some staff support. Legal fees increased rapidly from 1988 until 1991, but have tapered of since then. We also find that considering the research expenditures of the University of Arkansas, they invest less (about 50%) than average in technology transfer.

We found a positive correlation between the number of patent applications and legal fees in the following year. This is most likely because some of the legal fees are paid the year after the application is filed. There is a positive correlation between licenses and patent applications in the previous year, and consequently between licenses and legal expenditures in the same year.

5.4.6 University of Missouri

Figure 5-7 shows the research expenditures for the University of Missouri (all campuses). In 1995 research expenditures were $97 million in the Life Sciences, $26 million in Engineering, and $15 million in Physical Sciences. Research in the Life Sciences has

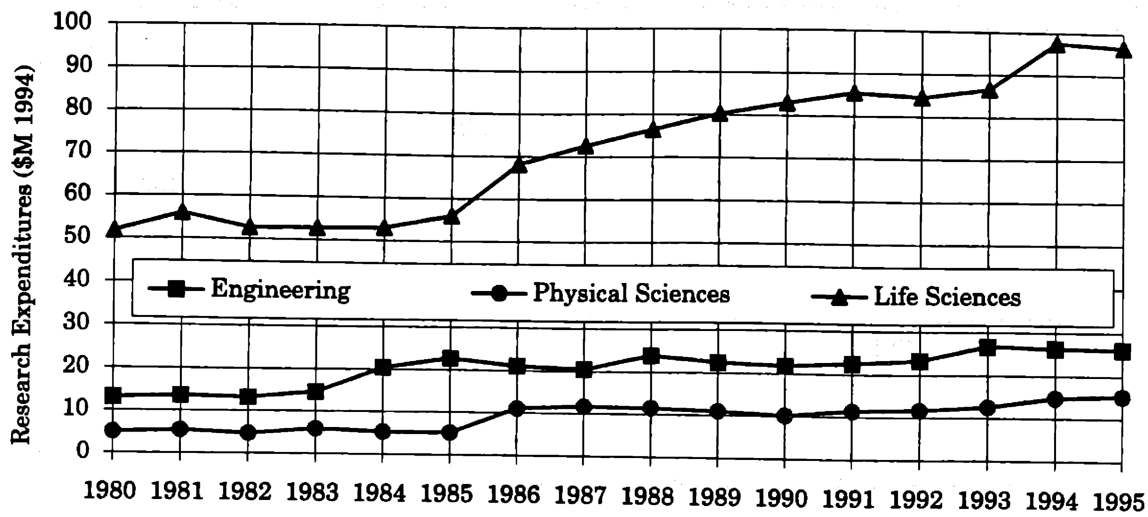

Figure 5-7: University of Missouri Research Expenditures Since 1980.

almost doubled since 1980 when $52 million were invested. Most of this increase was realized in the last ten years. Research in Engineering and Physical Sciences has also doubled since 1980.

Table 5.10 shows the aggregate statistics for technology transfer at the University of Missouri. One professional has been working on technology transfer since 1986. In 1986 1.25 full-time equivalence support staff members worked on technology transfer, but there were increases in 1988, 1991, and 1996.

Legal expenditures have increased in the last ten years. In 1986 through 1988 they rise from $82,000 to $100,000. Data are not available for 1989 and 1990, but in 1991 $126,000 was spent on legal fees. Since then there has been an increase, although there was some drop in 1996.

The number of options and licenses executed has increased substantially in the last ten years. Data are not available for 1986 and 1987, but in 1988 two agreements were made. It then increased year-by-year and peaked at 28 in 1995. In 1996 it dropped back to 15 agreements.

Data are not available on the number of new U.S. patent applications made in 1986 or 1987. From 1988 until 1994 about ten applications were filed each year, but in the last two years 29 applications were filed each year.

This increase in the number of both licenses and patents in the last eight years is very significant. We see that the number of patents has tripled, and the number of licenses has more than tripled. In the last ten years the research expenditures have grown about 65%. We see that the increase in licensing is much faster than both the increase in research expenditures and investment in technology transfer. Using the average estimates in

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	1.00	1.25	82,531	n/a	n/a
1987	1.00	1.25	98,735	n/a	n/a
1988	1.00	1.60	100,359	2	9
1989	1.00	1.60	n/a	6	10
1990	1.00	1.60	n/a	7	13
1991	1.00	2.00	126,136	9	9
1992	1.00	2.00	107,655	12	7
1993	1.00	2.00	209,080	14	12
1994	1.00	2.00	221,144	19	12
1995	1.00	2.00	318,851	28	29
1996	1.00	2.50	215,518	15	29

Table 5.10: University of Missouri Survey Data.

section E.2 as a reference point, a university with the same research expenditures as the University of Missouri should employ 4 professionals and 2.5 support staff members for technology transfer, and spend about $700,000 on legal fees.

Conclusions for the University of Missouri

The investment in technology transfer has not grown at the same rate as the research expenditures in the last ten years. Nevertheless, the number of new license agreements and patent applications have increased substantially since 1986.

Because the number of professionals has been unchanged since 1986, we have no chance of calculating the correlation of the variable with any of the others. The number of license agreements correlates positively with the number of support staff two years later (p-value 1.7%). This implies that the University of Missouri responds to increases in the number of licenses agreements by hiring more support staff two years later.

The number of new U.S. patent applications does not correlate with any of the input measures.

5.4.7 University of Notre Dame

Notre Dame is the only institution included in this time series study that is not in the AUTM database. Figure 5-8 shows that in 1995 they spent $12 million on research in Physical Sciences, $5.9 million in Engineering, and $3.3 million in Life Sciences. The research expenditures have grown in the last 15 years; in 1980 Notre Dame spent $8

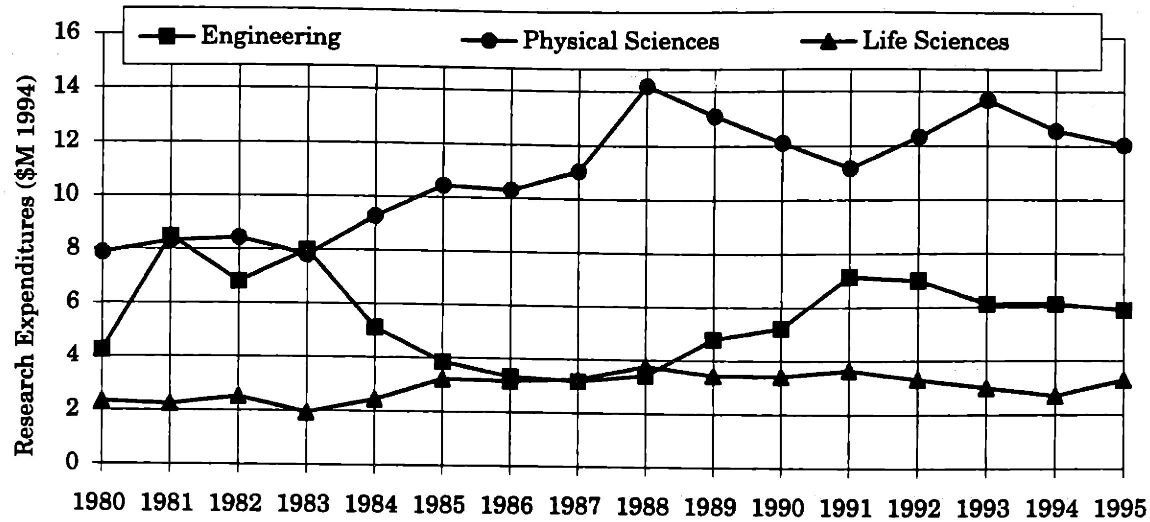

Figure 5-8: University of Notre Dame Research Expenditures Since 1980.

million on research in Physical Sciences, $4.2 million in Engineering, and $2.3 million the Life Sciences.

Table 5.11 summarizes the aggregate technology transfer measures for Notre Dame. From 1986 until 1994 there were 0.25 professionals working on technology transfer, but in 1995 it increased to 0.33. Throughout the period one person dedicated 10% of her time to provide staff support for technology transfer. No information is available about legal fee expenditures.

The University of Notre Dame has so far not made any license or option agreements. Data about patent applications are only available for the last three years, in each year either four or five new U.S. patent applications were filed.

5.4.8 University of Rhode Island

Figure 5-9 shows the research expenditures by department for the University of Rhode Island. In 1995 $10.4 million was spent on research in the Life Sciences, $5.5 million in Engineering, and $1.2 million in Physical Sciences. There was a huge increase in the expenditures in Life Sciences concentrated from 1985 until 1988. Research expenditures in Engineering did not grow quite as fast, and the expenditures in Physical Sciences have been below $2 million since 1980. The increase in the research expenditures in the last ten years is 35%.

As seen in table 5.12, data on the aggregate technology transfer measures are not available prior to 1991. Two professionals worked on technology transfer except in 1991 and 1993 when less resources were endowed. Simultaneously one staff member worked on

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	0.25	0.10	n/a	0	n/a
1987	0.25	0.10	n/a	0	n/a
1988	0.25	0.10	n/a	0	n/a
1989	0.25	0.10	n/a	0	n/a
1990	0.25	0.10	n/a	0	n/a
1991	0.25	0.10	n/a	0	n/a
1992	0.25	0.10	n/a	0	n/a
1993	0.25	0.10	n/a	0	n/a
1994	0.25	0.10	n/a	0	5
1995	0.33	0.10	n/a	0	4
1996	0.33	0.10	n/a	0	4

Table 5.11: University of Notre Dame Survey Data.

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	n/a	n/a	n/a	n/a	n/a
1987	n/a	n/a	n/a	n/a	n/a
1988	n/a	n/a	n/a	n/a	n/a
1989	n/a	n/a	n/a	n/a	n/a
1990	n/a	n/a	n/a	n/a	n/a
1991	1.0	1.0	49,870	n/a	5
1992	2.0	1.0	54,785	1	5
1993	0.8	0.2	40,985	3	3
1994	2.0	1.0	75,000	3	10
1995	2.0	1.0	72,897	9	4
1996	2.0	1.0	70,726	9	6

Table 5.12: University of Rhode Island Survey Data.

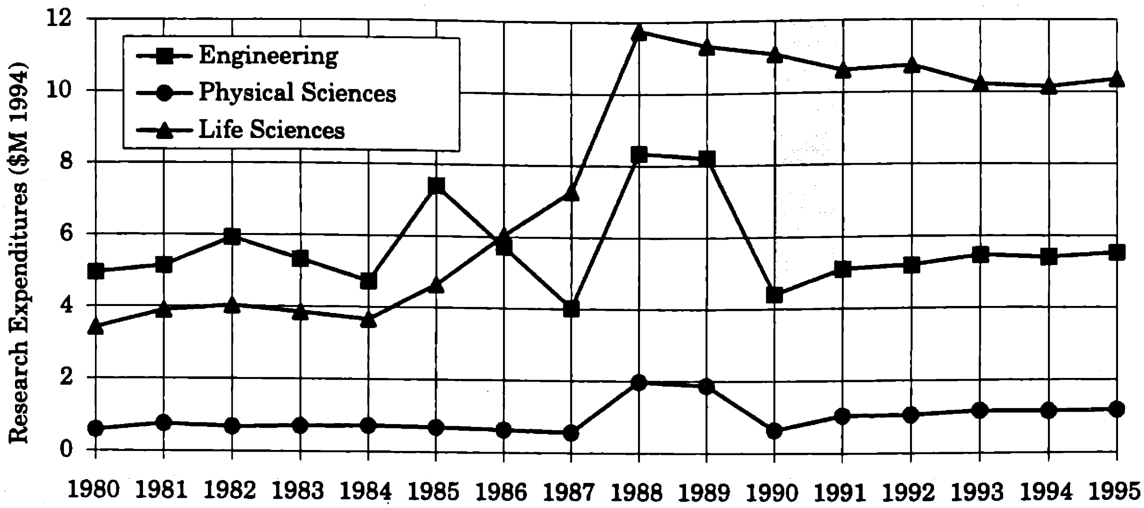

Figure 5-9: University of Rhode Island Research Expenditures Since 1980.

technology transfer except in 1993 when staff support was minimal. Legal expenditures in 1991 until 1993 ranged from $40,000 to $55,000. From 1994 until 1996 these ranged from $71,000 to $75,000. Of this figure the net expenses paid by the University of Rhode Island average $55,000 over the last three years. The difference are expenses corporations reimbursed the university.

Data about license and options agreements are not available before 1992 when one agreement was made. Since then there has been a substantial increase, and in 1995 and 1996 nine agreements were made each year.

On average, the University of Rhode Island has applied for 5.5 new U.S. patents in the last six years. There does not seem to be a long term trend in the number of patents, but there is a peak in 1994.

Licenses & Patents

When looking for a correlation between the change in the number of license agreements and the input measures, we find a positive relationship with all three input measures in the previous year (p-value 4.2% for each). At the same time we find a negative correlation between patent applications and all three input measures in the previous year. To complete the triangle, there also is a significant negative correlation between licenses and patent applications in the same year.

Conclusions for the University of Rhode Island

The research expenditures have grown fast at the University of Rhode Island, especially in the Life Sciences. The number of license agreements entered has increased substantially in the last five years, while the number of patent applications has stayed more or less the same. When looking at correlation relationships between inputs and outputs, we find a positive correlation between the change in the number of license agreements and all of the input measures of the TTO in the previous year. This implies that the people of the TTO are stimulating the licensing process.

5.4.9 University of Texas Medical Branch at Galveston

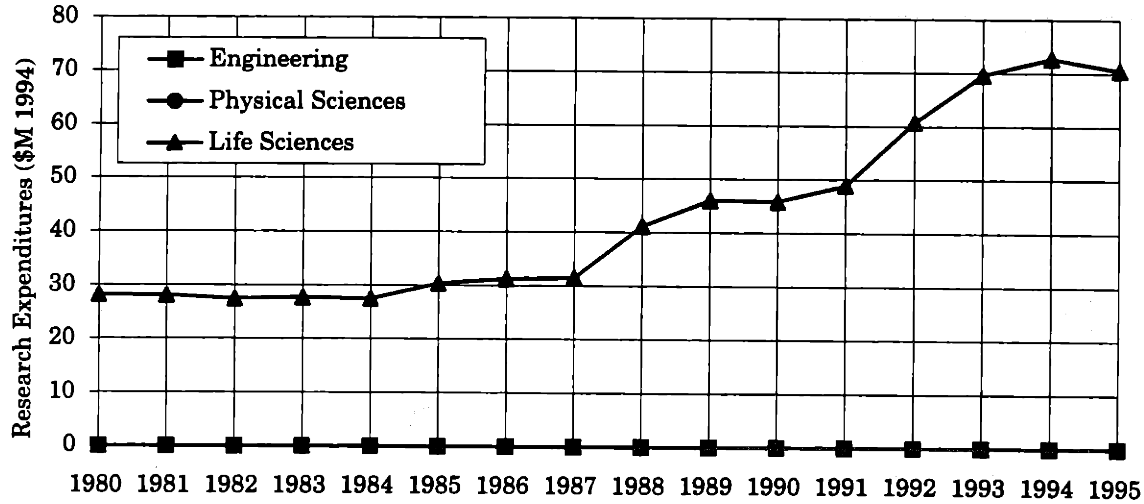

Figure 5-10: University of Texas Medical Branch Research Expenditures Since 1980.

As seen in figure 5-10, the University of Texas Medical Branch only performs research in the Life Sciences. From 1980 until 1987 the expenditures were stable at $30 million, but since then there has been a significant increase (about 130%). In 1995 the expenditures totalled $71 million.

Table 5.13 has the aggregate statistics for technology transfer. We see that between 1986 and 1991 one-half full-time equivalence professional is working on technology transfer. In 1992 this number increased up to one, and then there were increases in 1994, 1995, and 1996. From 1986 until 1993 one-half full-time equivalence staff members provided support, but since 1994 one full-time person has provided staff support for technology transfer.

Legal fee expenditures have increased at the Medical Branch in Galveston. From 1986 until 1989 the legal fee expenditures for patents and/or copyrights were about $120,000.

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	0.5	0.5	122,427	n/a	5
1987	0.5	0.5	153,153	n/a	7
1988	0.5	0.5	115,485	n/a	6
1989	0.5	0.5	100,380	n/a	4
1990	0.5	0.5	209,122	n/a	10
1991	0.5	0.5	247,249	2	9
1992	1.0	0.5	215,955	5	7
1993	1.0	0.5	273,976	6	13
1994	1.5	1.0	325,643	3	13
1995	2.5	1.0	207,354	4	14
1996	4.0	1.0	324,570	7	15

Table 5.13: University of Texas Medical Branch Survey Data.

In 1990 there was a large increase up to $210,000. The following four years there were relatively stable increases in the legal fee expenditures which reached $326,000 in 1994. In 1995 there was a temporary drop. In the last three years, corporations have reimbursed the University of Texas Medical Branch a substantial fraction of these legal expenditures. The net expenditures paid by the university average over the past three years about were $200,000.

Data are not available on options and licenses executed prior to 1991 when two agreements were made. Since then the number of licenses has been higher; between three and seven. The number of patent applications has increased substantially since 1986. Between 1986 and 1987 the number of new U.S. patent applications was about six, but in the last four years it was about 14.

Licenses & Patents

There are no significant rank correlations between licenses and any of the input variables. For patent applications the legal fee expenditures in the same year comes closest (p-value 5.3%).

Conclusions for the University of Texas Medical Branch

The Medical Branch of the University of Texas at Galveston does not do any research in Engineering or Physical Sciences, all research is in the Life Sciences. The expenditures have more than doubled since 1987, and at the same time the investment and success in technology transfer have about tripled. When calculating the rank correlation between the change in the inputs and outputs, we do not find any significant relationships.

5.4.10 Vanderbilt University

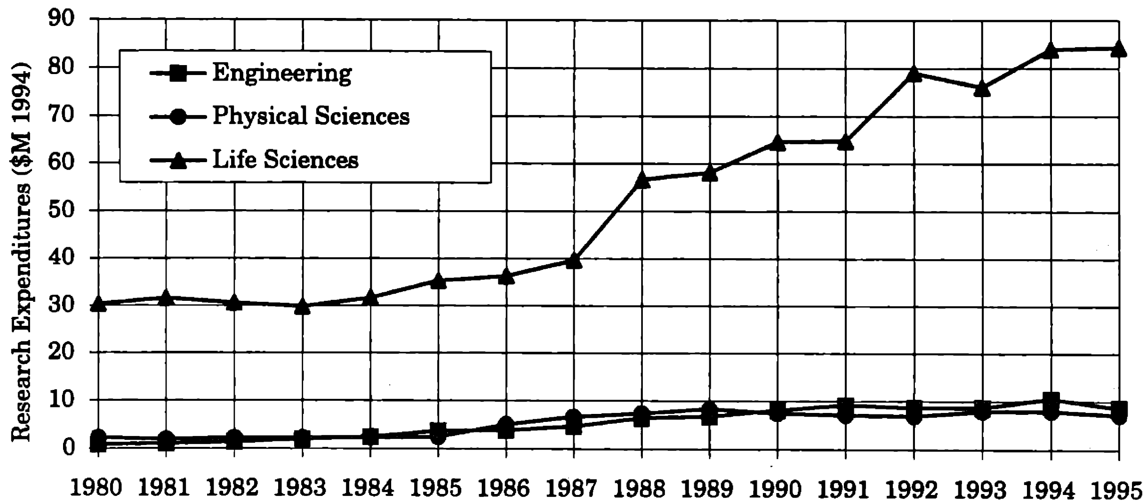

Figure 5-11: Vanderbilt University Research Expenditures Since 1980.

Figure 5-11 shows the research expenditures at Vanderbilt University. In 1995 Vanderbilt spent $84 million on research in the Life Sciences, $8.7 million in Engineering, and $7.3 million in Physical Sciences. The research in the Life Sciences has almost tripled since 1980 when only $30 million was spent on this research. The expenditures are stable from 1980 until 1987, but most of the growth is in the last ten years. The research expenditures in Engineering and Physical Sciences are much smaller, but have also increased substantially. These departments spent only $3.2 million combined on research in 1980, but in 1995 this figure was at $16.0 million. The net increase for the expenditures in the three department in the last ten years is about 140%.

Table 5.14 shows the key technology transfer statistics for Vanderbilt University. The number of professionals working on technology transfer has increased steadily since 1985. Starting then at 0.8 it increased to 1.0 in 1990. There was another increase in 1993 up to 1.5, but since then there has been a small decline. The first support staff person was not hired until 1991, and since then one person has provided staff support, except in 1994 when only 0.75 full-time equivalences provided staff support for technology transfer.

Legal fee expenditures have increased substantially since 1986 when they totalled $62,000. Although the following year showed a small decrease, the expenditures reached almost $100,000 in 1988 and almost $200,000 in 1990. Subtracting the reimbursements

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1985	0.80	0.00	29,925	0	9
1986	0.80	0.00	61,637	0	9
1987	0.80	0.00	53,911	2	7
1988	0.80	0.00	97,849	5	8
1989	0.80	0.00	109,743	2	14
1990	1.00	0.00	193,016	4	12
1991	1.00	1.00	155,466	4	13
1992	1.10	1.00	204,915	9	11
1993	1.50	1.00	191,606	15	10
1994	1.30	0.75	263,311	7	10
1995	1.40	1.00	316,190	13	17
1996	1.25	1.00	308,895	14	19

Table 5.14: Vanderbilt University Survey Data.

from industry, the net legal expenditures paid by Vanderbilt average $160,000 for the last few years.

Licenses & Patents

When calculating the correlation in the change in the number of license agreements and the TTO input variables we find:

1. A positive correlation with legal fee expenditures two years later (p-value 0.4%).

2. A positive correlation with the number of people providing professional service for technology transfer in the same year (p-value 0.5%).

3. A negative correlation with professionals in the following year (p-value 4.8%).

The second relationship is as predicted, but the first and third are more difficult to explain. A likely explanation for the first and third relationships is random noise.

When analyzing the correlation of patent applications and the inputs, we find that the only relationship is with legal fee expenditures in the previous year (p-value 3.7%). This could either mean that legal fees are paid early (in advance), or it could also just be statistical noise.

Conclusions for Vanderbilt University

The research expenditures at Vanderbilt have grown substantially. Most of the expenditures in the three departments is in the Life Sciences, and these have more than doubled since 1987. The investment in technology transfer has also increased, but using the average investment in section E.2 as a reference we find that they invest less than average in technology transfer (the average implies they should employ three professionals and two support staff persons, and spend about $500,000 on legal fees).

There has been a substantial growth in the number of license agreements in the past ten years, but the growth in the number of patent applications is slower than the growth in research expenditures. We find a positive correlation between the number of people providing professional services for technology transfer and license agreements in the same year, but other correlation relationships are likely statistical noise.

5.4.11 Yale University

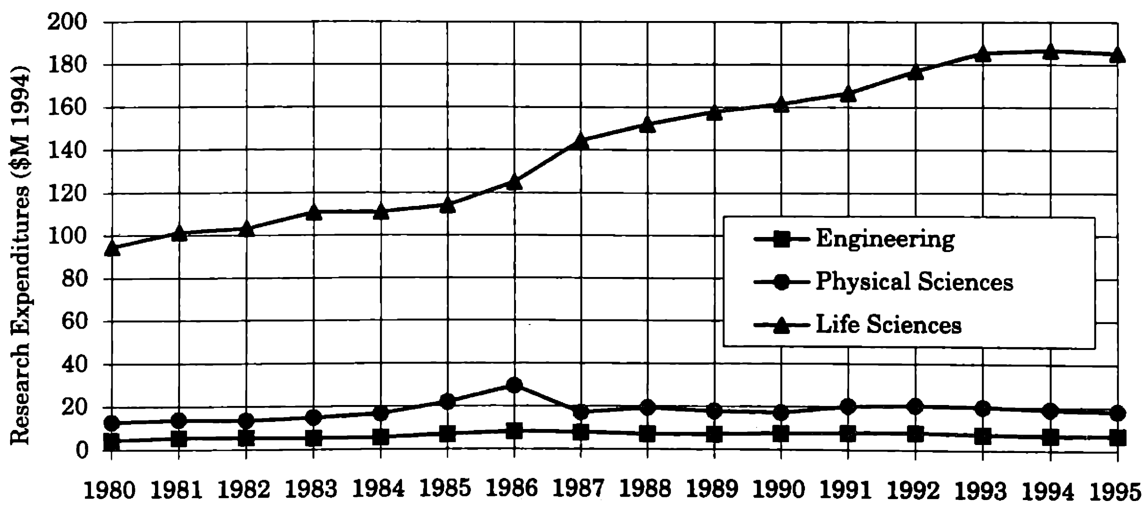

Figure 5-12: Yale University Research Expenditures Since 1980.

Figure 5-12 shows the research expenditures at Yale University. In 1995 most of the research expenditures were in Life Sciences or $185 million, while Physical Science accounted for $18 million, and Engineering for $7 million. The expenditures in the Life Sciences have doubled since 1980, while the expenditures in Physical Sciences and Engineering have grown about approximately 50%.

Table 5.15 shows the key technology transfer statistics for Yale. We see that the number of professionals working on technology transfer increases in 1984, 1985, and then

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1982	1.0	1.0	n/a	4	11
1983	1.0	1.0	n/a	9	7
1984	2.0	1.0	n/a	10	9
1985	3.0	1.0	n/a	6	14
1986	3.0	1.0	n/a	16	21
1987	3.0	1.0	n/a	15	22
1988	3.0	1.0	n/a	14	27
1989	3.0	1.0	n/a	15	33
1990	3.0	1.0	n/a	27	36
1991	3.0	1.0	n/a	22	50
1992	3.0	1.0	n/a	25	42
1993	3.0	1.0	n/a	20	41
1994	3.0	1.0	n/a	17	62
1995	3.0	1.0	n/a	37	49
1996	6.0	2.0	n/a	29	41

Table 5.15: Yale University Survey Data.

not until 1996. One person was providing staff support until 1996 when a second person was added. Data are not available on the legal fee expenditures at Yale.

The number of licenses executed has increased substantially. In 1982 until 1985 the average number of license agreements is between seven and eight, but in the last four years the average is about 24. Most of this increase is realized in the period between 1985 and 1990. Overall the number of licenses has more than tripled in the last twelve years. The number of patent application has even grown faster, approximately five-fold in the last twelve years. Between 1982 and 1985 the average number of patent application was between seven and eight, but in the last four years the average was about 48. This increase is incurred fairly evenly since 1983.

Licenses & Patents

There is a positive rank correlation between the change in number of license agreements and the change in the number of people providing professional services for technology transfer in the following year (p-value 4.5%). This is either statistical noise, or the TTO reacts to success in entering license agreements by hiring more people.

The number of patent applications is negatively correlated with the number of professionals working on technology transfer in the following year (p-value 2.5%). In the light of the finding for the licenses this is somewhat surprising, and the most likely explanation is that this is merely statistical noise.

Conclusions for Yale University

The research expenditures at Yale are much higher in the Life Sciences than both Engineering and Physical Sciences. The expenditures in the three department have grown about 60% in the last twelve years. At the same time there was a fairly even, but faster, increase in the number of people working on technology transfer. The number of licenses has grown faster and the number of patent applications fastest. There is some evidence that Yale responds to success in licensing by hiring more professionals in the following year.

5.4.12 Voting

In this section we use a direct approach to estimate which of the two hypotheses on page 73 the universities "vote" for.

If hypothesis 1—hiring professionals leads to increased licensing activity—is true, the correlation between the professionals hired for technology transfer ($\Delta N_{p,t}$) and the change in the number of licenses in the following year (ΔL_{t+1}) should be positive. Similarly, if hypothesis 2—universities respond to increased licensing activity by hiring more professionals—is true, the correlation between the change in the number of licenses (ΔL_t) and the number of professionals hired the following year ($\Delta N_{p,t+1}$) should be positive.

For each university we can calculate these correlation coefficients. If the first coefficient is higher than the second, we say that this university "votes" for hypothesis 1, but if the second is higher than the first we say that the university "votes" for hypothesis 2.

$$\text{if } Corr\,(\Delta N_{p,t}, \Delta L_{t+1}) \;>\; Corr\,(\Delta L_t, \Delta N_{p,t+1}) \text{ "vote" for hypothesis 1} \tag{5.5}$$
$$\text{if } Corr\,(\Delta N_{p,t}, \Delta L_{t+1}) \;<\; Corr\,(\Delta L_t, \Delta N_{p,t+1}) \text{ "vote" for hypothesis 2.} \tag{5.6}$$

The analysis above is for the professionals, but we could just as well perform this analysis for the support staff members, or for legal fee expenditures and patent applications. In table 5.16 we have presented the results for this analysis.

Input Variable:	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)
Output Variable:	Number of Licenses and Options Executed		New U.S. Patent Applications Filed
Harvard University	1	1	1
MIT	1	2	1
Ohio State University	1	2	1
Syracuse University	n/a	n/a	n/a
University of Arkansas	1	2	1
University of Missouri	n/a	1	1
University of Notre Dame	n/a	n/a	n/a
University of Rhode Island	1	1	2
University of Texas, Galveston	1	2	2
Vanderbilt University	1	1	2
Yale University	2	2	n/a
Total:	7-1	4-5	5-3

Table 5.16: Voting Results for Universities..

From table 5.16 we first observe that when looking at the influence of the professionals, there are seven votes in favor of hypothesis 1, while there is only one vote for hypothesis 2. The probability of getting seven or eight heads when flipping a fair coin eight times is 3.5%. When we look at the results for the staff members and legal fees, we find that the votes are fairly even between the two hypotheses.

These results lead us to believe that hiring more professionals to work on technology transfer will lead to more license agreements. For the support staff and legal expenditures, we do not get any hints about how the causal relationship between investment and success in technology transfer is. This discrepancy between professionals and staff is not all that surprising. The professionals focus on selling university discoveries, and consequently enter license agreements, while support staff handles other daily routines.

This evidence suggests that of the two hypotheses about the causal relationship between hiring professionals and entering license agreements on page 73, hypothesis 1—hiring professionals will lead to increased licensing activity—is closer to the truth.

5.4.13 Conclusions From Analysis of Single Universities

The relationships we have found for inputs and outputs at the eleven universities are of all kinds. Some of them may be caused by statistical noise, while others may be based on the causal relationship in the underlying process.

Overall there is no relationship that is consistent throughout, but the most consistent relationship is the negative auto-correlation in the change in the number of licenses. Seven of the eleven universities have a negative auto correlation, while the remaining four have either zero correlation or the data are not available. If there was no auto-correlation, the probability that all seven correlation coefficient are below zero is 0.8%. This finding does not tell us anything about the causal relationship at the TTOs, it just confirms that there is noise in the licensing process—if the number of licenses shoots up, it will most likely drop down in the following year.

The second most consistent correlation is the positive relationship between the change in the number of patent applications and legal expenditures. Of the nine universities with non-zero correlation, all but one have a positive coefficient. The probability that we get eight or nine heads when flipping a fair coin nine times is 2%. This relationship is as expected, we know that there is a considerable cost associated with filing and pursuing a patent application. Since there is no time shift, this finding does not provide us with any clues about the causal relationship between the two variables.

In section 5.4.12 we used a simple method to assess which of the two hypotheses about the causal relationship between investment and success in technology transfer, the eleven universities "vote" for. Our results imply that hiring more professionals will lead to an increase in the number of licenses (p-value 3.5%). We do not find a corresponding relationship when instead of hiring professionals we hire support staff personnel. This is not surprising, because professionals and staff have different roles at TTOs.

In section 5.5 we use other methods to try to identify consistent correlation patterns in the time series data sets without merging the data.

5.5 Local Rank Test

In section 5.4 we introduced some of the data from our collection effort. We found that there were no consistent patterns across all universities that determined which of the two hypotheses we are testing is correct. In this section we use a different methodology—we work out statistics for each university, and then draw conclusions from aggregating the statistics across the universities in our sample.

By aggregating the statistics we may have sufficient evidence to reject hypotheses collectively when we cannot reject them for single universities. Our results in this section do not provide us with evidence about the two hypotheses on page 73.

5.5.1 Methodology

We will work out the correlation between an input and an output variable at individual universities. In order to draw conclusions from significance statistics, we cannot make the usual "normal" assumptions. For this reason we work with the ranking of the data points instead of the underlying values themselves.

Let us define $R(X_i)$ as the rank of variable X over i. If X_1 is larger than all the other X's, then $R(X_1) = 1$. If there are any ties, we use the average value. This is further illustrated by the following example:

X_i	124	121	147	121	101	179
$R(X_i)$	3	4.5	2	4.5	6	1

Based on the ranking of the variables, the *Spearman Rank Correlation Coefficient* is defined in Conover [CON80] as:

$$\rho \equiv \frac{\sum_{i=1}^{n} R(X_i) R(Y_i) - n\left(\frac{n+1}{2}\right)^2}{\left(\sum_{i=1}^{n} R(X_i)^2 - n\left(\frac{n+1}{2}\right)^2\right)^{\frac{1}{2}} \left(\sum_{i=1}^{n} R(Y_i)^2 - n\left(\frac{n+1}{2}\right)^2\right)^{\frac{1}{2}}}. \tag{5.7}$$

Let us define a function that is the probability that the rank correlation is below the observed value when assuming the two variables are independent,

$$F_{\rho,n}(x) \equiv \Pr(\rho < x) + \frac{1}{2}\Pr(\rho = x). \tag{5.8}$$

If the two variables are independent the distribution of $F_{\rho,n}(x)$ will be almost uniform between zero and one. The only reason why the distribution is not exactly uniform is that the rank correlation coefficient is discrete. For large values of n the discreteness vanishes, and in the definition of $F_{\rho,n}(x)$ we have minimized the disturbance of the discreteness by adding half the probability that the statistic is exactly at that value.

Lets assume we have M different sets of data (in our case we have one set of data from each university). Let us further assume that each set consists of n_m observations (in our case n_m is the number of years we have valid measurements for both X and Y). We calculate the rank correlations for each data set using equation 5.7. We then calculate the $F_{\rho,n}(x)$-statistic for each university. This is not a trivial task. Conover [CON80] provides the quantiles for 90%, 95%, 97.5%, 99%, 99.5%, and 99.9%. These quantiles are not sufficient for our purposes because we need the entire distribution function. We therefore calculated the exact probabilities for cases where $n \leq 12$; used Monte-Carlo approximations for $12 < n \leq 35$; and used the approximation provided by Conover [CON80] when $n > 35$.

If there is on average a **small** positive correlation between the variables, we may not have sufficient data to reject the null-hypothesis of no correlation for any single data set. If $\alpha/2 < F_{\rho,n}(\rho) < 1 - \alpha/2$ we cannot reject the hypothesis for that set. But if there is a small correlation for each set, we may **collectively** have sufficient evidence to reject the independence hypothesis. Lets aggregate $F_{\rho,n}()$ across universities by calculating the statistic,

$$Z = \frac{\sum_{m=1}^{M} F_{\rho,n_m}(\rho_m) - \frac{M}{2}}{\sqrt{\frac{M}{12}}}. \tag{5.9}$$

If the two variables are independent for each data set, each $F_{\rho,n}(x)$ is (almost) uniformly distributed between zero and one. If we also have more than ten sets of data ($M \geq 10$), the distribution of Z is approximately normal with mean zero and variance one.

As an example, lets suppose we have 12 data sets and say we have $F_{\rho,n}(\rho) = 0.8$ for all twelve data sets. We cannot reject the null-hypothesis about no correlation for any single set of data; if we do, there is a 20% chance of rejecting the hypothesis while it is true. Plugging into equation 5.9 we find that $Z = 3.6$. The probability that a normal random variable with mean zero and variance one is greater than 3.6 is less than 1/6000. We can therefore very confidently reject the null-hypothesis based on the aggregated statistic.

5.5.2 Correlation between Inputs and Outputs

In section 5.4 we discussed the cases where the hypotheses about no correlation between inputs and outputs can be rejected for single universities. We now have a more powerful test to reject the hypothesis collectively using the Z-statistic defined in equation 5.9.

Analysis of Absolute Values

If the resources at each university are independent of the patent applications and license agreements, there should be no relationship between when these variables peak. For each university we have ranked the resources. For example, at Harvard (see table 5.5) the legal fee expenditures are at a maximum in 1995, and a minimum in 1986. The patent applications are similarly at a maximum in 1995, and a minimum in 1987.

When calculating the Z-statistic for our data, we **always** reject the hypothesis that there is no correlation between an input and an output with time lag in the inputs from minus one to plus four years. For licenses we can most confidently reject the hypothesis for:

1. Support staff in the following year (p-value 0.01%).

2. Legal expenditures in the previous year (p-value 0.03%).

3. Support staff in the same year (p-value 0.12%).

4. Professionals in the previous year (p-value 0.12%).

The first rejection suggests that TTOs respond to success by hiring more support staff. One explanation for the second rejection is that many patent applications in the previous year (strongly correlated with legal fees) provides the TTO with many marketable products (patents) that they can sell (license agreement). The fourth rejection suggests that professionals hired increase the number of license agreements in the following year.

Looking at the patent applications, we find the strongest correlation is between patent applications and:

1. Legal fee expenditures in the same year (p-value 0.03%).

2. Support staff in the following year (p-value 0.12%).

3. Support staff in the same year (p-value 0.18%).

The first and strongest rejection is not surprising. We know that there are substantial costs associated with a patent application. The largest part of this cost is incurred in the year the application is filed. The second and third rejections suggest again that staff is being hired to administer the process.

One should be careful not to put too much faith into the results above. In the past ten years there was an increase in almost all technology transfer activities, both outputs and inputs.

There has been a substantial growth in technology transfer at American universities in the past ten years. Figure 2-1 shows there has been an exponential growth in the number of patents, and in section E.2 we show that there has been a growth in all the TTO measures for the universities in our sample. This global growth carries into the correlation statistics here—the outputs and inputs are usually at a minimum at the start of the time window, and at a maximum towards the end. These correlation results may be more of a manifest of this fact, rather than telling us something about causal relationships at the TTOs.

Analysis of One-Year Differentials

Instead of focusing our analysis on the absolute numbers, it may be more appropriate to use the differentials. If a university hires one more professional to work on technology transfer this year, does it correlate with an increase in the number of license agreements? We denote the change in the number of license agreements by $\Delta L_t = L_t - L_{t-1}$; the change in the number of patent applications by $\Delta D_t = D_t - D_{t-1}$; the change in the legal fee expenditures by $\Delta N_{l,t} = N_{l,t} - N_{l,t-1}$; and the change in the number of professionals and support staff by $\Delta N_{p,t} = N_{p,t} - N_{p,t-1}$ and $\Delta N_{s,t} = N_{s,t} - N_{s,t-1}$.

When calculating the Z-statistics we find that for patent applications the only significant relationship is the positive correlation between the increase in legal fee expenditures and patent applications in the same year (p-value 0.3%). None of the other correlation coefficients is significantly different from zero. We find that the correlation we found using the absolute values above between patent applications and support staff is no longer present, and we must attribute the previous finding to the overall growth in the field in the last ten years.

When looking at the changes in the number of licenses executed we do not find any significant relationship with any of the input measures. The correlation we found when analyzing the absolute measures with the changes in the support staff, is close to or slightly below zero. Of the four most significant relationships we identified for the absolute values, we find that the strongest correlation in the corresponding differential measures is the positive correlation between the number of professionals working on technology transfer and the number of licenses agreements in the following year. The p-value for the hypothesis of no correlation is 22% and we cannot reject it.

When looking at the changes in the number of licenses executed we find that the change in the number of licenses executed is negatively correlated with the change in the previous year, i.e. we can reject the hypothesis that ΔL_t is independent of ΔL_{t-1} (p-value 0.5%). This implies convergence to the mean—if the number of license agreements entered increases, it will most decrease the following year.

5.5.3 AUTM Data

When performing the same analysis on the AUTM data we find that the hypotheses for the absolute values cannot be rejected as uniformly as before. This is understandable because although we have more than 100 universities in the AUTM database, we have at most five years of data for each one. The only significant relationship for licenses is with legal fee expenditures in the current, past, and following years. For patents the only significant relationship is with legal fee expenditures in the same year. Performing the analysis on the one-year differentials, we do not find any significant relationships; what comes closest is the positive relationship between the change in patent applications and legal fee expenditures (p-value of 8.9%). We do however find a significant convergence to the mean for both patents (p-value 0.002%), and licenses (p-value 0.2%).

5.5.4 Conclusions

We have shown that when working out some statistics for single universities and then aggregating the results, we can reject the hypothesis that there is no correlation between outputs and inputs for various time shifts. This finding can mostly be attributed to the overall growth that has taken place in the field of university technology transfer in the last ten years. This finding, in itself, does not help us to determine the causal relationship we are trying to uncover.

In order to filter out the effects from the global growth we have seen in the past ten years, we analyze the data looking at the one-year differentials in the outputs and inputs. We find that there is a strong positive correlation between the change in legal fee expenditures and patent applications in the same year—if the number of patents increases the legal fee expenditures most likely increase also. This is not surprising as we know that there is a substantial cost associated with each patent application.

When testing these findings on the AUTM data we find that it confirms the positive relationship between legal fees and patent applications in the same year. This database is, however, limited by at most five observations for each university, and although there are over 100 universities we do not find the strong relationship for the absolute values we find in the longer time series.

For both license agreements and patent applications, we find strong evidence of convergence to the mean—if the number of licenses (patents) increased last year, it will most likely decrease this year.

5.6 Probability Models

In this section we build probability models that predict how the number of licenses is influenced by changes in the number of people working on technology transfer, and vice versa. Based on the data from our collection effort, we estimate the probability of events that help us answer questions such as: "What is the difference in the probability we will enter more license agreements this year than last, if we hire one more professional now? Do we realize all the benefits from hiring this employee in the first year, or are there further improvements in the second year of employment?"

Our results in this section hint that for professionals, hypothesis 1—hiring professionals will lead to more license agreements—is true. The results also suggest that for support staff, hypothesis 2—universities respond to success in licensing by hiring more support staff—is true.

5.6.1 Staffing and Licenses: Hypothesis 1

If hypothesis 1—hiring more people to work on technology transfer will lead to more licenses—is true, we should think of the number of people as the independent variable, and the number of licenses as the dependent variable.

As before we let $N_{p,t}$ be the number of professionals working on technology transfer, $N_{s,t}$ be the number of people providing staff support for technology transfer, and $N_{l,t}$ be the legal fee expenditures in year t. Further, L_t is the number of options and license agreements entered in year t, and D_t is the number of new U.S. patent applications.

No Time Shift

We first look at the relationship between staffing and licensing in the same year. Lets start by looking at the changes we expect in the number of licenses from increasing (decreasing) the number of professionals working on technology transfer.

In an effort to only capture appreciable changes in the number of licenses and patents, we will for the purposes of this section adopt the convention that if the number of licenses or patents goes up or down by one, we say there is no change. As a result, approximately one-third of all our observations have no (one or less) change in the number of licenses or patents.

In all we have 92 observations from the eleven universities we surveyed. Of those 92 observations, the number of licenses dropped by two or more in 22 cases and in 36 cases the number of licenses went up by at least two licenses. We use these counts to estimate the following probabilities:

$$P(\Delta L_t \leq -2) = \frac{22}{92} \approx 24\% \tag{5.10}$$

$$P(|\Delta L_t| \leq 1) = \frac{34}{92} \approx 37\% \tag{5.11}$$

$$P(\Delta L_t \geq 2) = \frac{36}{92} \approx 39\%. \tag{5.12}$$

In the calculations above we considered all observations, independent of what changes there were in the number of professionals working on technology transfer. Let us now look at how the change in the number of people providing professional services for technology transfer influences these probability estimates.

Of the 92 observations, in 12 cases the number of professionals went down, in 53 cases it stayed unchanged, and in 27 cases the number of professionals increased. Observe that we have not set a limit on how much the number of professionals has to decrease in order to get into the "decrease" category; any change is sufficient. In some cases the change in the number of professionals is small—a person working three-quarters of a full work day, may have changed to a half-time work load, resulting in a drop of 0.25—while in other cases the change may be substantial. The average drop for the 12 observations was 1.0 full-time equivalences, and the average increase for the 27 observations was 1.1 full-time equivalences.

For the 27 observations where the number of professionals went up, in 14 cases the number of licenses went up by at least two, and in 6 cases the number of licenses went down by at least two licenses. From these numbers we can estimate the following probabilities:

$$P(\Delta L_t \leq -2 \,|\, \Delta N_{p,t} > 0) = \frac{6}{27} \approx 22\% \tag{5.13}$$

$$P(|\Delta L_t| \leq 1 \,|\Delta N_{p,t} > 0) = \frac{7}{27} \approx 26\% \tag{5.14}$$

$$P(\Delta L_t \geq 2 \,|\Delta N_{p,t} > 0) = \frac{14}{27} \approx 52\%. \tag{5.15}$$

From these estimates, we see that the probability that the number of licenses went up is higher if the number of professionals went up, $P(\Delta L_t \geq 2\,|\Delta N_{p,t} > 0) > P(\Delta L_t \geq 2)$. We can ask the question if the differences in the probabilities when conditioning on the number of professionals are significant. One way to do this is to calculate the probability that out of 27 observations we get 14 successes when the probability of success is 39%. We find that the probability of getting 14 or more successes is about 12%.[2] If we were to hypothesize that these probabilities were the same, we could thus not reject that hypothesis based on this evidence.

Of the 92 observations, in 53 cases the number of professionals stayed unchanged. In 9 cases the number of licenses also went down (by at least two licenses), but in 21 case the number of licenses went up (by at least two licenses). From these numbers we estimate the probabilities:

$$P(\Delta L_t \leq -2 \,|\Delta N_{p,t} = 0) = \frac{9}{53} \approx 17\% \tag{5.16}$$

$$P(|\Delta L_t| \leq 1 \,|\Delta N_{p,t} = 0) = \frac{23}{53} \approx 43\% \tag{5.17}$$

$$P(\Delta L_t \geq 2 \,|\Delta N_{p,t} = 0) = \frac{21}{53} \approx 40\%. \tag{5.18}$$

Finally, in 12 of the 92 observations, the number of professionals went down. In seven of these 12 the number of licenses also went down, but in only one case the number of licenses went up. We arrive at the following probability estimates:

$$P(\Delta L_t \leq -2 \,|\Delta N_{p,t} < 0) = \frac{7}{12} \approx 59\% \tag{5.19}$$

$$P(|\Delta L_t| \leq 1 \,|\Delta N_{p,t} < 0) = \frac{4}{12} \approx 33\% \tag{5.20}$$

$$P(\Delta L_t \geq 2 \,|\Delta N_{p,t} < 0) = \frac{1}{12} \approx 8\%. \tag{5.21}$$

In this section, we adopt a compact way of expressing all these probability estimates.

[2] $\sum_{i=14}^{27} \binom{27}{i} \frac{36}{92}^{i} \times \frac{56}{92}^{27-i} = 0.124256$.

$$\begin{pmatrix} & & \Delta L_t \leq -2 & |\Delta L_t| \leq 1 & \Delta L_t \geq 2 & N \\ P(\Delta L_t) & = & 24\% & 37\% & 39\% & 92 \\ P(\Delta L_t \,|\Delta N_{p,t} < 0) & = & 59\% & 33\% & 8\% & 12 \\ P(\Delta L_t \,|\Delta N_{p,t} = 0) & = & 17\% & 43\% & 40\% & 53 \\ P(\Delta L_t \,|\Delta N_{p,t} > 0) & = & 22\% & 26\% & 52\% & 27 \end{pmatrix} \tag{5.22}$$

The first row of numbers in equation 5.22 shows the probability estimates for all the observations (see equations 5.10 to 5.12). In the last column in equation 5.22 we show how many observations there were in all for these probability estimates. The second row in equation 5.22 lists the probability estimates when the number of professionals went down (see equations 5.19 and 5.21). The third and fourth rows show the probability estimates for the cases where the number of professionals stayed unchanged and went up.

Now that we have calculated all the conditional probability estimates, we can test if the differences in the probability estimates are statistically significant. Using a traditional χ^2-test we find that the p-value for the hypothesis that changes in the number of licenses are independent of the change in the number of professionals is 1.3%. We thus reject the hypothesis that the differences in the probability estimates in equation 5.22 are due to chance alone. We must conclude that by adding to the number of professionals working on technology transfer, the probability that the number of licenses goes up improves significantly.

If we calculate the average change in the number of licenses, we find that for all 92 observations there was an average increase of 1.3 licenses. For the 12 observations where the number of professionals went down, the average change in the number of licenses was -8.1. For the 53 observations where the number of professionals stayed unchanged, the average number of licenses went up by 1.5, and for the 27 observations where the number of professionals went up the average increase in the number of license agreements was 5.2. We conclude that not only do the chances of getting more licenses improve when more people are hired to work on technology transfer, but the expected increase is also quite substantial.

If we analyze how the number of people providing staff support affects the chances of getting more licenses, we find the same pattern as for professionals. If the number of people providing staff support went down, there was only a 14% chance of entering more license agreements in the same year (the average decrease in the number of agreements was 4.1), if the number of support staff was unchanged the probability of entering more license agreement was 38% (the average number of agreements went up by 1.5), and if the number of support staff increased, the probability is 50% (the average number of agreements went up by 2.5). These differences in the probabilities are, however, not significant (p-value 9.4%).

We have found that if the number of people working on technology transfer increased, the probability the university entered more licenses in the same year agreements is higher. Comparing a university that increased the number of professionals working on technology transfer, to one that kept that number unchanged, we find that the probability of entering more license agreements is 52% instead of 40%.

These findings do not tell us about the causal relationships in technology transfer, they only show that there is a positive correlation between the variables. This confirms our results from Chapters 3 and 4.

Time Shift of One Year

We have shown that there is a positive correlation between the number of people working on technology transfer and the number of license agreements that the university enters. But what happens the year after both these measures increase? Does the number of licenses drop down to the level it was at before adding this person to the staff, does it stay unchanged, or is there an additional increase in the second year after hiring the person?

If the employees of the TTOs are really stimulating the commercialization process, adding to the staff should not only increase the number of license agreements entered in the same year, but also in the following years. Lets look at the universities that kept the number of professionals working on technology transfer unchanged, but increased, kept it unchanged, or decreased it in the previous year. If there is time lag between when professionals are hired and when they start **fully** contributing to the licensing activities of the TTO, we should find that in the second year of employment there is a **further** increase in the number of licenses (on top of the increase in the first year).

$$\left(\begin{array}{lcccccc} & & \Delta L_t \leq -2 & |\Delta L_t| \leq 1 & \Delta L_t \geq 2 & N \\ P\left(\Delta L_t \,|\Delta N_{p,t} = 0\right) & = & 19\% & 40\% & 42\% & 48 \\ P\left(\Delta L_t \,|\Delta N_{p,t-1} < 0, \Delta N_{p,t} = 0\right) & = & 0\% & 0\% & 100\% & 2 \\ P\left(\Delta L_t \,|\Delta N_{p,t-1} = 0, \Delta N_{p,t} = 0\right) & = & 21\% & 45\% & 34\% & 38 \\ P\left(\Delta L_t \,|\Delta N_{p,t-1} > 0, \Delta N_{p,t} = 0\right) & = & 12\% & 25\% & 63\% & 8 \end{array}\right) \tag{5.23}$$

Using a traditional χ^2-test to test for statistical differences in these probability estimates we find that the p-value is 28%. These estimates do thus not constitute conclusive evidence, but they provide us with hints about the causal relationship.

We see first of all that there are only two observations where the number of professionals decreased and then stayed unchanged the following year. We will thus focus our comparisons on the universities that did not change and those that increased the number of professionals. We find that for those that increased the number of professionals the probability of an additional increase in the number of license agreements in the second year is 63% for an average increase of 4.9 licenses; while the probability is about 34% for the ones that kept the number of professionals unchanged for an average increase of only 0.4 licenses. This suggests that there may be an additional improvement in the second year of employment, in addition to the already realized improvement in the first year. The impact of hiring a new professional may not only be immediate, there may be some time lag and in the second year there may be an additional improvement.

Performing this analysis for the third year—look at universities that changed the number of professionals working on technology transfer, but then kept it unchanged for the next two years—we do not find any appreciable difference in the change in the number of licenses. This suggests that when adding to the number of professionals, there is an improvement in the first year. There also seems to be an improvement in the second year on top of the improvement of the first year, but the improvements stop there. By the end of the second year, the new professional has become a fully effective member of the TTO, and the evidence does not suggest there is an additional improvement (or degeneration) in the third year.

Carrying this analysis out for the support staff, we find some evidence of time lag. Universities that added to the support staff are estimated to have a 64% chance of increasing the number of licenses in the second year (average increase was 3.2 licenses), while the universities that kept the number of staff unchanged are estimated to have only a 35% chance (for an average increase of 1.3 licenses). These differences in the probabilities are not statistically significant (p-value 26%).

Conclusion

Lets illustrate our findings by comparing two scenarios. Suppose we have two universities, university A increased the number of professionals working on technology transfer by one at the start of fiscal year 1996 by hiring a new full-time person. For the rest of fiscal years 1996 and 1997 they did not make any changes to the staffing of the office. At university B there were no changes in the staffing of the TTO in fiscal years 1996 or 1997.

If we look at the number of license agreements these two universities entered in fiscal year 1996, we find that university A has a 52% chance of entering more licenses than in the previous year, while university B has only a 38% chance of doing so. Our analysis suggests that university A should expect to enter about five more license agreements in FY1996 than FY1995, while university B should only expect to increase the number of license agreements by one or two.

Lets now look at fiscal year 1997. In FY1997, neither university changes their staffing of the TTO, but we see that the new person that university A hired at the beginning of FY1996 will make a difference. Our results suggest that university A has a 63% chance of entering more license agreements in FY1997 than in FY1996, while university B has only a 38% chance of entering more license agreements than it did in FY1996. We see that not only does university A have a higher probability, but it has a higher probability to even exceed the level it reached in FY1996.

The difference in the probabilities for the first year (1996) is statistically significant, but the difference in the second year is not statistically significant for the limited data we have to make those estimates.

We collect further evidence about this time lag in section 5.7.

5.6.2 Staffing and Licenses: Hypothesis 2

If hypothesis 2—universities respond to increased number of licenses by hiring more people to work on technology transfer—is true, it is more appropriate to think of the number of licenses as the independent variable, and the number of people as the dependent variable.

No Time Shift

Similar to the analysis for hypothesis 1, we first calculate how the change in the number of licenses influences the probability that the university changes the number of people working on technology transfer in the same year. We arrive at the following probability estimates:

$$\left(\begin{array}{lccccc} & & \Delta N_{p,t}<0 & \Delta N_{p,t}=0 & \Delta N_{p,t}>0 & N \\ P\left(\Delta N_{p,t}\right) & = & 13\% & 58\% & 29\% & 92 \\ P\left(\Delta N_{p,t}\,|\Delta L_t \leq -2\right) & = & 32\% & 41\% & 27\% & 22 \\ P\left(\Delta N_{p,t}\,||\Delta L_t| \leq 1\right) & = & 12\% & 68\% & 20\% & 34 \\ P\left(\Delta N_{p,t}\,|\Delta L_t \geq 2\right) & = & 3\% & 58\% & 39\% & 36 \end{array}\right) \tag{5.24}$$

The estimated probability matrix of equation 5.24 is just the "transpose" of the probability matrix in equation 5.22. The p-value is of course the same, 1.3%, for the hypothesis that the change in the number of professionals working on technology transfer is independent of the change in the number of license agreements.

From equation 5.24 we see that if the number of licenses went up by two or more, our estimates imply that the probability the university increased the number of professionals working on technology transfer is 39%. If the number of licenses did not go up by two or more, the probability the university hires more professionals is smaller. Performing the same kind of analysis for the number of support staff we find similar, but not statistically significant, differences in the probability estimates.

Time Shift of One Year

Lets now look for evidence that the change in the number of licenses influences the probability estimates of the change in the number of professionals in the following year. We arrive at the following probability estimates:

$$\left(\begin{array}{lccccc} & & \Delta N_{p,t}<0 & \Delta N_{p,t}=0 & \Delta N_{p,t}>0 & N \\ P\left(\Delta N_{p,t}\,|\Delta L_t = 0\right) & = & 13\% & 63\% & 23\% & 30 \\ P\left(\Delta N_{p,t}\,|\Delta L_{t-1} \leq 2, |\Delta L_t| \leq 1\right) & = & 25\% & 25\% & 50\% & 4 \\ P\left(\Delta N_{p,t}\,||\Delta L_{t-1}| \leq 1, |\Delta L_t| \leq 1\right) & = & 13\% & 81\% & 6\% & 16 \\ P\left(\Delta N_{p,t}\,|\Delta L_{t-1} \geq 2, |\Delta L_t| \leq 1\right) & = & 10\% & 50\% & 40\% & 10 \end{array}\right) \tag{5.25}$$

The p-value for the hypothesis that these estimates are independent of the change in the number of licenses is 14%, using a traditional χ^2-test. Taking the probability estimates at face value, these results imply that universities respond to an increase or a decrease in the number of licenses by hiring more professionals. If the number of licenses went up last year, the average number of professionals goes up by 0.42, if the number of licenses did not change the average number of professionals goes up by 0.01, and if the number of licenses went down, the average number of professionals goes up by 0.25. We should keep in mind that the differences between these estimates are not statistically significant.

If we look at how the change in the number of licences influences the number of staff working on technology transfer in the following year, we find statistically significant differences in the probability estimates:

$$\begin{pmatrix} & & \Delta N_{s,t} < 0 & \Delta N_{s,t} = 0 & \Delta N_{s,t} > 0 & N \\ P(\Delta N_{s,t} \,|\Delta L_t = 0) & = & 10\% & 80\% & 10\% & 30 \\ P(\Delta N_{s,t} \,|\Delta L_{t-1} \leq 2, |\Delta L_t| \leq 1) & = & 50\% & 50\% & 0\% & 4 \\ P(\Delta N_{s,t} \,||\Delta L_{t-1}| \leq 1, |\Delta L_t| \leq 1) & = & 0\% & 94\% & 6\% & 16 \\ P(\Delta N_{s,t} \,|\Delta L_{t-1} \geq 2, |\Delta L_t| \leq 1) & = & 10\% & 70\% & 20\% & 10 \end{pmatrix} \quad (5.26)$$

Using a χ^2-test to test the hypothesis that these estimates are independent of the change in the number of licenses, the p-value is 3.2%. The average change in the number of support staff when the number of licences decreased in the previous year was -0.31, +0.02 if the number of licenses stayed unchanged, and +0.10 if the number of licenses went up.

This evidence supports implies that for support staff, hypothesis 2—universities respond to increased licensing activity by hiring support staff.

Conclusion

We get different evidence for professionals and staff. Looking at the professionals, we find a statistically significant difference within the same year—universities that enter more licenses agreements, also hire more professionals to work on technology transfer than others. Looking at what happens to the number of professionals in the following year, our results are not statistically significant, but suggest that universities where the number of licenses went either up or down, hire more professionals to work on technology transfer in the following year. Taken at face value, this implies that universities that are either doing better or slipping respond by hiring more professionals.

When we look at how the changes in the number of licenses influences the probability estimates for the change in support staff we find a different pattern. Changes within the same year are not statistically significant, but the results hint that universities that enter more licenses also hire more people to provide staff support for technology transfer than others. Looking at the influence in the second year, we find a significant relationship. We find that universities where the number of licenses went down are more likely to reduce the number of support staff in the following year (+0.04) than others, and similarly that universities that entered more licenses agreements respond by hiring more support staff (+0.30 full-time equivalences). This evidence supports hypothesis 2 for support staff—universities respond to changes in licensing by changing the number of people providing staff support in the same direction. We collect further evidence about this in section 5.7.

5.6.3 Patents and Legal Fee Expenditures

We want to understand the relationship between legal fee expenditures and patent applications. If we look at how the legal fee expenditures affect the number of patent applications we find the following:

$$\left(\begin{array}{lccccc} & & \Delta D_t \leq -2 & |\Delta D_t| \leq 1 & \Delta D_t \geq 2 & N \\ P(\Delta D_t) & = & 31\% & 34\% & 35\% & 74 \\ P(\Delta D_t\,|\Delta N_{l,t} \leq -\$50K) & = & 40\% & 40\% & 20\% & 10 \\ P(\Delta D_t\,||\Delta N_{l,t}| < \$50K) & = & 28\% & 50\% & 22\% & 32 \\ P(\Delta D_t\,|\Delta N_{l,t} \geq \$50K) & = & 31\% & 16\% & 53\% & 32 \end{array}\right) \quad (5.27)$$

We see that when the legal fee expenditures are increased about at least \$50,000 the probability of filing for more patents goes from 20% to over 50%. When we look at the influence the legal fees have on the number of patent applications in the following year, we find that the two variables are essentially independent. This is as expected—the legal fee expenditures are usually incurred **after** the application is filed. Instead of working with the probability matrix above, it is more appropriate to work with a matrix that targets answering the question: "If we file more patent applications, will we also need to pay more in legal fees in the same year?" The probability matrix for this question is:

$$\left(\begin{array}{lccccc} & & \Delta N_{l,t} \leq -\$50K & |\Delta N_{l,t}| < \$50K & \Delta N_{l,t} \geq \$50K & N \\ P(\Delta N_{l,t}) & = & 14\% & 43\% & 43\% & 74 \\ P(\Delta N_{l,t}\,|\Delta D_t \leq -2) & = & 17\% & 39\% & 43\% & 23 \\ P(\Delta N_{l,t}\,||\Delta D_t| \leq 1) & = & 16\% & 64\% & 20\% & 25 \\ P(\Delta N_{l,t}\,|\Delta D_t \geq 2) & = & 8\% & 27\% & 65\% & 26 \end{array}\right) \quad (5.28)$$

The p-value for the hypothesis that the probability estimates do not depend on how the number of patents changes is 2.4%, using a traditional χ^2-test. We see that if the number of patent applications went up by at least two, the probability the legal fees increased by at least \$50,000 is 65%. If the number of patent applications went down or stayed unchanged these probabilities are 43% and 20% respectively. Looking at how the number of patents applications influences the legal fees in the following years, our estimates imply that these two variables are essentially independent.

5.6.4 AUTM Data

Performing the analysis above on the AUTM data we find the same hints, but none of the relationships between staffing of the TTO and licenses is statistically significant. The only statistically significant relationship is between the number of patent applications and the legal fee expenditures in the same year (p-value 0.004%). This finding only confirms that legal fee expenditures correlate with patent applications.

5.6.5 Conclusions

For the relationship between the number of professionals and licenses agreements, we find that the changes in the number of licenses is positively correlated with the change in the number of professionals working on technology transfer in the same year (p-value 1.3%). This finding confirms our findings from Chapters 3 and 4, but does not provide any hints about the causal relationship. When we look for evidence in support of the two hypotheses on page 73 we find some evidence in support of hypothesis 1—hiring more professionals to work on technology transfer will lead to increases in the number of license agreements. We find that by hiring a person to provide professional services for technology transfer the university not only increases its chances of entering more license agreements in the same year, but it also increases the chances of exceeding the already increased number in the second year (p-value 28%). This suggests there may be some delay in realizing all the rewards from adding a professional.

When we look at the relationship between the number of support staff and licenses agreements, we also find there is a positive correlation between the variables in the same year, but the relationship is not statistically significant (p-value 9.4%). When we investigate the evidence in support of the two hypotheses about the causal relationship between support staff and licenses, we find some insignificant evidence in support of hypothesis 1—hiring support staff leads to increases in licensing—(p-value 26%), but we find statistically significant (p-value 3.2%) evidence in support of hypothesis 2—universities respond to increases in the number of licenses by hiring more people to provide staff support for technology transfer.

Looking at the relationship between legal fee expenditures and patent applications, we find there is a strong correlation within the same year; universities that increase the number of patent applications, also end up paying a higher bill for legal fees in the same year (p-value for our data 2.4% and for AUTM data 0.004%). We do, however, not find evidence of time lags between patent applications and legal fee expenditures.

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5.7 Regression of Merged Time Series Data

In this section we merge the data set from the eleven universities and build regression models to further quantify the time lag we observed in section 5.6.

For the causal relationship between professionals and licenses we find evidence supporting hypothesis 1—hiring professionals will lead to an increase in the number of licenses. We build models that estimate the expected increase in the number of licenses resulting from hiring a professional to work on technology transfer. For support staff, we find significant evidence supporting hypothesis 2—universities respond to an increase in the number of licenses by hiring more support staff.

5.7.1 Staffing and Licenses: Hypothesis 1

As discussed in the previous sections, if hypothesis 1—increasing the number of professionals working on technology transfer will lead to increased number of licenses—holds, we should think of the number of licenses as the dependent variable.

One-Year Differentials

We build simple models to predict the number of licenses as a function of the resources. We focus on modeling the **differentials** in these variables, because as we mentioned earlier there has been an global increase in all the measures over the past ten years and we want to minimize the effect this has on our parameters.

The change in the number of licenses is,

$$\Delta L_t = L_t - L_{t-1}. \tag{5.29}$$

The first model we estimate is a simple model that focuses exclusively on the resources in the same year,

$$\begin{aligned} \Delta L_t &= \beta_0 + \alpha_p \Delta N_{p,t} + \alpha_s \Delta N_{s,t} + \alpha_l \Delta N_{l,t} && (5.30) \\ &= -0.14 + 6.4\Delta N_{p,t} + 4.2\Delta N_{s,t} - 5.8\Delta N_{l,t}. && (5.31) \end{aligned}$$

The p-value for the constant is 45% and for the legal fee expenditures $\Delta N_{l,t}$ it is 18%. This is consistent with our results from Chapter 3—when looking at the resources in the same year, the number of licenses is primarily determined by the number of professionals and support staff working on technology transfer, not by legal expenditures. Setting the legal expenditures coefficient to zero, we arrive at the estimates,

$$\Delta L_t = 0.05 + 4.4\Delta N_{p,t} + 3.3\Delta N_{s,t}. \tag{5.32}$$

The p-values for the parameters of equation 5.32 are 48%, 0.01%, and 1.1% respectively. We see that there is some change in the estimates for the parameters going from equation 5.31 to equation 5.32. One reason why the difference is as large as we see is that we do not have the legal fee expenditures data for some observations. Consequently the estimates in equation 5.31 are based 75 observations, while the estimates in equation

5.32 are based on 92 observations.[3]

Our ultimate goal is to determine which of the two hypotheses about the causal relationship between technology transfer resources and commercialized technologies is true. To do so we must have time lags, and we therefore estimate a model based on the resources in the current and past year:

$$\begin{aligned}
\Delta L_t &= \beta_0 + \alpha_{p,0}\Delta N_{p,t} + \alpha_{p,1}\Delta N_{p,t-1} + \\
&\quad \alpha_{s,0}\Delta N_{s,t} + \alpha_{s,1}\Delta N_{s,t-1} + \alpha_{l,0}\Delta N_{l,t} + \alpha_{l,1}\Delta N_{l,t-1} && (5.33) \\
&= -0.44 + 6.0\Delta N_{p,t} - 1.0\Delta N_{p,t-1} + \\
&\quad 4.1\Delta N_{s,t} + 0.8\Delta N_{s,t-1} - 11.6\Delta N_{l,t} + 7.4\Delta N_{l,t-1}. && (5.34)
\end{aligned}$$

The estimates in equation 5.32 are based on 68 observations. The p-values for the coefficients are greater than 5% except for $\Delta N_{p,t}$ and $\Delta N_{s,t}$. Setting the legal fee parameters (p-values 6.7% and 15%) to zero we arrive at,

$$\Delta L_t = -0.04 + 4.1\Delta N_{p,t} - 0.8\Delta N_{p,t-1} + 3.4\Delta N_{s,t} + 0.1\Delta N_{s,t-1}. \qquad (5.35)$$

The p-values are 49% for the constant, 30% for $\Delta N_{p,t-1}$, and 47% for $\Delta N_{s,t-1}$. Setting these coefficients to zero we end with the same result as in equation 5.32. This suggests that the change in the number of license agreements entered by year is primarily driven by the resources in that same year.

Taking the parameter estimates of equation 5.35 at face value, adding one professional to the staff working on technology transfer will increase the expected number of licenses in the same year by 4.1 (p-value 0.05%), but will decrease the change in the following year by about 0.8 licenses (p-value 30%). This expected decrease in the second year is on top of the increase in the first year, so the net effect on the expected number of licenses in the second year after adding the person is +3.3 licenses.

Looking at more than a one year delay we do not obtain any further insights.

Two-Year Differentials

Lets say that we are at the start of fiscal year 1998. Suppose we are contemplating if we should: 1) hire one more professional (or support staff person) now, 2) hire one more professional (or support staff person) in twelve months (at the start of FY1999), or 3) not add anyone for the next 24 months. We are interested in understanding what effect these three alternatives have on the expected number of license agreements we will enter in fiscal year 1999 (note that FY1999 does not start until 12 months from now). To answer this question, we want to estimate how the number of licenses will be different in FY1999 compared to FY1997. We define the operator for the two-year differentials as,

[3] If we calculate the estimates for equation 5.32 only on the 75 observations used for estimating the parameter values for equation 5.31 we arrive at $\Delta L_t = -0.44 + 6.1\Delta N_{p,t} + 4.1\Delta N_{s,t}$.

$$\Delta^2 L_t = L_t - L_{t-2}. \tag{5.36}$$

To answer our question, we want to estimate the following model:

$$\Delta^2 L_t = \beta_0 + \alpha_{p,0}\Delta^2 N_{p,t} + \alpha_{p,1}\Delta N_{p,t-1} + \alpha_{s,0}\Delta^2 N_{s,t} + \alpha_{s,1}\Delta N_{s,t-1}. \tag{5.37}$$

Of the model parameters, $\alpha_{p,0}$ will give us the estimated increase in the number of license agreements we will enter in FY1999 if we add one more professional to the staff in 12 months (option 2 above), $\alpha_{p,1}$ is the estimated **additional** increase if we add a professional now, and $\alpha_{s,0}$ and $\alpha_{s,1}$ are the estimated increases from adding a support staff person. The effect of adding one professional now is thus $\alpha_{p,0}+\alpha_{p,1}$ (option 1 above). Estimating the model parameters above we get,

$$\Delta^2 L_t = 0.9 + 2.1\Delta^2 N_{p,t} + 3.4\Delta N_{p,t-1} + 2.6\Delta^2 N_{s,t} + 0.1\Delta N_{s,t-1}. \tag{5.38}$$

The p-values for the model parameters are 25%, 8.2%, 6.2%, 9.9%, and 48%. Taking the parameter estimates of equation 5.38 at face value, we find that adding one professional now, we expect the number of licenses in FY1999 to go up by $(2.1+3.4=)$ 5.5, but if we wait until the start of FY1999 and add a professional then, the expected increase is only 2.1. By adding the professional now instead of at the start of FY1999 we increase the expected number of licenses in FY1999 by 3.4. The new person will have a greater impact in the second year of employment than the first. This suggests that when we add new people to provide professional services for technology transfer they do not contribute fully from the first day. It takes time for them to get the necessary training, get acquainted with the practices of the technology transfer office, etc. In the first year the contribution to the increase in the number of license agreements is only 40% ($\approx 2.1/5.5$) of the contribution in the second year.

If, instead of adding a professional, we were thinking of adding one person to the support staff, the parameter estimates in equation 5.38 show that adding a support staff person now will increase the number of license agreements in FY1999 by 2.6, but adding the person at the beginning of FY1999 will increase the expected number of license agreements about 2.7. The p-value for the $\Delta N_{s,t-1}$ parameter is 46%. If we re-estimate the model parameters after setting $\alpha_{s,1}=0$, the new estimates for adding to the number of professionals are unchanged, but adding to the staff either now or at the beginning of FY1999 will increase the number of license agreements by 2.7:

$$\Delta^2 L_t = 0.9 + 2.1\Delta^2 N_{p,t} + 3.4\Delta N_{p,t-1} + 2.7\Delta^2 N_{s,t}. \tag{5.39}$$

The p-values for these three parameter estimates are 24%, 7.9%, 6.1%, and 6.8% respectively.

5.7.2 Staffing and Licenses: Hypothesis 2

As discussed in previous sections we should think of the number of professionals and staff as the dependent variable if hypothesis 2—universities respond to increased number of licenses by hiring more people—is true.

One-Year Differentials

We first estimate the parameters of simple models for the change in the number of professionals and staff.

$$\begin{aligned} \Delta N_{p,t} &= \beta_0 + \alpha_L \Delta L_t + \alpha_D \Delta D_t && (5.40)\\ &= 0.19 + 0.030\Delta L_t - 0.012\Delta D_t. && (5.41) \end{aligned}$$

The p-values for the parameters are 2.3%, 0.05%, and 17%. Once again this confirms that professionals working on technology transfer primarily focus on license agreements. Estimating a corresponding model for the change in the number of support staff, we find exactly the same pattern. The p-values are 9.5%, 4.6%, and 11%. This shows that the staff also primarily contribute to the licenses processes, but the relationship is not as strong as for the professionals.

To quantify time lags, we estimate the parameters of the following models:

$$\begin{aligned} \Delta N_{p,t} &= \beta_0 + \alpha_{L,0} \Delta L_t + \alpha_{L,1} \Delta L_{t-1} && (5.42)\\ &= 0.18 + 0.022\Delta L_t - 0.014\Delta L_{t-1}. && (5.43) \end{aligned}$$

The p-values for the estimates are 2.1%, 0.9%, and 6.5%. The negative coefficient for ΔL_{t-1} works against hypothesis 2—universities (do not) respond an increase in the number of licenses by hiring more professionals. The p-value is greater than 5%, so this does not provide statistically significant evidence.

Estimating the same coefficients for the change in the number of support staff, we find:

$$\Delta N_{s,t} = 0.11 + 0.016\Delta L_t + 0.009\Delta L_{t-1}. \qquad (5.44)$$

The p-values for these estimates are 9.0%, 3.0%, and 14%. We observe that the coefficient for ΔL_{t-1} is positive, suggesting hypothesis 2—universities respond to increases in the number of license by hiring support staff— may be true for the support staff, but the estimate is not statistically significant.

If we look at longer time delays, we do not find any relationships for the number of professionals, but for the number of support staff we find,

$$
\begin{aligned}
\Delta N_{s,t} &= \beta_0 + \alpha_{L,0}\Delta L_t + \alpha_{L,1}\Delta L_{t-1} + \alpha_{L,2}\Delta L_{t-2} && (5.45)\\
&= 0.04 + 0.026\Delta L_t + 0.023\Delta L_{t-1} + 0.026\Delta L_{t-1}. && (5.46)
\end{aligned}
$$

The p-values for these parameters are 33%, 0.3%, 1.1%, and 0.4%.[4] This evidence implies that universities respond to increases in the number of licenses by hiring more support staff. While some of the increase in personnel is in the same year, these parameter estimates suggest that there are similar increases in the following two years.

Two-Year Differentials

Just as in the analysis for hypothesis 1, we estimate the parameters of the models for the two-year differentials.

$$
\begin{aligned}
\Delta^2 N_{p,t} &= \beta_0 + \alpha_{L,0}\Delta^2 L_t + \alpha_{L,1}\Delta L_{t-1} && (5.47)\\
&= 0.23 + 0.031\Delta^2 L_t - 0.005\Delta L_{t-1} && (5.48)\\
\Delta^2 N_{s,t} &= 0.25 + 0.015\Delta^2 L_t + 0.007\Delta L_{t-1} && (5.49)
\end{aligned}
$$

The p-values for the professionals model are 1.9%, 0.3%, and 34%. As before the $\alpha_{L,0}$ parameter estimates the total influence of a change in the number of licenses in second year of the two year period, but $\alpha_{L,1}$ evaluates the **incremental** influence if the increase in the number of licenses is in the first of the two years. The net effect of an increase in the first year is thus $\alpha_{L,0}+\alpha_{L,1}$. As with the one-year differentials the negative coefficient for ΔL_{t-1} works against hypothesis 2—universities do not) respond to an increase in the number of licenses by hiring professionals—for the professionals.

The p-values for the support staff model are 0.2%, 3.6%, and 23%. The positive coefficient for ΔL_{t-1} implies hypothesis 2—universities respond to increases in the number of licenses by hiring more support staff—may be true, but the estimate is not statistically significant.

[4] The R^2-statistic for the estimates in equation 5.46 is much higher that the R^2-statistic for equation 5.44 (0.16 vs. 0.05). A part of the reason is that the estimates of the latter model are based on 70 observations, while the former is based on 81 observations. If we estimate the model parameters of the former model, but only use the 70 observations, we arrive at,

$$\Delta N_{s,t} = 0.11 + 0.021\Delta L_t + 0.012\Delta L_{t-1}.$$

The p-values for these estimates are 10%, 1.6%, and 10% respectively. The R^2-statistic is still low at 0.07, so we must conclude that there is significant "information" in the data about how many support staff members are added two years after the change in license agreements.

5.7.3 Patents and Legal Fee Expenditures

The results of Chapter 3 and throughout this chapter we have seen that of all the inputs, patent applications are most strongly correlated with legal fee expenditures. We find that people employed for technology transfer purposes are much less important when predicting the number of patent applications. To further illustrate the point, lets estimate the model:

$$\begin{aligned} \Delta D_t &= \beta_0 + \alpha_p \Delta N_{p,t} + \alpha_s \Delta N_{s,t} + \alpha_l \Delta N_{l,t} && (5.50) \\ &= 0.12 - 1.1 \Delta N_{p,t} + 1.6 \Delta N_{s,t} + 17 \Delta N_{l,t} [\$M] && (5.51) \end{aligned}$$

The p-values for the four parameter estimates are 44%, 13%, 6.3%, and 0.02%. This shows that, as expected, the patent applications are primarily driven by legal fee expenditures.

Looking for evidence of hypothesis 1 for legal fee expenditures we estimate the parameters of a model that predicts the number of patents based on legal fee expenditures in the current and previous years. Our results are not statistically significant, but the hints we get work against hypothesis 1 for legal fee expenditures and patent applications.

To investigate the evidence for hypothesis 2 for the relationship between legal fee expenditures and patent applications, we build models that predict the legal fee expenditures based on patent applications. But first, we estimate the parameters of the model,

$$\begin{aligned} \Delta N_{l,t} &= \beta_0 + \alpha_L \Delta L_t + \alpha_D \Delta D_t && (5.52) \\ &= \$55,000 - \$200\ \Delta L_t + \$9,000\ \Delta D_t. && (5.53) \end{aligned}$$

The p-values for these parameter estimates are 0.6%, 45%, and 0.1%. This confirms that the legal fee expenditures depend on patents but not licenses.

There is also no inherent capacity in the system—there is a fairly fixed cost associated with each patent application. Instead of modelling the **change** in legal fees, we model the gross legal fee expenditures.

We want to estimate a model like the following:

$$N_{l,t} = \alpha_{D,0} D_t + \alpha_{D,1} D_{t-1} + \alpha_{D,2} D_{t-2} + \alpha_{D,3} D_{t-3} + \alpha_{D,4} D_{t-4} + \alpha_{D,5} D_{t-5} \qquad (5.54)$$

If all the legal fees are paid in the same year as the application is filed, $\alpha_{D,0}$ will be large and the other parameters will be small. If the legal fees are paid in the first two years, $\alpha_{D,0}$ and $\alpha_{D,1}$ will be large, but the other parameters will be small.

When estimating the parameters of equation 5.54, we find there is a strong autocorrelation in the legal fee expenditures—a university that pays much in legal fees, will most likely do so in the following years. The reason is simply that large universities apply for many patents and pay large legal fees. The sum of the parameters in equation 5.54 is invariably between \$30,000 and \$34,000, implying that on average it costs about \$32,000 to file for a patent.

In table 5.17 we have estimated five single parameter models for the legal fee expenditures:

Model	R^2-statistic
$N_{l,t} = \$27,000D_t$	0.832
$N_{l,t} = \$29,000D_{t-1}$	0.888
$N_{l,t} = \$31,000D_{t-2}$	0.914
$N_{l,t} = \$33,000D_{t-3}$	0.910
$N_{l,t} = \$34,000D_{t-4}$	0.886

Table 5.17: Single Parameter Models for Legal Fee Expenditures.

We see that all years provide a fairly good estimate for the gross legal fee expenditures. These models consistently suggest that it costs on average between \$27,000 and \$34,000 to file a patent application.

5.7.4 Legal Fee Expenditure Models Based on AUTM Data

Estimating the parameters for a model like that of equation 5.54 based on the AUTM data we arrive at,

$$N_{l,t} = \$15,000D_t + \$10,000D_{t-1} + \$6,000D_{t-2}. \qquad (5.55)$$

The p-values for these parameters are all small, but because of the multicolinearity these p-values are too low. These parameter estimates imply that the total cost of a single patent is about \$31,000.

5.7.5 Conclusions

For the relationship between people providing professional services for technology transfer and license agreements, we find no evidence in support of hypothesis 2—universities (do not) respond to an increase in the number of licenses by hiring more professionals. We find some evidence in support of hypothesis 1—hiring more professionals will lead to increases in the number of licenses. When we estimate models for the two-year differentials we find evidence that is not quite statistically significant (p-values 6% and 8%), but it provides us with clues. Equation 5.39 implies that when adding a new professional to the staff of the TTO, there will be an expected increase about 5.5 licenses per year, in two years time. About 40% of the increase in licensing rate is estimated to occur in the first year, but the remaining 60% in the second year. We find no evidence of time lags in excess of this.

When we analyze the one-year differentials, our parameter estimates suggest that hiring one more professionals, the expected number of licenses in the same year will increase by 4.1 but in the following year 0.8 of that growth is returned (p-value 30%). While the p-value is quite high, taken at face value this contradicts our finding from analyzing the two-year differentials. Because of the high p-value we should not draw any conclusions from this finding.

When we analyze the causal relationship between support staff and licenses, we find no evidence in support of hypothesis 1—hiring more support staff (will not) lead to an increase in the number of license agreements. When investigating the evidence for hypothesis 2—universities respond to an increase in the number of licenses by hiring more support staff—we find consistent (and some significant) clues that the hypothesis may be true. Looking at both the one-year and two-year differentials we find there is a time lag—if the number of licenses goes up, the university will respond by hiring more people to provide staff support for technology transfer activities. Some of the resulting increases in the number of staff are in the same year, some are in the following year, and as the estimates in equation 5.46 imply some of the increase is as late as two years later. This finding is consistent with our findings in section 5.6.

Our results confirm that the primary resource determining the number of patent applications is legal fee expenditures, and that the primary determinant of legal fee expenditures is patent applications. This is consistent with what industry experts say. Our results also hint that there is a time lag in the legal fees—a university that files a patent application in 1997, should expect to incur some legal expenses related to the application in that same year, but also in the following two years. On average the expenditures for a patent application total $32,000. This estimate for the aggregate legal expenditures for a single patent application is similar to what industry experts have suggested.

5.8 Limitations of the Time Series Analysis

In this chapter we first discuss how we can approximate how much technology is transferred from each university. We must reluctantly make the assumption that all licenses are equal. If we do not make this assumption, we could not use data on licenses executed in the last few years, because it is in most cases impossible to determine how successful a new license will be. We argue that this assumption is reasonable by analyzing income profiles for licenses.

The data we use for this analysis are not perfect. We only have the full-time equivalences for the number of people providing professional services and staff support for technology transfer. So, for example, if five people were providing professional services for technology transfer in 1995 and 1996, it does not necessarily mean that there were no changes in personnel; one person might have left and another one hired in his/her place. Furthermore, in our analysis we assumes that all professionals are the same and that all support staff are the same. It is, however, clear that some people are more energetic and productive than others. In other words, our proxy variable for the effectiveness of the TTO employees—their numbers—is necessarily somewhat crude.

While we get some insights into the causal relationship between investment and success in technology transfer from the time series analysis, this analysis does not provide us with models that explain cross-sectional differences: Why is one university more successful than another? The analyses in Chapters 3 and 4 addresses this issue more directly.

The analysis in this chapter attributes all changes (except a linear long term trend) to the changes in the resources committed to technology transfer. In the cross-sectional analysis in Chapter 3 we show that licensing activity also depends on research expenditures and faculty quality. While it is unlikely that the faculty quality has changed significantly in the last ten years, the research expenditures have changed at some of the universities in our sample. When we introduce the data for the universities in section 5.4 we therefore also plot how the research expenditures have changed since 1980. We discuss how this may explain the changes in the "rate" of transferred technologies, but we do not use this "research expenditures" variable in the numerical time series analyses.

In Chapter 3 we found that the relationship between research expenditures and licensing is concave—universities that spend twice as much do not get twice the number of patents and licenses. The aggregate increase in research expenditures for the universities in our database is 40% in the last ten years. Our models in this chapter filter out a linear long term trend, but aside from that we assume that the variations in the research expenditures over time are secondary compared to the variations in the TTO resources. It is unlikely that these secondary variations in the research expenditures influence our findings.

5.9 Conclusions from Time Series Analysis

The main goal of the time series analysis is to determine the causal relationship between adding professionals to work on technology transfer and increases in transferred technologies. On page 73 we introduce two hypotheses about how the causal relationships might be.

We went out in the field and collected detailed data from eleven universities. This was necessary because the available data do not provide long enough time series to analyze causal relationships.

We use a variety of methods to collect evidence about the causal relationships. We first analyze patterns at single universities, we then develop statistics for each university and aggregate these statistics across universities, and finally we merge the data for the eleven universities into one database and build simple regression and probability models for the relationship between inputs and outputs from technology transfer.

The first, and most important, causal relationship is between licenses and people providing professional services for technology transfer. Of the two hypotheses on page 73 we do not find any evidence for hypothesis 2—universities (do not) respond to increases in the number of licenses by hiring more professionals. On the other hand, we find many clues for hypothesis 1—adding to the number of professionals working on technology transfer will lead to increased number of license agreements. The strongest evidence we find is from the analysis in section 5.4.12 where we develop a "voting" rule. We find that of the two hypotheses, the data from seven of eight universities imply that hypothesis 1 is closer to the truth (p-value 3.5%). Both the probability and regression models provide further evidence in support of this hypothesis, but we do not find any single clue that is statistically significant. It is the weight of the accumulated evidence that suggests the direction of causality rather than any particular piece of evidence.

Our best estimate of the delay in realizing the full benefits of hiring a professional to work on technology transfer suggests that in the first year the new staff member contributes about 40% of what he/she contributes in the second year (see equation 5.39). We do not find any evidence of longer time lags than this. Our estimates suggest that the expected increase in the number of licenses realized from adding one full-time professional to the staff is between three and six licenses (see equations 5.32 and 5.39).

The second causal relationship we analyze is between licenses and people providing staff support for technology transfer. We do not find evidence in support of hypothesis 1—hiring more support staff (will not) lead to an increase in the number of licenses—but we find some significant relationships that support hypothesis 2—universities respond to an increase in the number of licenses by hiring more staff support. In section 5.7 we show that the number of staff hired is dependent on the change in the total number of licenses in the last three years (see equation 5.46). The parameters of this model all have p-values of 1% or less. In section 5.6 we also show that the number of licenses changes the probability the university will increase or decrease the number of support staff the following year (see equation 5.26). The p-value for this finding is 3.2%.

The third and last causal relationship is between legal fee expenditures and patent applications. We do not find evidence in support of hypothesis 1 for patent applications. There is some evidence for hypothesis 2—if a university files patent applications, they will need to pay legal fees. Our estimates suggest that the universities pay legal fees after the application is filed (see table 5.17). Analyzing the AUTM data we also collect more clues in support of hypothesis 2 (see equation 5.55). The regression models imply that the average cost of a patent application is about $31,000. This estimate is a little higher than what industry experts have suggested ($25,000), but this difference can partly be explained by maintenance fees.

Chapter 6

Summary and Final Remarks

This research focused on analyzing the influence of technology transfer offices in commercializing discoveries made at American universities. Prior work in this area has been limited to simple statistics based on the data from the Association of University Technology Managers. We built more sophisticated models that evaluate the influence of the technology transfer office **and** other variables. Instead of only looking at the aggregate research expenditures, we looked at expenditures by department and concluded that not all departments contribute to the commercialization process. We introduced a variable for the quality rating of faculty, and conclude that highly rated faculty perform research more cost effectively than others. We also collected detailed time series data directly from eleven universities to assess the causal relationships between investment and success in technology transfer.

There are clearly limits to what we can expect from aggregate analyses of university technology transfer offices. Although the data we used are more detailed than prior analyses have used, there are imperfections. We assumed that the effectiveness of the people of the technology transfer offices is captured by the raw numbers of professionals and support staff; but some people are more productive than others. We assumed that the "rate" of technology transfer can be approximated by the number of licenses and patents; but it is clear that some licenses and patents are more valuable than others. We did not consider the historical background and philosophy of universities; some universities pride themselves in successfully commercialized inventions, while others are more concerned with awards and other "non" technology transfer measures.

When we started our work on this topic, the most immediate goal was to gather evidence to determine if the university technology transfer offices were hindering the commercialization of university research discoveries. Early on we found evidence implying that this was indeed not the case—there seems to be a positive correlation between the resources and success in technology transfer at American universities.

We refined the main question to incorporate the causal relationships between the resources and outcomes: Do universities first commit resources and then realize increases in technology transfer, or does the success lead to an increase in the resources? In order to answer this question we collected detailed time series data directly from eleven universities. Analyzing these data we find evidence suggesting that some resources precede the outcomes—universities first decide to increase the number of professionals working on technology transfer, and consequently enter more license agreements with industry.

The analytical work of this thesis consists of three major parts. None of these analyses provides a complete answer to our question on their own, it is not until we integrate the results from the three analyses that we get a clear picture of how the dynamics of university technology transfer offices may be.

The Three Analyses

In Chapter 3 we built cross-sectional regression models that use the most important determinants of research outputs to predict the number of licenses and patents. Our results imply that the most important determinants are: departmental research expenditures, professionals and support staff working on technology transfer, legal fee expenditures for patents and/or copyrights, and the faculty quality rating. Using these variables we built models that fit empirical data to predict the number of patents a university enters in a given year, the number of license agreements made with industry, and the number of invention disclosures received from faculty. We estimated the parameters of the model on empirical data. The parameter estimates imply that there is a strong positive correlation between the resources universities commit to technology transfer and the number of licenses and patents universities get; universities that invest more (per research activity) in technology transfer enter more licenses agreements and apply for more patents. Our parameter estimates also imply diminishing rates of return for research expenditures and that highly rated faculty perform research (that results in licenses and patents) more cost effectively than other faculty.

In Chapter 4 we used Data Envelopment Analysis to calculate an "excellence" score for universities. This excellence score is based on six output measures, the number of: 1) patent applications, 2) license agreements, 3) royalties received (dollars), 4) faculty publications, 5) enrolled graduate students, and 6) awarded Ph.D. degrees. We considered one input measure, the total research expenditures, and we used a variation of the method that is flexible enough to capture diminishing rates of return for research expenditures. After calculating the "excellence" score for the universities, we looked at how these scores correlate with the resources universities commit to technology transfer. As in Chapter 3, our results imply there is a positive correlation between the investment in technology transfer and university excellence. Our results also suggest that universities that invest in technology transfer derive a higher **fraction** of their score from the output measures related to technology transfer. In other words, the universities that invest in technology transfer tend to emphasize technology transfer related activities when they put their best foot forward.

The result from the analyses in Chapters 3 and 4 imply that there is a positive correlation between investment and success in technology transfer. However, they cannot determine the causal relationships between the investment and the success. In Chapter 5 we used time series analysis to gather evidence about the causal relationships. For this analysis it was necessary to collect longer time series data. We went out in the field and gathered detailed information from eleven universities. We used several methods to analyze these data. Most of the methods we employed did not provide us with statistically significant findings, but from the weight of the combined evidence we can make inferences. When we looked at the causal relationship between professionals that work on technology transfer and license agreements, our analysis suggests that hiring more professionals will lead to more license agreements. This finding is encouraging for university technology transfer specialists, because it supports the hypothesis that professionals are actively stimulating the commercialization process of university discoveries. Our results also suggest that universities respond to a change in the number of licenses by a change in the same direction in the number of support staff. Again, this result is intuitive; the support staff members provide more general services, and if the work load goes up or down it is reasonable that the university makes a corresponding change in the number of support staff.

The variable cost of employing one person to provide professional services for technology transfer is about \$100,000. The expected increase in revenue for the university from one license agreement is about \$34,000. We see that if a new professional can increase the number of licenses by about three per year, hiring a professional is a good investment for the university. Our results in Chapter 5 suggest that a university should expect between three and six additional licenses (per year) for each professional (our median estimate for this increase based on the analysis in Chapter 3 is somewhat lower at 2.2, but these models are cross-sectional and not designed to capture changes over time). This suggests that all things being equal, it is a good investment to hire more professionals to work on technology transfer.

Integrating the Results from the Three Analyses

The general conclusions of the analyses in this thesis are:

- Only three departments—Engineering, Physical Science, and the Life Sciences—contribute appreciably to the patenting process. This finding is consistent with what industry experts have suggested.

- Faculty that are highly rated by faculty colleagues at other universities perform research that results in licenses and patents more cost effectively than others. This suggests that the rewards from hiring "good" faculty outweigh the additional cost.

- There are diminishing rates of return for research expenditures. Universities that spend twice as much on research as others, do not, on average, produce twice as many licenses and patents. Our estimates imply that a university with twice the research expenditures produces on average about 60% more.

Our conclusions relating directly to technology transfer offices are:

- Universities that hire people to provide professional services for technology transfer should expect an increase in the number of license agreements. Some part of this increase should be realized in the first year the new person is employed, but in the second year the new person should contribute fully to the licensing activities of the TTO. The expected increase in the number of license agreements from hiring the new person is between three and six licenses per year (after the first year).

- If the number of licenses increases by three or more as a result from hiring one more professional, our results about the increased revenue for the university imply that hiring a professional to work on technology transfer is a good investment.

- Universities respond to changes in the number of licenses by similar changes in the number of people providing staff support for technology transfer; our results imply that if the number of licenses goes up the number of support staff will also go up, and if the number of licenses goes down the number of support staff also goes down. If the number of licenses agreements goes down by one per year, our results imply that the number of support staff goes down by 0.07 full-time equivalences.

- Universities that invest more in technology transfer derive a higher fraction of their "excellence" from technology transfer; in other words, they are more successful in technology transfer than other activities.

- The hypothesis that initiated this thesis work was about the negative impact of university technology transfer offices for the pharmaceuticals industry. Looking across all industries our results suggest that there is a positive correlation between the investment and success in technology transfer. The results in section C.4 suggest that the influence of the TTO is essentially the same at universities that perform most of their research in the Life Sciences and those that perform most of their research in Engineering and Physical Sciences. Pharmaceutical companies get most of their licenses from research in the Life Sciences and we conclude that TTOs are just as effective for the pharmaceuticals industry as any other industry that utilizes university research discoveries.

Open Topics

Our analyses focused on analyzing patterns that appear at many universities. We have not performed a detailed case study of single technology transfer programs. A different approach to answering our initial question would be to closely analyze the practices at a single technology transfer program. Case study analyses have been performed for the MIT licensing office and some other TTOs, but these studies have not specifically targeted the question if these offices are stimulating or hindering the commercialization process.

It would be interesting to perform a detailed case study of a few university TTOs. The results of such a study may confirm or contradict the results of this thesis. This case study should collect evidence about the stimulatory effect of the TTOs. The researcher should work directly with a few universities. He/she should gather evidence about the historical background of the TTO: Does it have a long successful track record? How is the budget of the office determined? What are the other "variables" in the environment of the TTO that matter? The researcher should collect information about the perception faculty have about the TTO: Do they know what the TTO does? Do they hold a favorable opinion about the staff of the TTO? How have their experiences with the TTO been? The study should also analyze how the inner dynamics of the TTO are: Is the director of the TTO an enthusiastic person with many corporate contacts? Does the director push the office towards sustained excellence in technology transfer? Are the licensing managers of the TTOs the key people? What are the (stated and unstated) objectives of the office? How is the performance of the office and its employees evaluates in relation to these objectives? Is there any evidence that corporations have decided not to license a technology from a university because of the bureaucratic obstacles, and consequently, the invention not been utilized by anyone else?

Final Remarks

We used data from various sources to build models for the influence of university technology transfer offices in the commercialization process of universities discoveries. Contradicting the hypothesis that initiated our interest in this work, our conclusions imply that technology transfer offices are stimulating and not hindering the process. The weight of our evidence implies that investment in university technology transfer programs is a good investment: It is good for the university, because it may yield a positive return on the investment. It is good for industry, because it can take further advantage of university research outcomes. And finally, the investment is good for society as a whole, because contrary to what President Lyndon Johnson was concerned about in 1966, discoveries are **not** being locked up in the laboratory (see page 9).

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Appendix A

University Performance

In this appendix we list the performance of each university relative to the predictions of the cross-sectional model in Chapter 3. In tables A.1 to A.4 we have listed the performance of all the universities in the database relative to the models. The "Model" column refers to the median prediction using the model parameters from table 3.5, and "Real" reefers to the true median number of licenses, patents, and invention disclosures in 1992-1995.

In tables A.1 to A.4 the universities are ordered by the normalized performance—in entering license agreements—relative to the model (see equation 3.30),

$$\frac{\text{Real} - \text{Model}}{\sqrt{\text{Model}}}. \tag{A.1}$$

University	Licenses Executed		New Patent Applications		Invention Disclosures	
	Model	Real	Model	Real	Model	Real
Marquette	1.1	6.0	1.4	4.0	4.9	6.0
Stanford	83.0	125.0	76.2	61.5	233.0	171.0
Cornell	40.0	66.0	51.6	94.5	167.9	171.5
U. of Miami	11.7	25.0	10.9	5.0	33.8	23.0
Iowa State	63.6	93.0	77.0	50.0	151.0	141.0
U. of Mass, Amherst	6.7	16.0	5.7	4.0	26.2	10.5
U. of Illinois, Urbana	29.9	48.5	22.7	18.0	103.3	62.0
Washington U.	26.3	43.5	26.2	23.0	75.3	24.0
U. of Utah	26.0	38.0	20.5	24.5	64.3	129.0
U. of Alabama, Birm.	16.9	24.5	16.4	24.5	49.1	78.0
U. of Maryland, C. Park	30.1	39.5	26.1	20.0	118.8	72.5
Texas A&M	25.1	33.0	29.9	24.0	101.2	76.0
U. of Missouri System	11.5	16.5	15.6	12.0	51.9	57.0
Harvard	45.2	55.0	50.5	39.5	147.2	104.0
Wright State	0.3	1.0	1.6	0.0	5.5	3.0
U. of Minnesota	37.7	46.0	43.3	31.5	127.4	142.5
Indiana U.	14.3	19.0	17.1	18.5	70.2	63.0
Montana State	3.3	5.5	5.5	3.0	21.8	11.0
U. of Kentucky	10.6	14.0	13.2	18.0	38.6	44.0
SUNY	29.1	34.5	39.7	33.0	129.2	155.0
Purdue	32.9	38.0	30.2	24.0	100.7	116.0
Ohio State	21.8	25.5	24.6	21.5	83.9	62.0
Washington State	11.5	14.0	11.7	9.5	37.6	29.5
U. of Georgia	13.2	15.0	20.2	9.5	59.2	32.5
U. of Oregon	4.5	5.5	5.4	5.0	24.7	14.5
Med. Coll. of Ohio	2.0	2.5	3.2	4.0	8.6	7.0
Wayne State	9.0	10.0	17.2	10.5	48.4	32.0
Baylor College	21.6	23.0	21.8	16.5	55.4	79.5
Thomas Jefferson	14.8	15.5	13.9	33.5	32.2	53.0
Brandeis	7.6	8.0	5.0	4.0	19.3	13.0
Virginia Tech	16.5	17.0	13.0	23.0	52.0	78.0
North Dakota State	1.9	2.0	6.8	1.0	20.5	6.0

Table A.1: University Performance Relative to Model. First Quartile.

University	Licenses Executed		New Patent Applications		Invention Disclosures	
	Model	Real	Model	Real	Model	Real
Marshall	0.0	0.0	0.2	0.0	0.7	1.5
U. of TX Hlth Sci Ctr,	9.5	9.5	13.5	8.5	32.9	22.0
San Diego State	0.6	0.5	2.5	1.0	10.0	3.5
U. of South Florida	8.2	8.0	10.7	10.0	31.1	25.0
Hahnemann	7.3	7.0	4.1	6.0	12.3	16.0
Vanderbilt	14.0	13.5	15.7	10.5	46.9	38.5
Northeastern	5.4	5.0	10.8	17.0	26.2	32.0
North Carolina State	30.4	29.5	31.8	33.5	90.9	80.5
Boston U.	9.8	9.0	20.1	27.0	57.7	60.5
Brigham Young	16.9	15.5	8.2	5.5	23.5	19.0
U. of Dayton	7.0	6.0	6.0	3.5	17.6	21.5
U. of Florida	27.5	25.5	32.8	22.0	87.6	79.5
Ohio U.	5.4	4.5	5.5	6.0	16.3	17.5
Florida State	2.7	2.0	13.4	10.5	63.7	18.0
U. of Maine	2.1	1.5	1.7	0.0	5.5	3.0
Miami U.	0.2	0.0	0.4	1.0	1.3	6.0
Columbia	37.6	34.5	43.5	38.0	120.2	95.5
U. of Denver	0.3	0.0	1.9	1.0	6.8	7.0
Emory	10.7	9.0	16.7	11.5	48.0	35.0
Michigan State	15.1	13.0	22.1	17.0	73.4	79.0
Florida Atlantic	3.6	2.5	2.5	2.0	6.5	6.0
Tufts	8.8	7.0	10.3	7.5	31.5	34.5
California State	0.4	0.0	0.6	0.0	1.9	2.0
Kansas State	12.2	10.0	14.8	14.0	42.6	28.0
Duke	29.6	26.0	31.9	41.5	88.2	92.0
U. of South Alabama	1.3	0.5	2.6	0.5	7.7	1.5
Rice	5.6	4.0	8.0	2.0	28.8	2.0
Dartmouth	10.4	8.0	10.9	4.0	31.9	11.0
U. of NC/Chapel Hill	17.7	14.5	17.6	21.5	58.8	76.5
Tulane	8.2	6.0	11.1	7.5	33.4	21.0
U. of NC/Charlotte	3.5	2.0	3.2	4.0	6.7	13.0
U. of TX Med. Branch	6.6	4.5	9.8	4.5	25.3	15.5

Table A.2: University Performance Relative to Model. Second Quartile.

University	Licenses Executed		New Patent Applications		Invention Disclosures	
	Model	Real	Model	Real	Model	Real
Auburn U.	6.1	4.0	8.8	5.0	29.2	17.0
Northern Illinois U.	0.9	0.0	2.4	2.5	9.6	7.0
Mississippi State	4.6	2.5	6.1	5.0	20.5	17.5
Hunter College	1.0	0.0	1.3	0.0	7.7	0.0
Georgia Tech.	27.4	22.0	24.3	32.5	84.6	118.0
New York Med. C.	3.4	1.5	3.0	1.0	10.4	5.5
U. of Akron	10.4	7.0	11.9	14.5	33.3	27.0
Illinois Inst. of Tech.	2.8	1.0	3.8	5.0	10.8	11.0
U. of Pittsburgh	13.0	9.0	23.9	17.0	72.0	34.0
U. of Tennessee	14.3	10.0	19.9	10.0	60.1	77.0
Med. Univ. of SC	4.4	2.0	5.4	3.0	17.5	9.0
U. of Cincinnati	11.4	7.5	12.7	10.5	39.8	47.0
New Mexico State	7.3	4.0	7.7	4.0	25.4	15.0
U. of New Hampshire	1.5	0.0	1.5	1.0	5.6	6.0
Wake Forest	8.7	5.0	8.7	6.5	26.3	20.0
U. of Iowa	19.0	13.5	22.4	16.5	70.2	58.5
U. of TX SW Med. Ctr.	16.7	11.5	22.4	16.5	47.3	44.5
U. of Alabama in Hunts.	3.5	1.0	4.0	2.0	16.2	9.0
Princeton	16.5	11.0	14.6	12.5	64.0	59.5
U. of Central Florida	4.3	1.5	3.8	7.5	13.4	29.0
U. of Tulsa	2.1	0.0	1.7	0.0	5.7	1.0
Johns Hopkins	58.5	47.0	60.3	48.0	227.0	182.0
U. of Arizona	18.9	12.0	20.9	11.0	102.2	83.5
U. of Hawaii	9.4	4.5	12.4	9.0	53.5	16.5
U. of Maryland, Balt.	11.7	6.0	10.5	11.0	35.1	51.0
U. of TX Houston	11.3	5.5	11.7	4.0	28.7	22.5
U. of Nebraska-Lincoln	7.8	3.0	12.6	12.0	40.3	27.0
Temple	11.3	5.5	12.1	10.0	30.1	26.0
Cal. Tech.	23.4	15.0	31.9	52.5	128.3	304.0
Rutgers	26.5	17.5	29.0	29.5	87.3	64.5
U. of Arkansas, Fayett.	5.6	1.5	8.9	6.5	28.5	22.0
Oregon State	10.8	5.0	12.6	8.5	37.5	21.5

Table A.3: University Performance Relative to Model. Third Quartile.

University	Licenses Executed		New Patent Applications		Invention Disclosures	
	Model	Real	Model	Real	Model	Real
U. of Virginia	16.1	9.0	17.5	12.5	58.1	39.0
Drexel	8.1	3.0	8.3	2.0	21.8	8.5
Yale	23.8	15.0	23.7	23.5	78.4	83.5
U. of California	157.7	135.0	166.1	176.5	541.5	542.0
U. of Connecticut	12.5	6.0	15.0	10.5	44.3	36.0
U. of Mass, Med. Ctr.	8.4	3.0	8.1	4.0	23.9	24.5
MIT	90.1	72.5	94.8	91.0	322.5	281.0
U. of Pennsylvania	39.3	27.5	48.2	52.0	132.1	119.0
Illinois State	3.6	0.0	1.1	0.0	3.7	4.0
Georgetown	10.1	4.0	14.7	9.0	40.2	37.0
Michigan Technol. U.	8.8	3.0	6.5	2.0	18.9	17.0
Clemson	9.1	3.0	11.6	9.5	36.9	30.0
U. of Rochester	18.1	9.5	21.0	12.0	68.0	39.5
U. of Southern CA	20.7	11.0	22.6	22.5	68.5	60.5
Brown	11.1	4.0	9.4	5.0	35.5	19.0
Arizona State	12.6	5.0	19.1	8.0	57.4	24.0
U. of Illinois at Chi.	14.2	6.0	14.4	7.0	48.4	35.0
Syracuse	13.6	5.5	8.8	2.5	30.5	12.0
U. of Colorado	24.3	13.5	24.4	22.5	89.9	77.0
Colorado State	11.5	4.0	12.1	6.5	41.3	34.0
Case Western	22.6	12.0	16.8	9.0	58.1	39.0
Carnegie Mellon	27.2	15.5	22.0	11.0	62.7	73.0
U. of Kansas	18.9	8.0	12.9	7.0	48.2	51.0
Northwestern	20.5	9.0	23.3	18.5	71.8	45.0
U. of Delaware	13.4	4.0	11.5	4.0	39.0	14.0
Stevens	8.9	1.0	4.9	3.0	13.4	6.0
New Jersey Inst. of Tech.	9.6	1.0	4.8	6.0	13.6	23.0
Penn State	34.4	18.0	28.5	32.0	106.8	112.5
U. of Chicago	24.2	10.0	27.5	18.5	100.3	56.0
U. of South Carolina	8.6	0.0	7.6	3.0	30.6	12.5
U. of Wisconsin-Madison	53.0	29.5	65.2	54.0	185.8	137.0
U. of Michigan	55.0	28.5	51.6	44.5	160.7	108.0
U. of Washington	63.3	34.5	45.0	32.5	137.2	147.5

Table A.4: University Performance Relative to Model. Fourth Quartile.

Appendix B

The CDF for the Q-statistics

In this Appendix we analyze the empirical evidence we have to figure out how much compounding there is in the patenting and licensing processes.

The empirical value of Q is,

$$Q_i^* = \frac{\sigma_{D_i}^{2*}}{\overline{D_i}}, \tag{B.1}$$

where $\sigma_{D_i}^{2*}$ is an unbiased estimator of the variance and $\overline{D_i}$ is the mean. We aggregate this statistic across universities in two ways. First of all, we use the median, that is,

$$Q^{1*} = \underset{i}{\text{median}} \left[\frac{\sigma_{D_i}^{2*}}{\overline{D_i}} \right]. \tag{B.2}$$

Secondly, we sum the numerator and the denominator over all universities to get,

$$Q^{2*} = \frac{\sum_i \sigma_{D_i}^{2*}}{\sum_i \overline{D_i}}. \tag{B.3}$$

From [TAF96] we have the number of patents that have been granted to US universities since 1975. Figure 2-1 plots the total number of patents awarded to U.S. universities. We see that the number of patents granted has been steadily increasing for the last two decades. We can therefore not assume that this is a stationary process over time. For each university we need to correct for this exponential growth.

We use five simple models that show how the expected value changes over time. The models are:

1. Constant rate; $\lambda_{i,t} = \overline{D_i}$.

2. Perfect seasonal; $\lambda_{i,t} = s_t \times \beta_i$, where s_t are the same for all universities.

3. Linear; $\lambda_{i,t} = \alpha_i + \beta_i \times t$, where α_i and β_i are university specific constants.

4. Exponential; $\lambda_{i,t} = \alpha_i \times \beta_i^t$, where α_i and β_i are university specific constants.

5. Best of the above; $\lambda_{i,t}$ is the best of the four models above (picked for each university based on the squared errors).

For each university we used least squares estimation to get estimates for the parameters in the above models for $\lambda_{i,t}$.

For the constant rate and perfect seasonal we lose one degree of freedom in estimating the mean and the unbiased estimate for each university's variance is,

$$\sigma^{2*}_{D_{i,t}} = \frac{1}{n_i} \sum_t (d_{i,t} - \lambda_{i,t})^2 , \tag{B.4}$$

where n_i is the number of observations for university i. For the linear and exponential adjustment methods we lose two degrees of freedom and the estimate for the variance is,

$$\sigma^{2*}_{D_{i,t}} = \frac{1}{n_i - 2} \sum_t (d_{i,t} - \lambda_{i,t})^2 . \tag{B.5}$$

		Q^{1*}-Model for $D_{i,t}$				
Time Horizon	Variable	1	2	3	4	5
1991-1995	New Patent Applications	2.07	2.00	1.18	1.10	1.08
1991-1995	New Invention Disclosures	2.13	1.61	1.42	1.51	1.32
1991-1995	Licenses and Options Executed	2.08	1.57	1.21	0.92	0.89
1991-1995	New Patents	1.18	1.14	0.95	1.03	0.94
1990-1995	New Patents	1.49	1.28	1.06	1.09	1.05
1989-1995	New Patents	1.40	1.36	1.12	1.15	1.08
1988-1995	New Patents	1.85	1.41	1.24	1.22	1.18
1987-1995	New Patents	2.06	1.56	1.29	1.30	1.24
1986-1995	New Patents	2.23	1.59	1.29	1.36	1.20
1985-1995	New Patents	2.54	1.58	1.34	1.36	1.27
1984-1995	New Patents	2.79	1.61	1.34	1.42	1.27
1983-1995	New Patents	3.01	1.64	1.37	1.40	1.29
1982-1995	New Patents	3.24	1.65	1.42	1.43	1.32
1981-1995	New Patents	3.50	1.65	1.43	1.43	1.32
1980-1995	New Patents	3.82	1.69	1.49	1.41	1.33
1979-1995	New Patents	4.06	1.68	1.50	1.42	1.33
1978-1995	New Patents	4.21	1.75	1.55	1.42	1.34
1977-1995	New Patents	4.37	1.81	1.61	1.43	1.35
1976-1995	New Patents	4.51	1.88	1.61	1.44	1.41
1975-1995	New Patents	4.64	1.92	1.65	1.45	1.39

Table B.1: Q^{1*}-statistic values; Data Source: The first three variables are from [AUT96], but the rest from [TAF96] .

		Q^{2*}-Model for $D_{i,t}$				
Time Horizon	Variable[1]	1	2	3	4	5
1991-1995	New Patent Applications	3.83	2.52	1.64	1.60	1.56
1991-1995	New Invention Disclosures	2.98	2.58	1.38	1.35	1.26
1991-1995	Licenses and Options Executed	2.89	2.32	1.26	1.22	1.12
1991-1995	New Patents	2.87	2.13	0.76	0.66	0.63
1990-1995	New Patents	3.48	2.36	0.97	0.83	0.78
1989-1995	New Patents	3.62	2.44	1.24	1.01	0.96
1988-1995	New Patents	4.55	2.52	1.56	1.37	1.25
1987-1995	New Patents	5.12	2.59	1.72	1.52	1.37
1986-1995	New Patents	5.86	2.56	1.86	1.67	1.48
1985-1995	New Patents	6.67	2.59	1.95	1.77	1.56
1984-1995	New Patents	7.30	2.64	2.02	1.82	1.58
1983-1995	New Patents	7.95	2.72	2.12	1.90	1.65
1982-1995	New Patents	8.48	2.80	2.25	1.97	1.73
1981-1995	New Patents	8.86	2.96	2.41	2.03	1.84
1980-1995	New Patents	9.59	3.14	2.45	2.06	1.90
1979-1995	New Patents	10.41	3.27	2.49	2.10	1.93
1978-1995	New Patents	10.72	3.40	2.62	2.11	1.99
1977-1995	New Patents	10.98	3.47	2.78	2.13	2.02
1976-1995	New Patents	11.17	3.65	2.97	2.17	2.08
1975-1995	New Patents	11.43	3.78	3.09	2.18	2.11

Table B.2: Q^{2*}-statistic values; Data Source: The first three variables are from [AUT96], but the rest from [TAF96].

In tables B.1 and B.2 we have calculated the Q^{1*} and Q^{2*}-statistics for the empirical data. The five columns correspond to the five ways of correcting for the trend: 1) constant, 2) perfect seasonal, 3) linear, 4) exponential, and 5) best of the previous methods selected for each university.

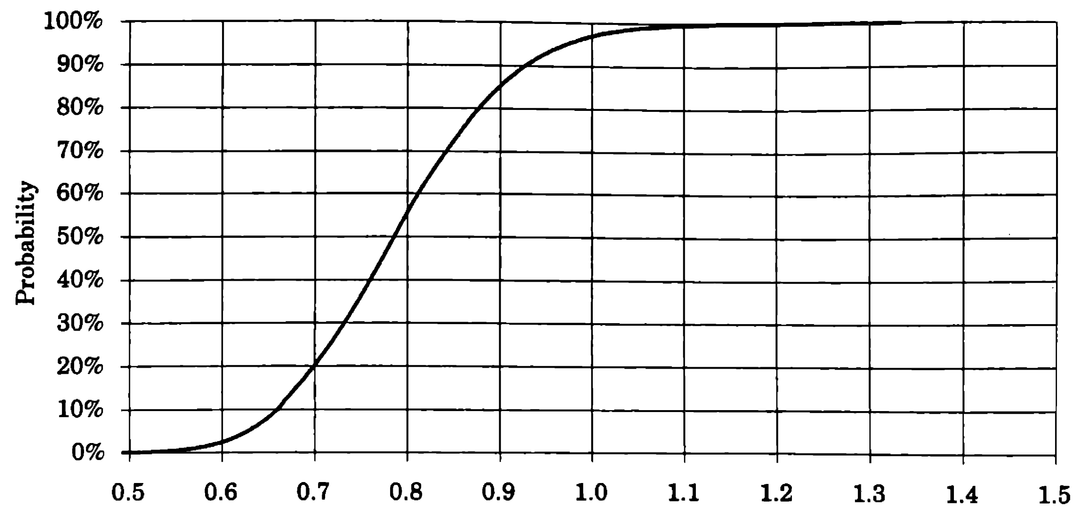

Figure B-1: The Simulated Cummulative Distribution Function for the Q^{1*}-statistic.

In order to get a theoretical benchmark, we used Monte Carlo simulations to simulate the Q^{1*} and Q^{2*}-statistics when the underlying random variable is a true Poisson random variable with linear trend. We used the trend estimated from the variable "New U.S. Patent Applications". Figures B-1 and B-2 show the approximations for the distribution functions after more than 370,000 runs.

The simulated Q^{1*}-statistic has almost exactly a normal distribution with mean 0.79 and standard deviation of 0.11. Similarly, the Q^{2*}-statistic is close to being $N(1.00, 0.15^2)$. The accurate medians for the statistics are 0.7855 and 0.9873 respectively.

The first three variables are from the AUTM database [AUT96] and thus represent the data we use for the regression models later on. The New Patents variable from 1975-1994 is from the U.S. Patent and Trademark Office database [TAF96].

For new patent applications the empirical value for the exponentially adjusted Q^{1*}-statistic is 1.10. From the Monte Carlo simulation we have that for a pure Poisson process this value should be close to 0.78. By equation B.1 this suggests that the compounding is $1.10/0.78 \approx 1.4$. Using the results from the Q^{2*}-statistic in a similar manner the estimate for the compounding is $1.60/1.00 \approx 1.6$.

Table B.3 summarizes the results from evaluating the compounding for our processes using both the Q^{1*} and Q^{2*}-statistics.

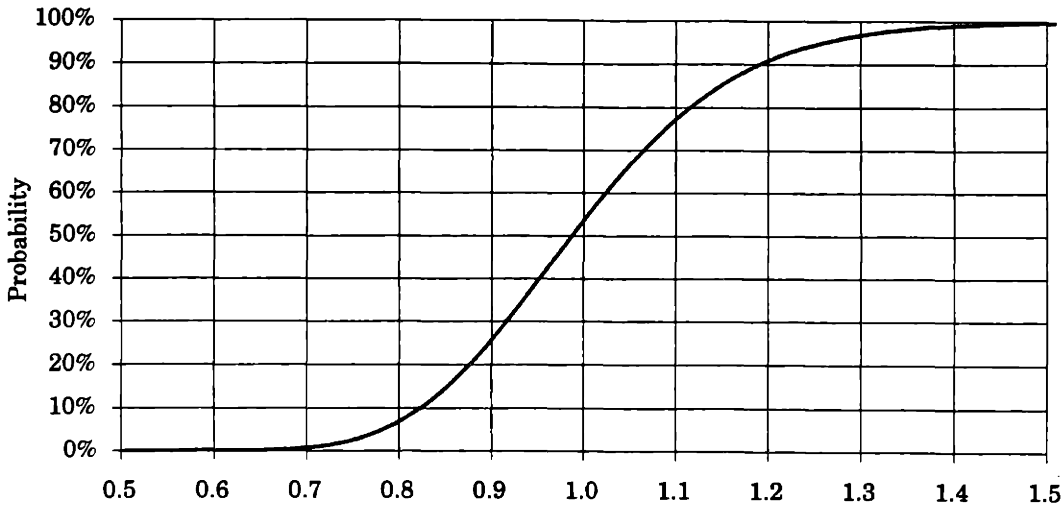

Figure B-2: The Simulated Cummulative Distribution Function for the Q^{2*}-statistic.

Output Measure	Q^{1*}-statistic	Q^{2*}-statistic
New U.S. Patent Applications	1.4	1.6
Licenses and Options Executed	1.2	1.2
New Invention Disclosures	1.9	1.4

Table B.3: The Poisson Compounding for Patents, Licenses, and Invention Disclosures.

Appendix C

The CDF for the Bootstrap Simulated Parameters

In this Appendix we test hypotheses that the Engineering and Physical Science departments have the same parameter values for returns to scale for 1) research expenditures ($\beta_{\text{Eng}} = \beta_{\text{Phy}}$) and for 2) the faculty quality rating ($\delta_{\text{Eng}} = \delta_{\text{Phy}}$).

C.1 Distribution Functions for Fully Relaxed Parameter Estimates

In figures C-1 to C-13 we have the bootstrap simulated distribution functions for the model parameters of the full model. These results are based on the bootstrap technique introduced in section 3.3.5.

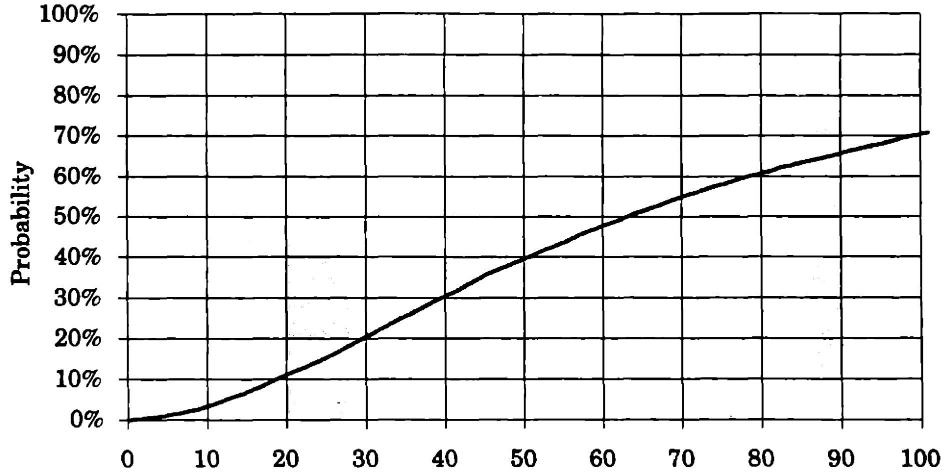

Figure C-1: The Bootstrap Simulated CDF for: α_{Eng}.

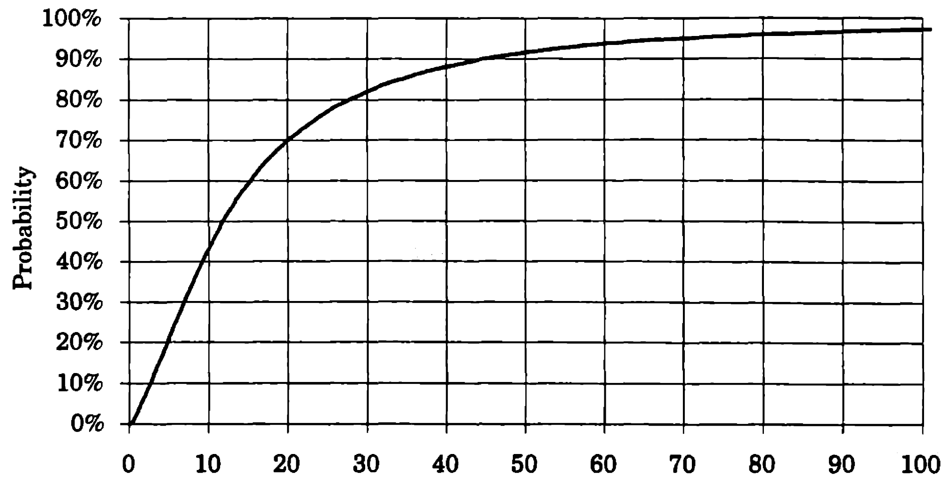

Figure C-2: The Bootstrap Simulated CDF for: α_{Phy}.

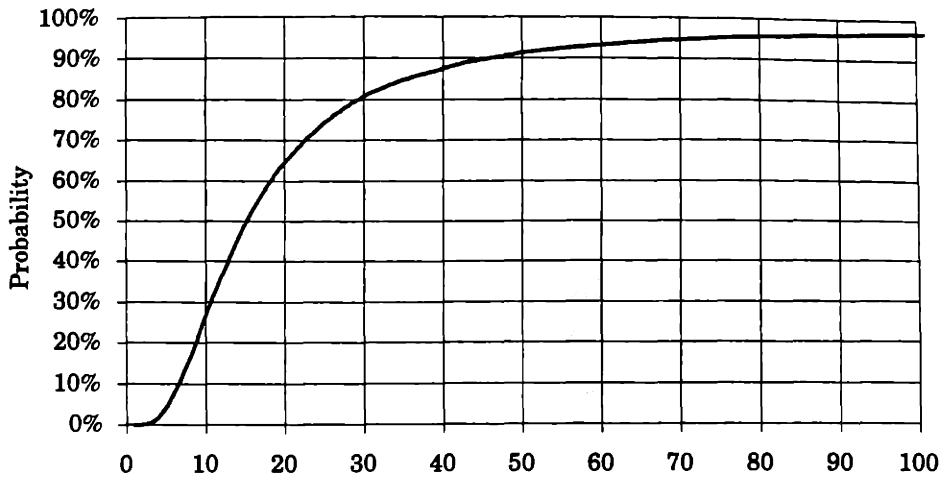

Figure C-3: The Bootstrap Simulated CDF for: α_{Lif}.

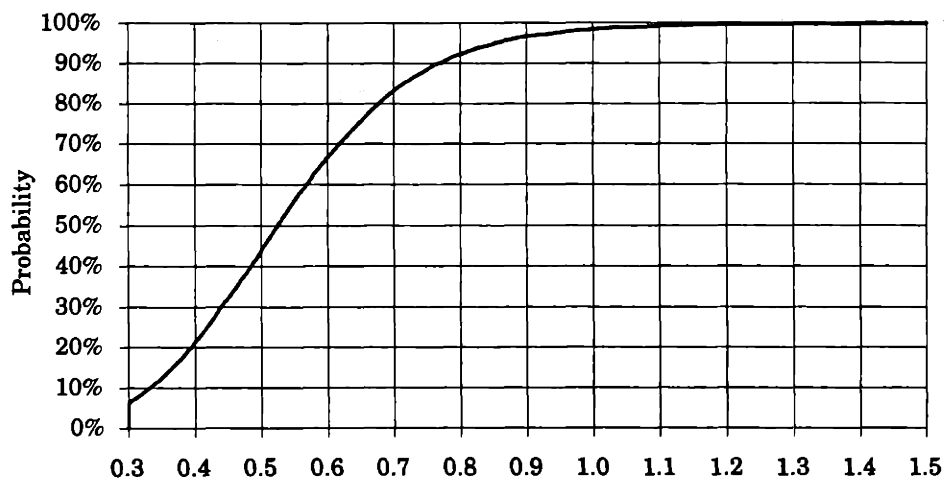

Figure C-4: The Bootstrap Simulated CDF for: β_{Eng}.

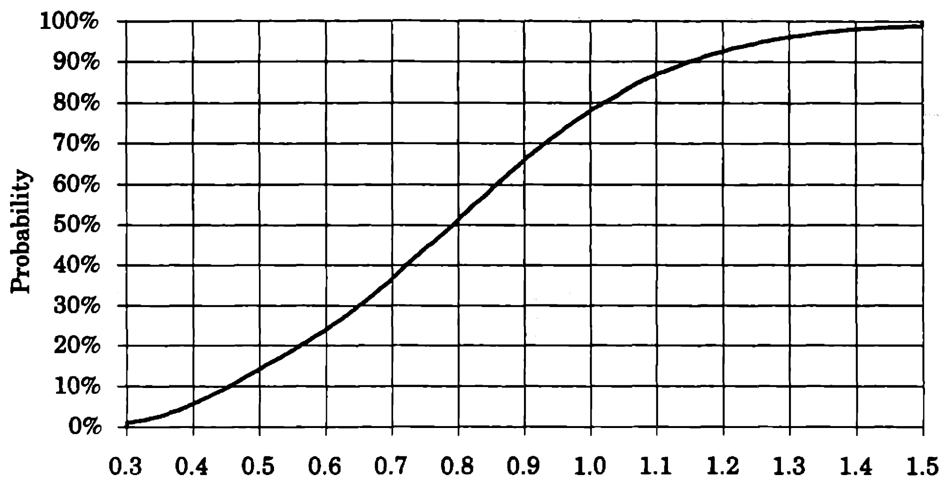

Figure C-5: The Bootstrap Simulated CDF for: β_{Phy}.

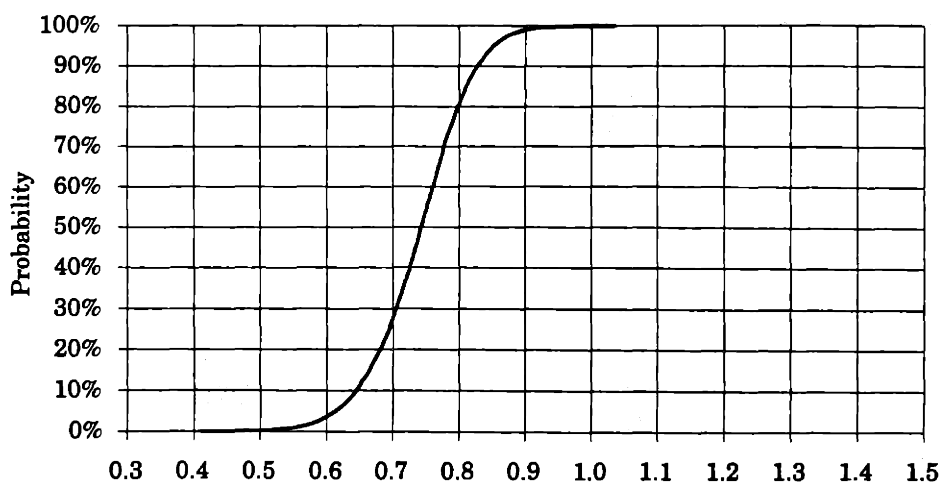

Figure C-6: The Bootstrap Simulated CDF for: β_{Lif}.

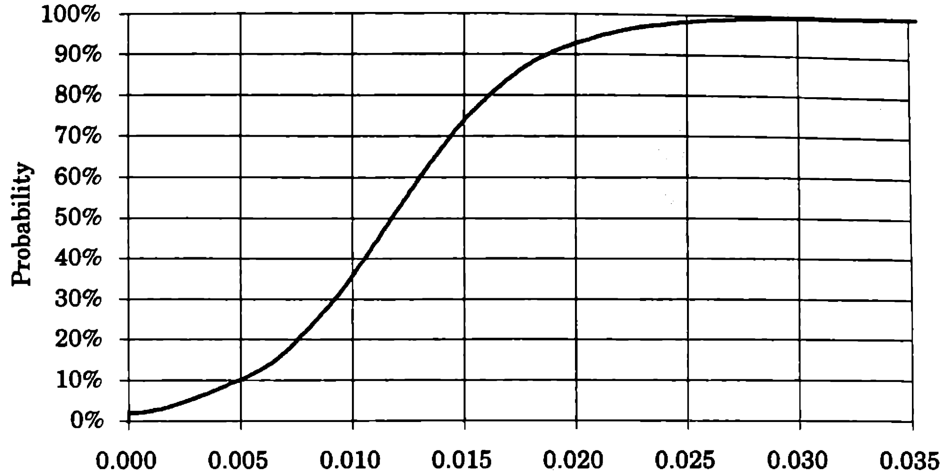

Figure C-7: The Bootstrap Simulated CDF for: γ_1.

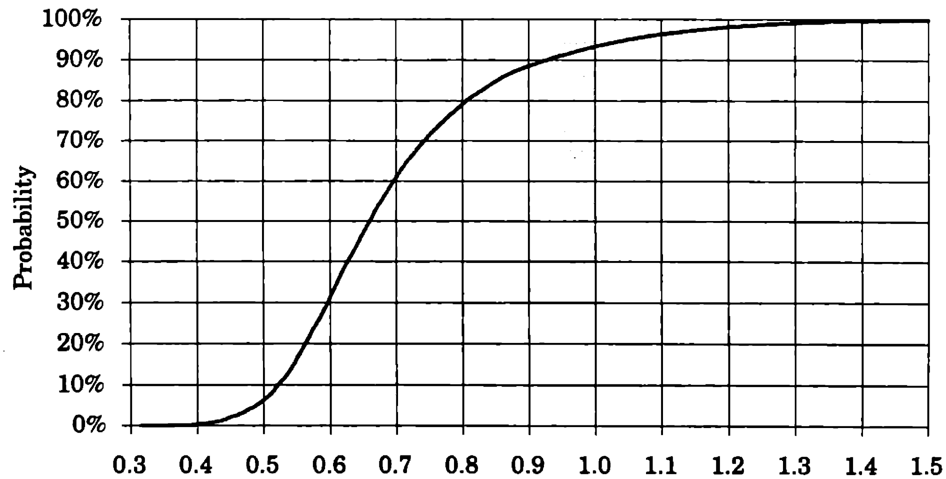

Figure C-8: The Bootstrap Simulated CDF for: γ_2.

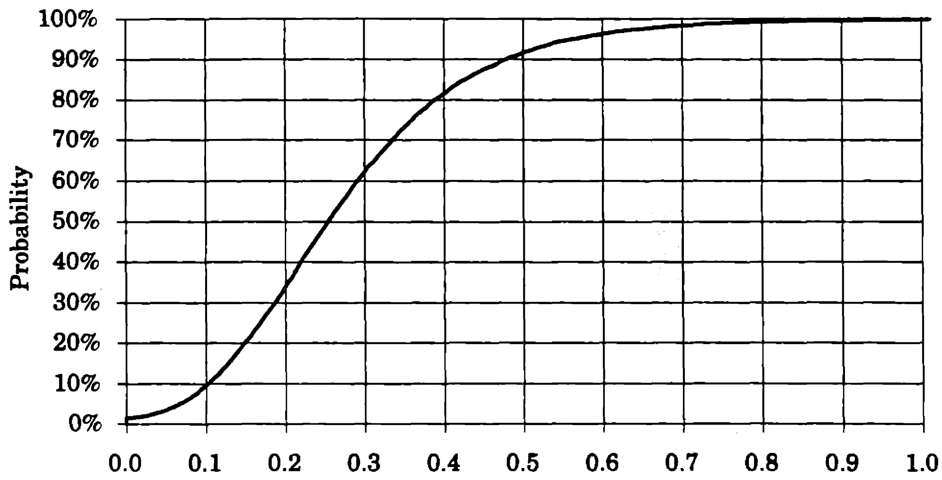

Figure C-9: The Bootstrap Simulated CDF for: γ_3.

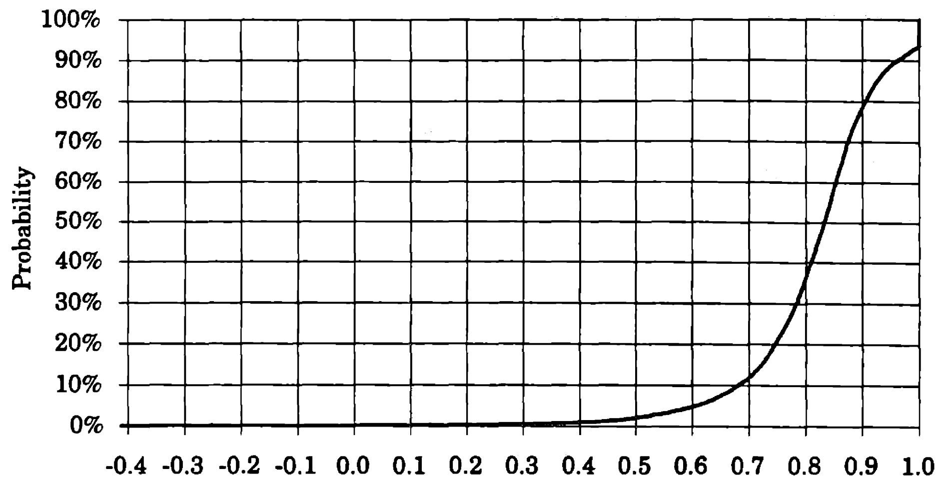

Figure C-10: The Bootstrap Simulated CDF for: δ_{Eng}.

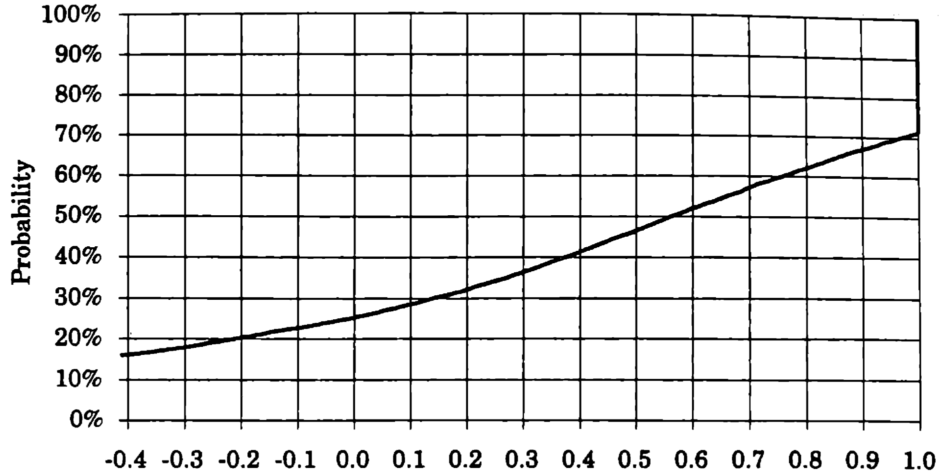

Figure C-11: The Bootstrap Simulated CDF for: δ_{Phy}.

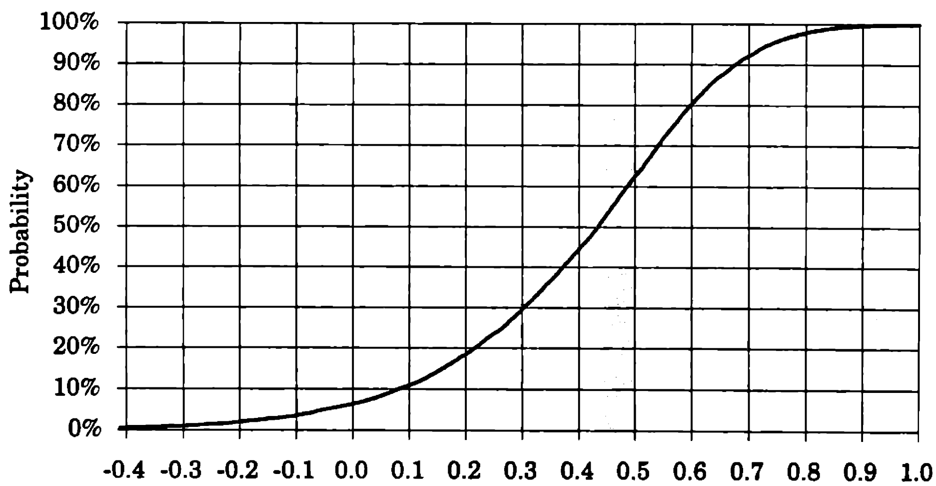

Figure C-12: The Bootstrap Simulated CDF for: δ_{Lif}.

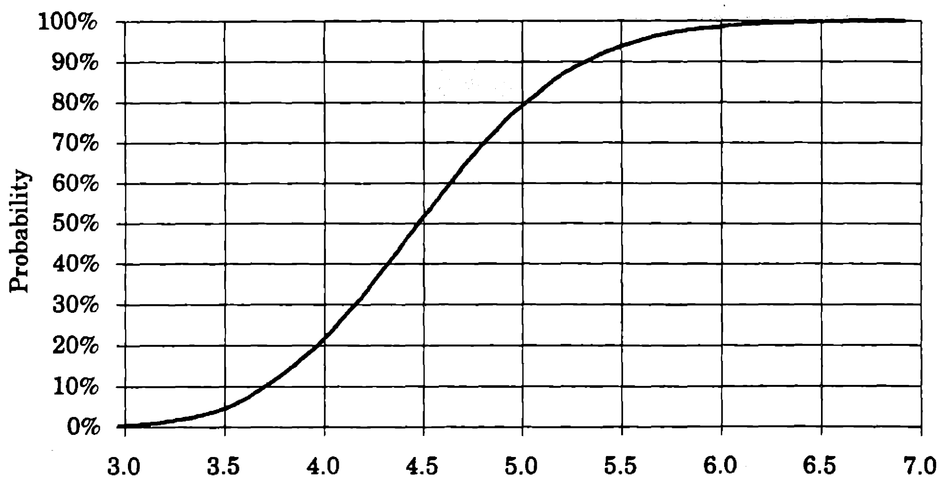

Figure C-13: The Bootstrap Simulated CDF for: Q^{2*}-statistic.

C.2 Hypotheses

One concern with the parameters of the fully relaxed model, is that the correlation between the Engineering and Physical Sciences elasticities (β_{Eng} and β_{Phy}) is very strong—the correlation coefficient is -0.64. This may be due to over-fitting. Universities with large Engineering programs are also likely to have large Physical Sciences programs. Likewise, universities with no or small Engineering programs are likely to have no or small programs in the Physical Sciences. When estimating the model parameters the objective function can be lowered by reducing the number of patents derived from Physical Sciences research and increasing the number derived from Engineering research (or vice versa) in order to get a better fit to some peculiarities in the data. To circumvent this problem one might want to impose the restriction that both departments experience the same efficiencies of scale.

C.2.1 Hypothesis 1: Engineering and Physical Sciences have the same Economies of Scale Parameter

The first hypothesis we want to test is if the Engineering and Physical Sciences departments experience the same economies of scale for research expenditures, $\beta_{\text{Eng}} = \beta_{\text{Phy}}$. From figures C-4 and C-5 we see that there is a great overlap of the probability density functions. It is however not appropriate to use these cumulative distribution functions to test the hypothesis because as we discussed earlier the two parameter estimates are not independent.

If the hypothesis was true and we had the joint distribution function for the two parameters, the probability that $\beta_{\text{Eng}} > \beta_{\text{Phy}}$ should be about 50% and the probability that $\beta_{\text{Eng}} < \beta_{\text{Phy}}$ should also be about 50%. We would reject the null hypothesis ($\beta_{\text{Eng}} = \beta_{\text{Phy}}$) in favor of the alternate ($\beta_{\text{Eng}} \neq \beta_{\text{Phy}}$) if either of these probabilities is less than 2.5%.

The bootstrap simulations provide us with an approximation of the joint distribution function. Of the 10,000 simulations 2,703 have $\beta_{\text{Eng}} > \beta_{\text{Phy}}$ while the other 7,297 have $\beta_{\text{Eng}} < \beta_{\text{Phy}}$. The p-value for the hypothesis is therefore approximately $2,703/10,000 \approx 27\%$ and we accept the hypothesis that the Engineering and Physical Sciences departments have the same economies of scale parameter, $\beta_{\text{Eng}} = \beta_{\text{Phy}}$.

C.2.2 Hypothesis 2: The Faculty Quality Coefficient is the Same for Engineering and Physical Sciences

The second hypothesis has to do with the impact of faculty quality. We want to test the hypothesis that the coefficient for the faculty quality is the same for Engineering and Physical Sciences, $\delta_{\text{Eng}} = \delta_{\text{Phy}}$. Using the same methodology as above we find that of the 10,000 simulations $\delta_{\text{Eng}} < \delta_{\text{Phy}}$ in 3,947 cases. We can therefore not reject the null hypothesis that the impact of the faculty quality in the two departments is the same.

C.2.3 Hypothesis 3: Engineering and Physical Sciences have the same Economies of Scale Parameter and the same Faculty Quality Coefficient

We now want to test the hypothesis that both parameter sets are equal; the Economies of scale parameters are the same and the influence of the faculty quality rating is the same. To test this hypothesis we look at a 2-by-2 table showing in how many cases: 1) $\beta_{\text{Eng}} > \beta_{\text{Phy}}$ and $\delta_{\text{Eng}} > \delta_{\text{Phy}}$, 2) $\beta_{\text{Eng}} < \beta_{\text{Phy}}$ and $\delta_{\text{Eng}} > \delta_{\text{Phy}}$, 3) $\beta_{\text{Eng}} > \beta_{\text{Phy}}$ and $\delta_{\text{Eng}} < \delta_{\text{Phy}}$, and 4) $\beta_{\text{Eng}} < \beta_{\text{Phy}}$ and $\delta_{\text{Eng}} < \delta_{\text{Phy}}$.

Using a hypothesis test with a 5% chance of incorrectly rejecting the null hypothesis we accept the null hypothesis if the probability mass in each of these four boxes is greater than 1.25%.

	$\delta_{\text{Eng}} > \delta_{\text{Phy}}$	$\delta_{\text{Eng}} < \delta_{\text{Phy}}$
$\beta_{\text{Eng}} > \beta_{\text{Phy}}$	2,461	242
$\beta_{\text{Eng}} < \beta_{\text{Phy}}$	3,592	3,705

Table C.1: Counts for Hypothesis 3.

From table C.1 we see that we have the fewest occurrences of $\beta_{\text{Eng}} > \beta_{\text{Phy}}$ and $\delta_{\text{Eng}} < \delta_{\text{Phy}}$, but it is still 2.4% of all cases. We therefore accept the hypothesis that both sets of parameters are the same.

We have shown that with these data we cannot reject the hypothesis that the Engineering and Physical Sciences departments both have: 1) the same economies of scale for research expenditures, and 2) the same coefficient for the faculty quality.

The primary purpose of the nonlinear model is to determine the correlation of resources provided for technology transfer and patents and licenses. We therefore reestimate our model parameters imposing the constraints we have accepted in our hypothesis testing.

C.3 The New Model Parameters

In figures C-14 to C-24 we have the bootstrap approximation for the parameter distributions of the restricted model. We will use these results in Chapter 3.

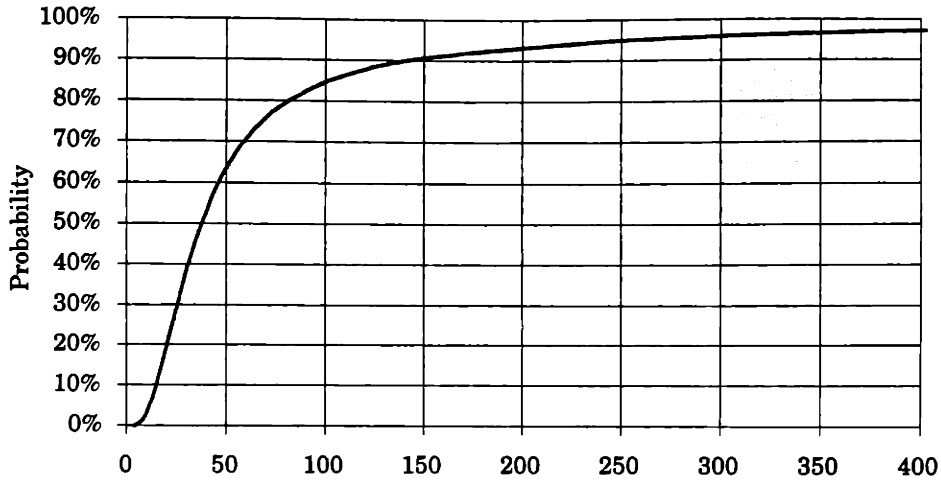

Figure C-14: The Bootstrap Simulated CDF for New Model: α_{Eng}.

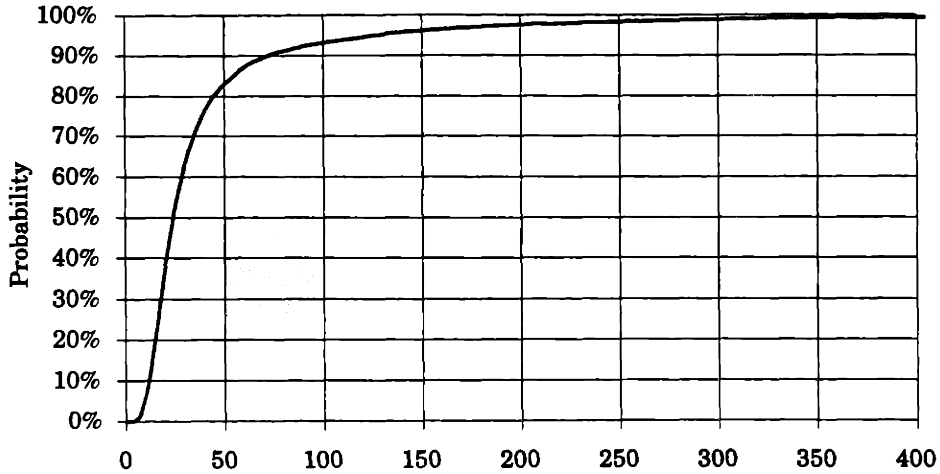

Figure C-15: The Bootstrap Simulated CDF for New Model: α_{Phy}.

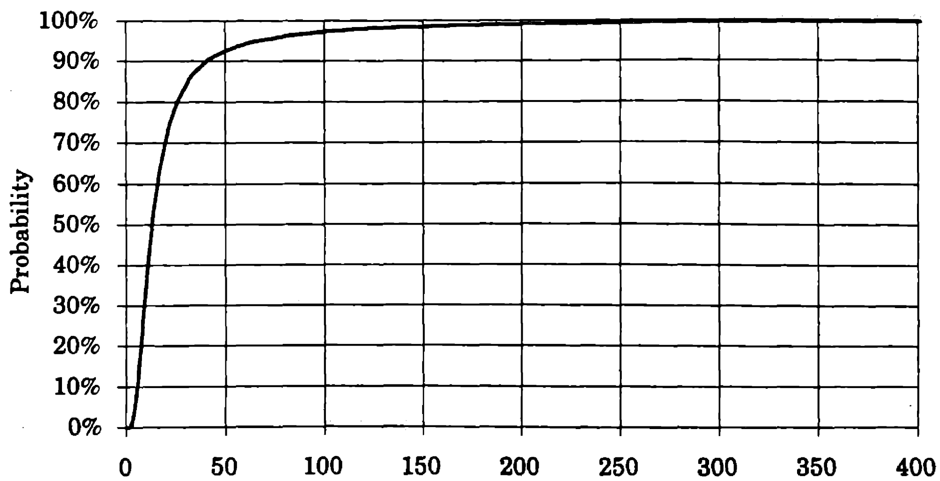

Figure C-16: The Bootstrap Simulated CDF for New Model: α_{Lif}.

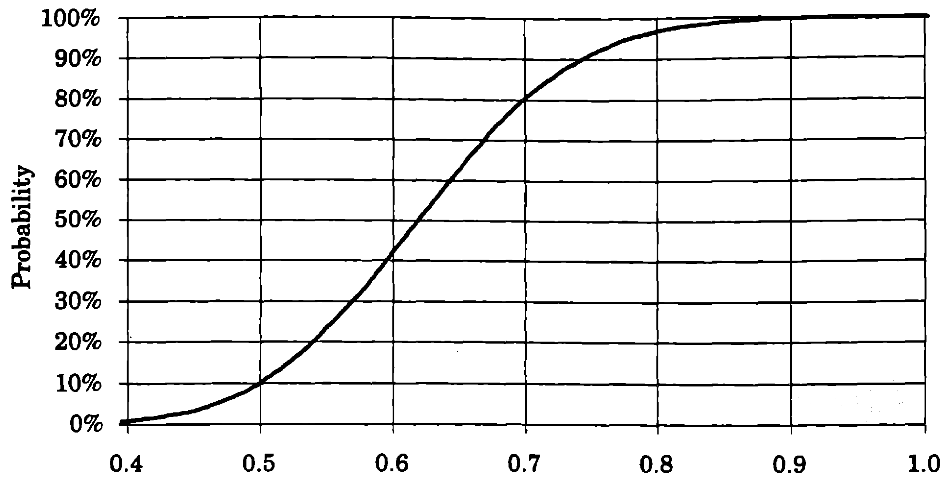

Figure C-17: The Bootstrap Simulated CDF for New Model: $\beta_{Eng} = \beta_{Phy}$.

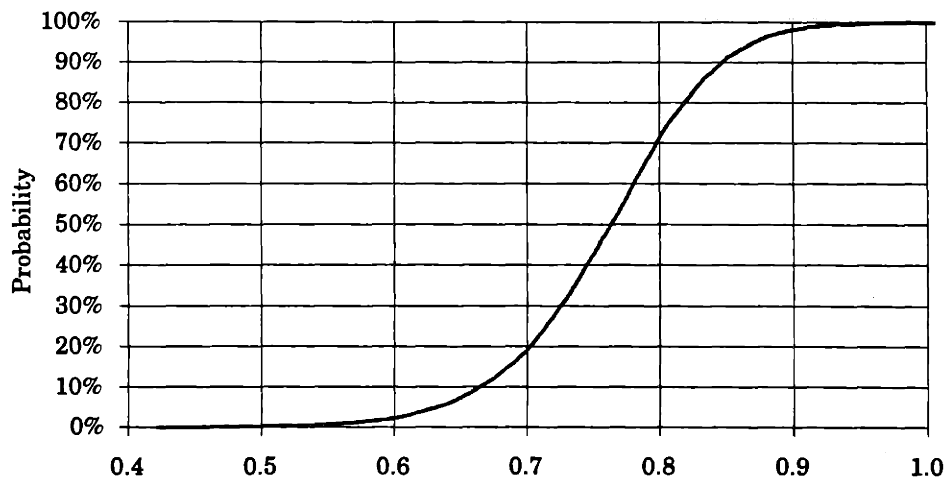

Figure C-18: The Bootstrap Simulated CDF for New Model: β_{Lif}.

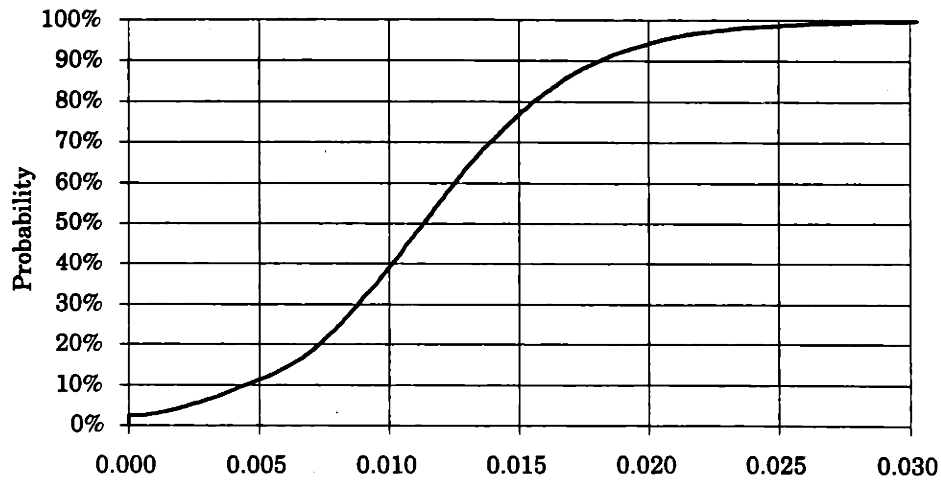

Figure C-19: The Bootstrap Simulated CDF for New Model: γ_1.

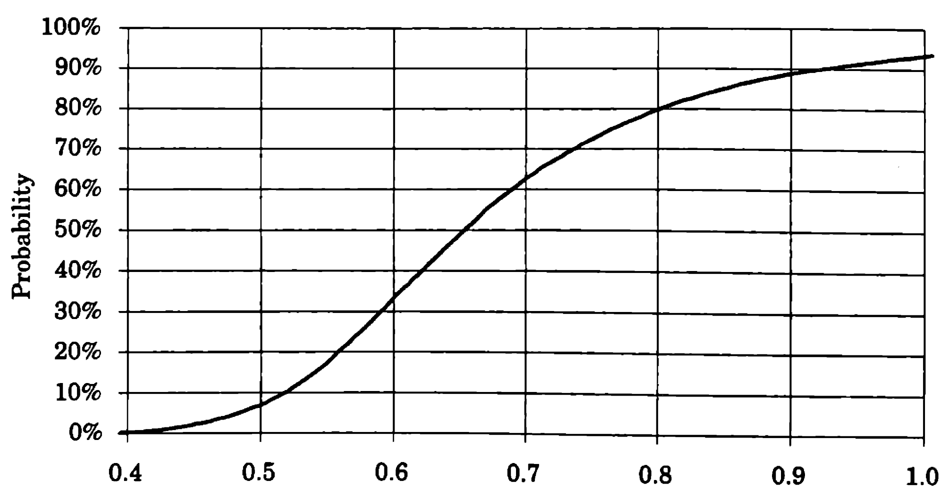

Figure C-20: The Bootstrap Simulated CDF for New Model: γ_2.

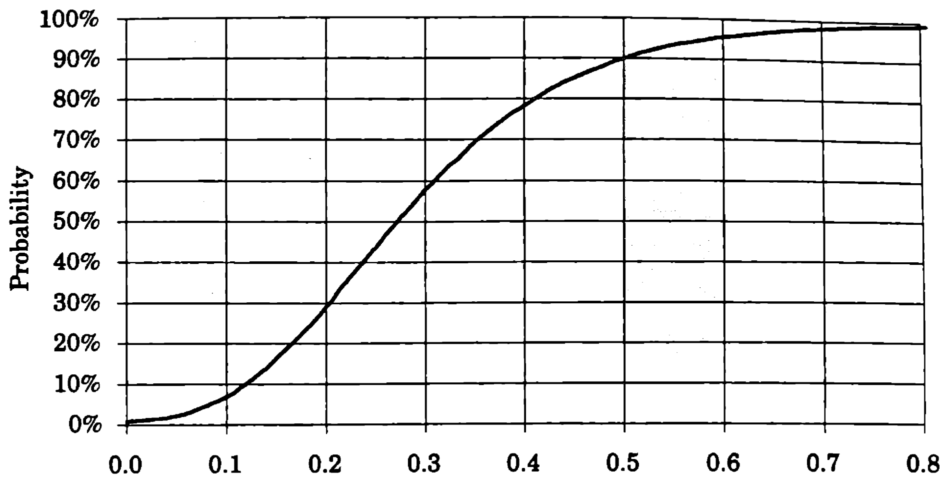

Figure C-21: The Bootstrap Simulated CDF for New Model: γ_3.

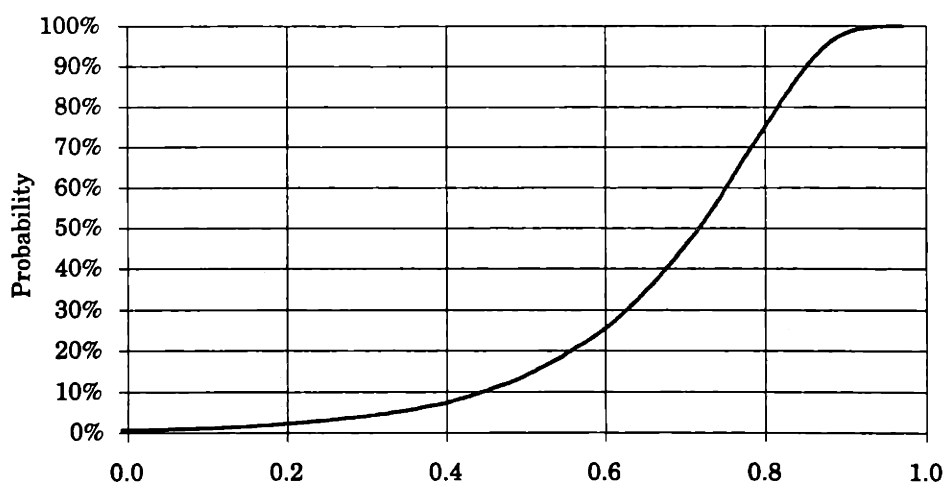

Figure C-22: The Bootstrap Simulated CDF for New Model: $\delta_{Eng} = \delta_{Phy}$.

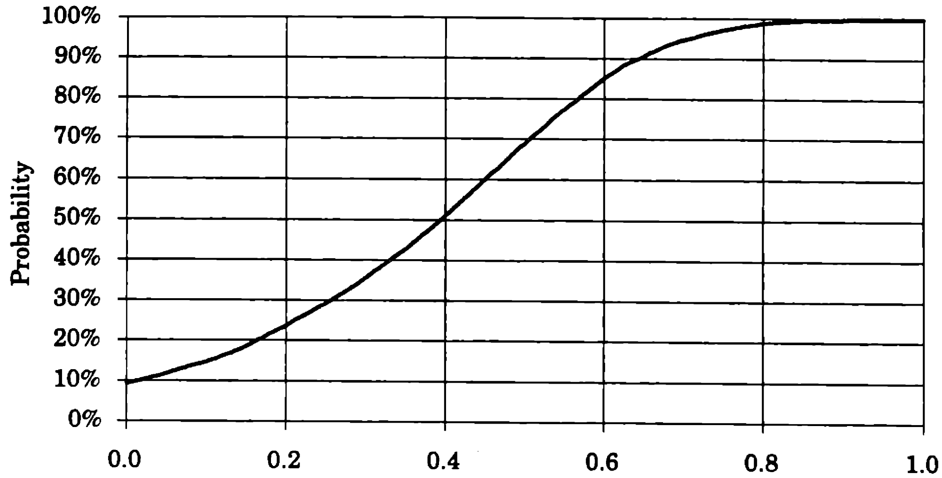

Figure C-23: The Bootstrap Simulated CDF for New Model: δ_{Lif}.

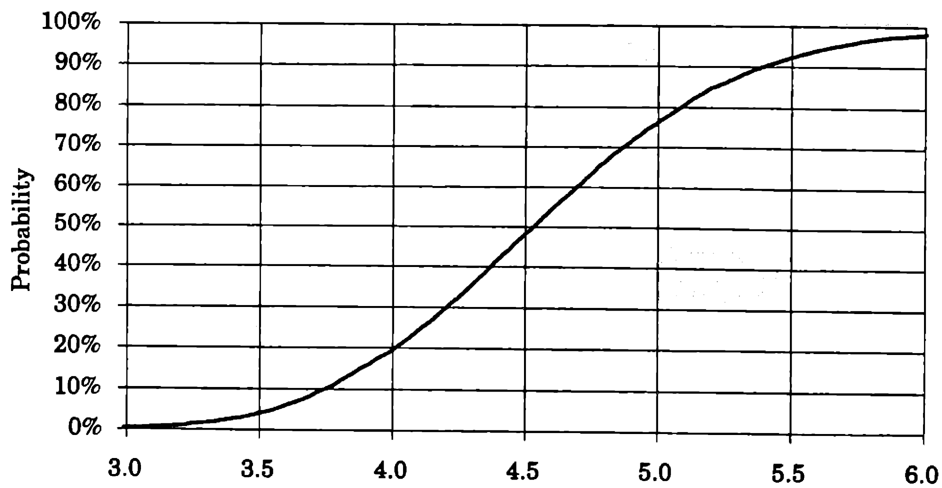

Figure C-24: The Bootstrap Simulated CDF for New Model: Q^{2*}-statistic.

C.4 Impact of the TTO in the Life Sciences

In this section we try to answer the question if the influence of the TTOs is the same for all research. More specifically: Is the TTO especially effective in the Life Sciences, or is it less effective when working with discoveries in the Life Sciences?

We split the universities in our database into two groups, 1) universities that spend more than 70% of their research money in the Life Sciences and 2) universities that spend less than 70% on the Life Sciences. Using this split, one-half of the universities in our database fall into each category.

We have reestimated the parameters related to the TTO on each of these two data sets. The TTO multipliers are plotted in figure C-25 for patent applications and in figure C-26 for licenses.

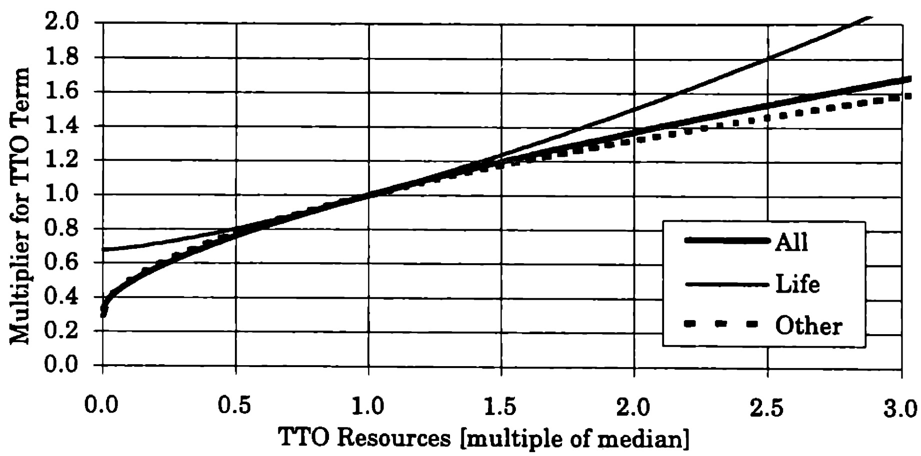

Figure C-25: The Impact of TTO Resources on Patent Applications for Universities that Focus on Life Sciences Research and Others.

We see that the difference in the multiplier is very small. For patent applications, the influence of the TTO is a little higher in the Life Sciences, but for license agreements the influence of the TTO is a little lower. If we were to hypothesize that there is no difference for the two data sets, it is *doubtful* if we can reject that hypothesis.

We conclude that the influence of the TTO is the same in the Life Sciences— where a substantial proportion of licenses concern new pharmaceutical products—and in the other Sciences. Our evidence suggests that university TTOs are just as effective for the pharmaceuticals industry as any other industry.

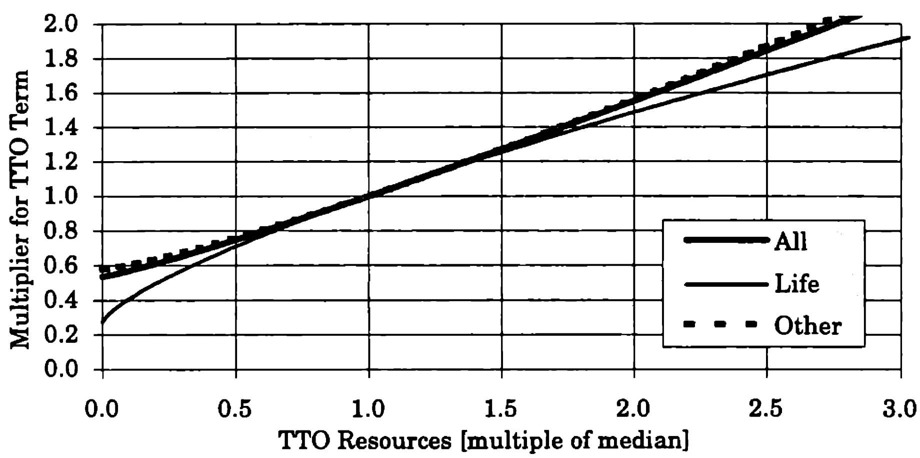

Figure C-26: The Impact of TTO Resources on License Agreements for Universities that Focus on Life Sciences Research and Others.

Appendix D

Data Envelopment Analysis

I table 4.3 in Chapter 4 we list the extended efficiency scores and the output contributions for universities with efficiency scores above 80%. In tables D.1 through D.4 we have listed these statistics for all universities in our database.

University	Extended Efficiency	Contribution: Patent Appl.	Lic. Exe.	Roy. Rec.	Fac. Pub.	Grad. Stud. Enr.	Ph.D. Stud. Grad.
U. California	∞	n/a	n/a	n/a	n/a	n/a	n/a
Stanford	403%		100%				
Brigham Young	332%		23%				77%
U. Akron	219%	30%				70%	
Cal. Tech.	173%	100%					
MIT	172%	89%	11%				
Iowa State	171%	40%	60%				
Marquette	148%	17%	83%				
U. NC, Charlotte	138%	95%	5%				
U. Chicago	136%	15%				26%	59%
U. Penn.	132%	14%			86%		
IL Inst. of Tech.	127%					51%	49%
U. Mass., Amh.	124%				79%	6%	15%
Columbia	122%			49%		51%	
SUNY	117%					100%	
Northeastern	116%	100%					
U. IL, Urbana	112%		15%		40%	36%	9%
Thomas Jeff.	111%	88%	12%				
Michigan State	110%			41%	59%		
Vanderbilt	104%		10%		90%		
U. TX, Houston	98%			3%	97%		
Rutgers	97%		3%	5%	70%	22%	
U. Florida	91%	2%	7%	14%	74%		4%
Purdue	90%	7%	15%				78%
Arizona State	90%	6%		3%	91%		
Washington U.	85%		24%		72%	4%	
Syracuse	85%			1%	99%		
Northern IL U.	84%				100%		
Ohio State	83%		8%	1%	67%		24%
U. NC, Chap. H.	82%		8%		73%	19%	

Table D.1: The Extended Efficiency Scores and Output Contributions for American Universities: First Quartile.

		Contribution					
University	Extended Efficiency	Patent Appl.	Lic. Exe.	Roy. Rec.	Fac. Pub.	Grad. Stud. Enr.	Ph.D. Stud. Grad.
Princeton	82%						100%
U. Alabama	82%	13%	12%		75%		
U. WI, Madison	81%	24%		8%	26%	42%	
Northwestern	81%			1%	75%		24%
NC State	78%	16%	12%		70%		2%
U. Oregon	78%				90%		10%
U. Utah	77%	17%	25%		56%	2%	
U. Denver	76%			11%		57%	32%
Rice	75%					49%	51%
U. Virginia	74%	7%		12%	58%	23%	
Penn State	73%				67%	33%	
Harvard	71%		22%	3%	56%		19%
Duke	70%	24%	8%		53%	15%	
Indiana	69%		21%			79%	
U. Rochester	69%	6%		14%	80%		0%
Brown	68%			3%	2%	49%	46%
Brandeis	68%		9%		91%		
U. Minnesota	67%		19%		63%		18%
U. MD, College	66%		30%			70%	
U. Washington	65%		6%	15%	63%	17%	
U. Iowa	63%	12%	6%		62%		20%
Ohio University	63%		9%		91%		
Drexel	63%			1%	99%		
Washington St.	61%	5%	17%		78%		
Yale	61%	15%	2%	4%	62%		18%
U. Michigan	60%	20%	5%		34%	39%	2%
U. South Car.	59%				90%		10%
Boston U.	59%	45%	5%			50%	
Tulane	58%			65%		35%	
U. Delaware	57%			3%	97%		
U. Kentucky	55%	15%	5%	7%	71%	2%	

Table D.2: The Extended Efficiency Scores and Output Contributions for American Universities: Second Quartile.

University	Extended Efficiency	Contribution					
		Patent Appl.	Lic. Exe.	Roy. Rec.	Fac. Pub.	Grad. Stud. Enr.	Ph.D. Stud. Grad.
U. South CA	55%	27%				73%	
Clemson U.	55%	15%		85%			
U. Cincinnati	54%			9%		44%	47%
New York Med.	53%				100%		
Medical C. OH	53%		9%		91%		
Baylor C.	53%	11%	4%	8%	77%		
Florida State	52%			5%	2%	49%	44%
U. TX SW Med.	51%	15%	4%	8%	73%		
U. Nebraska	51%	100%					
Wayne State	51%		20%		59%	21%	
Oregon State	50%	7%		2%	91%		
Hahnemann U.	49%	32%	35%		33%		
U. Colorado	49%	13%	2%	4%	61%	20%	
Georgia Tech.	49%	43%	9%			48%	
Emory U.	49%	8%		9%	83%		
Temple	45%			5%		54%	41%
U. Mass. Med.	44%			2%	98%		
Virginia Tech	42%	28%	11%		39%	3%	19%
OR Health Sci.	39%	48%	52%				
Texas A&M	38%		20%		63%		17%
U. Pittsburgh	38%	15%	3%	2%	56%	25%	
U. Tennessee	38%	7%	5%	6%	82%		
Stevens	37%				45%	25%	30%
U. IL, Chicago	37%			9%	88%	3%	
U. Kansas	37%		18%		4%	51%	27%
U. Hawaii	37%			1%	99%		
U. Connecticut	35%			2%		98%	
U. TX Med. Br.	35%			1%	99%		
Florida Atlantic	35%	45%	44%	8%		4%	
U. Arizona	35%	10%	7%		64%	19%	

Table D.3: The Extended Efficiency Scores and Output Contributions for American Universities: Third Quartile.

		Contribution					
University	Extended Efficiency	Patent Appl.	Lic. Exe.	Roy. Rec.	Fac. Pub.	Grad. Stud. Enr.	Ph.D. Stud. Grad.
Carnegie Mellon	35%	6%	10%	12%	72%		
U. Georgia	34%	5%	8%	7%	80%		
Case Western	33%	10%	5%	5%	80%		
Tufts	32%		9%		91%		
Georgetown U.	31%			2%	98%		
Auburn U.	30%			1%	99%		
U. Rhode Island	30%			16%		83%	1%
Dartmouth	28%		12%		88%		
Montana State	27%			3%	97%		
U. Tulsa	27%				44%	28%	28%
Colorado State	27%			3%	97%		
U. Miami	26%		40%		60%		
U. MD, Baltim.	26%	2%		3%	95%		
U. AL, Hun.	26%				100%		
U. TX Hlth., SA	26%		12%		88%		
NJ Inst. of Tech.	24%	98%				2%	
U. NH	23%				100%		
U. Central FL	22%	94%		6%			
U. Maine	21%				100%		
U. AR, Fayet.	19%			8%	92%		
Johns Hopkins	18%	24%	14%		49%		13%
Michigan Tech.	18%		69%		14%	17%	
U. South Florida	16%		10%		90%		
ND State	15%			39%	54%	7%	
Wake Forest	14%	38%	27%		35%		
U. Dayton	14%	37%	35%	28%		0%	
New Mexico St.	10%		11%		89%		
Mississippi St.	8.7%	52%		31%		8%	9%
U. South AL	6.0%	30%	32%		38%		
Wright State	4.3%		93%	7%			
San Diego State	2.6%	100%					

Table D.4: The Extended Efficiency Scores and Output Contributions for American Universities: Fourth Quartile.

Appendix E

Data Collection

E.1 Cover Letter and Survey Instrument

On the following four pages we have a copy of the cover letter and survey instrument that was sent to the universities we collected data from.

Árni G. Hauksson, agh@mit.edu
Massachusetts Institute of Technology
77 Massachusetts Avenue, E40-130
Cambridge, MA 02139
TEL: (617) 253 6185
FAX: (617) 258 9214

Mr. Larry R. Steranka
Director, Technology Transfer
Vanderbilt University
405 Kirkland Hall
Nashville, TN 37240
TEL: (615) 343 2430
FAX: (615) 343 0488

Cambridge, March 27, 1997

Dear Mr. Steranka;

I am working on my Ph.D. dissertation in Operations Research here at MIT. The research focuses on analyzing University Technology Transfer with special emphasis on the important role Technology Transfer Offices play.

My preliminary results suggest there is a strong relationship between the resources provided for Technology Transfer Offices and university performance with respect to licensing activities. These results might prove very interesting for universities pondering whether to increase resources made available for Technology Transfer. While I find these preliminary findings very exciting, I need to tighten some of my arguments.

I am hoping you can help me with providing some data that is very important for addressing some of those issues. So far my research is based on the data that AUTM collects annually and some additional details from the NSF and NRC. While this data is very rich, it does not tell about the order of things; does the increase in resources precede the success in Technology Transfer, or vice versa. In order analyze this issue, I have selected 12 universities that will be specially illuminating for further analysis.

While I have tried to minimize the amount of information I need, the request is not small. I am therefore more than willing to come to Nashville to help collecting the data. I will make the results from my analysis accessible to you as early as I can. Later, all data, analysis, and results will be made publicly available.

The survey consists of two sets of data. The first set is very similar to a part of what you report each year to AUTM, the only difference being that we will look at years before 1991. The other set aims at understanding the revenue stream from a sample of licenses you have executed since 1986. I have put in the numbers I have from the AUTM surveys. Please feel free to make corrections to these numbers as necessary.

I will be following up on this letter with a phone call. I look forward to speaking to you, and hope we will be working together soon.

Sincerely Yours,

Árni G. Hauksson

1. For each fiscal year, starting in FY1986, please provide the following information
   (note that all of the variables are defined in exactly the same way as in the AUTM surveys)
   (please DO NOT include licenses and patents resulting from sponsored research):
   - How many individuals employed at your institution provide professional services for Technology Transfer? (Full-Time Equivalents)
   - How many individuals employed at your institution provide staff support for Technology Transfer? (Full-Time Equivalents)
   - How much did your institution spend in external legal fees for patents and/or copyrights?
   - How many licenses/options did your institution execute in each fiscal year?
   - How many new U.S. patent applications did your institution file each fiscal year?

	Individuals providing professional services for Technology Transfer (FTEs)	Individuals providing staff support for Technology Transfer (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights	Number of Licenses/Options Executed	New U.S. Patent Applications Filed
FY1986					
FY1987					
FY1988					
FY1989					
FY1990					
FY1991					
FY1992					
FY1993					
FY1994					
FY1995					
FY1996					

2. All licenses your institution has executed since 01/01 1986, please list for each license the following information:
   a) The effective date of the license.
   b) The income for each license by fiscal year, since execution.
   c) Termination date for the license.

- Please include all licenses, also those that did not yield any income.
- Include license issue fees, payments under options, annual minimums, running royalties, termination payments, the amount of equity received when cashed-in, and software end user license fees. Do not include research funding, legal fee reimbursements, valuation of equity when not cashed-in, or trademark licensing royalties from university insignia.
- If this data can be provided in electronic format, that would be most useful.
- If it is easier for you to report for each license the amounts received by date, that would even be more useful.

	License Executed	License Terminated	FY1986	FY1987	FY1988	FY1989	FY1990	FY1991	FY1992	FY1993	FY1994	FY1995	FY1996
1st License													
2nd License													
3rd License													
4th License													
5th License													
6th License													
7th License													
8th License													
9th License													
10th License													
11th License													
12th License													
13th License													
14th License													
15th License													
16th License													
17th License													
18th License													
19th License													
20th License													
21st License													
22nd License													
23rd License													
24th License													
25th License													
26th License													
27th License													
28th License													
29th License													
30th License													

3. When did fiscal year 1997 start: ___________

4. What is the stated objective of the office of Technology Transfer at your institution? (PLEASE RANK THE FOLLOWING IN TERMS OF IMPORTANCE)
    _____ Provide service for faculty.
    _____ Generate support for sponsored research.
    _____ Push the technologies invented at the university to the marketplace.
    _____ Generate income for the university.
    _____ Other (PLEASE SPECIFY: ________________________)

5. To whom does the office of Technology Transfer report?

____

6. How is the decision about increases (decreases) in the staffing of the Technology Transfer Office made?

____

7. How is the decision about legal fee expenditures for Technology Transfer made?

____

Please direct all questions to:

Árni G. Hauksson, agh@mit.edu
Massachusetts Institute of Technology
77 Massachusetts Avenue, E40-130
Cambridge, MA 02139
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E.2 Aggregate Measures for Survey Respondents

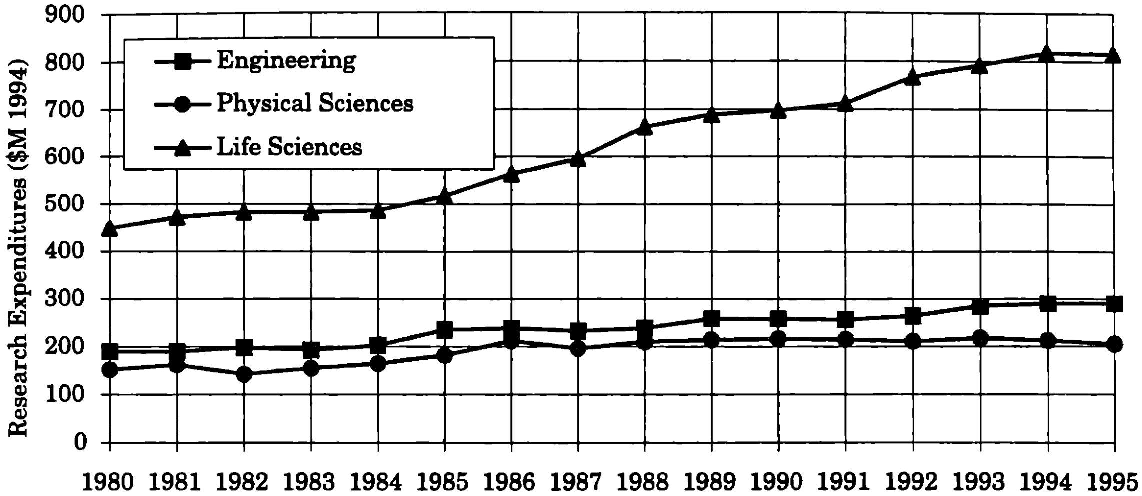

Figure E-1: Aggregate Research Expenditures Since 1980.

In figure E-1 we show how the aggregate research expenditures have changed for the eleven universities in our sample. We see that the increase in the research expenditures since 1986 in the Life Sciences is about 45%, in Engineering the increase is 22%, and in Physical Sciences there is a 3% decrease in the research expenditures.

In table E.1 we list a **conservative approximation** of how the inputs and outputs from technology transfer have increased since 1986 for the eleven universities in our sample. This approximation is conservative because in the cases where the data were not available, we use the data in the closest available year. So, for example, for Syracuse university (see table 5.8 on page 92) we assume that between 1986 and 1990 the number of professionals was constant at 2.0, staff members at 1.0, legal fees at $167,003, licenses at 2, and patents at 7.

The results from table E.1 imply that from 1986 until 1996 the legal fee expenditures have more than tripled, number of people providing staff support has more than doubled, and the number of professionals has grown by 80%. The growth in the resources for technology transfer has thus been substantially faster than the growth in research expenditures.

The results from table E.1 also imply that the number of licenses has almost tripled, and the number of patents approximately doubled. We also observe that the number of licenses takes a big jump in 1992 (mostly caused by a jump in licensing at Harvard), and that there is a small decrease in the last two years.

These results show that there has been an overall growth in technology transfer in the last ten years, beyond what we expect from increased research activity.

	Individuals Providing Professional Services for TT (FTEs)	Individuals Providing Staff Support for TT (FTEs)	Legal Fee Expenditures for Patents and/or Copyrights ($ 1994)	Number of Licenses and Options Executed	New U.S. Patent Applications Filed
1986	20.4	12.5	2,000,162	78	170
1987	22.1	14.3	2,823,896	104	187
1988	25.9	15.1	3,196,794	142	215
1989	27.1	16.0	4,286,517	105	235
1990	29.1	19.5	5,196,303	138	249
1991	30.2	20.1	5,426,591	137	217
1992	35.3	24.9	5,520,943	219	208
1993	32.8	23.1	6,051,173	230	229
1994	35.6	23.7	6,363,250	236	264
1995	32.6	27.4	6,571,526	224	308
1996	36.7	24.7	6,803,671	195	295

Table E.1: Aggregate Survey Data Approximation.

We see that in 1996, these eleven universities paid about 6.8 million in legal fees, while at the same time the total research expenditures for the three departments were about 1.3 billion. This suggests that the ratio of research expenditures in the three departments to the legal fee expenditures is about 200:1. Similarly we have on average $35 million in research expenditures per professional working on technology transfer, and about $50 million in research expenditures per support staff member. Assuming that the variable cost for each professional is $100,000, $50,000 for each staff member, and about 50% of the legal fee expenditures are reimbursed by corporations, we find that the ratio of research expenditures in the three department to the investment the universities make in technology transfer is about 160:1. So on average the universities invest $1 in technology transfer for every $160 spent on research in these three departments

Appendix F

License Income Profiles

F.1 License Quality

Our results imply that hiring additional professionals to work on technology transfer, leads to an increase in the number of license agreements. This is a very significant finding because it implies that the TTOs are stimulating the process of commercializing university discoveries.

We use license agreements as our unit of measure. But not all license agreements are equally important. Some are of no value—a firm may decide to enter a license agreement, but may then choose never to use the licensed technology, and as a result there is no benefit for the university, or the common good. Other license agreements are very important. They may lead to new products or treatments of illnesses that would otherwise not have been possible.

In the light of our finding that hiring more professionals to work on technology transfer may lead to an increase in the expected number of license agreements, we want to answer the question: "The new additional agreements that are entered as a result of hiring an extra person, are they as valuable as other agreements, or are they basically worthless?"

We build a scoring function for licenses. This scoring function is aimed at evaluating the importance of each license—if a license is worthless we want the score to be close to zero, but if the license is very important we want the score to be high. After building this scoring function we approximate the average worth of recent licenses. We build regression models that approximate the scoring function, but use limited data.

By looking at how the average score has changed over the years we can tell if the recent surge in the number of transferred technologies was at the expense of the quality of the average license, or not.

F.1.1 Scoring Function for Licenses

When evaluating the importance of a license we ideally look at each license and evaluate its importance based on the follow up research that was done, the investment that was made in developing commercial products using the licensed technology, and then look at how these products increase the well-being of the general public. This approach would eliminate license agreements from the last several years, because we don't know the impact they will have. We must find a reasonable way to evaluate the importance of a license.

The only data that are available at most universities is income data. In the data collection we asked for the income profiles of single licenses, and in table F.1 we show the universities that were able to comply with this request. We see that in all we have information about 1,850 licenses from seven universities.

University	Licenses with at least eight years of income data	Licenses with any income data
Harvard University	24	633
MIT	149	704
Syracuse University	0	15
University of Arkansas	1	14
University of Missouri	11	85
Vanderbilt University	13	98
Yale University	72	301
Total:	270	1,850

Table F.1: The Number of License Agreements Where Income Data are Available.

Using the income data, we have several alternatives for evaluating the importance of a license. One way is to use the net present value of the aggregate income. While this does intuitively make sense, it does not focus on the aspect we are primarily concerned with: the overall **influence** of the license. While it is better to have more income than less, income in the latter years is a stronger indication that the licensed technology is being used than income in the earlier years. A license that generates great income for a couple of years, and then nothing after the third year from execution, is most likely of limited use. The technology was most likely promising when the industrial party entered the agreement (thus the high income in the first two years), but the technology then turned out to be of little value and the license agreement basically "died". Another example is when a moderate income is realized in the first four years, but then a significant income is realized after that. In this case, the licensed technology may have been an unknown quantity when it was licensed to the company. The licensee performed some research for four years, and then found great use for the invention and subsequently generated substantial sales.

This shows that in terms of the license importance, income in the latter years is a stronger indication of success than income in the earlier years. Consequently, we weigh income in the latter years higher than income in the earlier years.

The more the income, the stronger the signal about the importance of a license. But is \$20,000 income twice as valuable in terms of assessing the importance of a licenses as \$10,000? Most likely not. Most license agreements involve both minimum fees and portion of profits from sales. The minimums are quite often in the range from \$1,000 to \$20,000. These minimums serve the purpose of generating some income for the university, and more importantly give the industrial party an incentive to cancel the license agreement if the licensed technology is not being used. In building the scoring function, we have chosen to take the square root of the dollar income in each year. This means that a license that has twice the income of another gets a ($\sqrt{2}-1=$) 41% higher score. Intuitively this seems to strike the right balance between differing dollar amounts.

Ideally, we look at the income for the first twenty years after execution, and then calculate the score of the license. This is however not feasible because it eliminates all the licenses executed in the last twenty years from the calculation. We use the first eight years after license execution to evaluate the score of a license. Of the 1,850 licenses, we have eight years of data for 270 licenses as listed in table F.1.

Calling $R_{i,t}$ the revenue in the t-th year for license i, the scoring function we use is,

$$S_i = \min\left[1, K\sum_{t=1}^{8}\sqrt{t}\sqrt{R_{i,t}}\right]. \tag{F.1}$$

We multiply the income factor by $\sqrt{t}$ in order to weigh the income in the latter years more. Income in the fourth year is thus twice as important as income in the first year.

We limit the score of licenses above by 1. The reason for doing this is that when a license has reached some status of quality, the income beyond that is primarily determined by factors that are not controllable or predictable. The TTO employees do not play a role in securing that a license becomes a huge success beyond some point, and the success can to some extent be attributed to luck. We have chosen the constant K such that licenses generating \$5,000 every year scores exactly one.[1]

In figure F-1 we have the cumulative distribution function for the 270 licenses. We see that of the 270 licenses, about 16% score a perfect one, while 27% score a zero.

F.1.2 Approximations of Scoring Function

To evaluate the score of a license we need the first eight years of income data. For license agreements entered in the last eight years, we do not have the full eight years of data and we need to develop a method for forecasting what the score will be. In this section we introduce models that approximate the scoring function, based on limited data.

The models we use are of the type,

[1] $K = \frac{1}{\sum_{t=1}^{8}\sqrt{t}\sqrt{5000}} = 8.67296 \times 10^{-4}$.

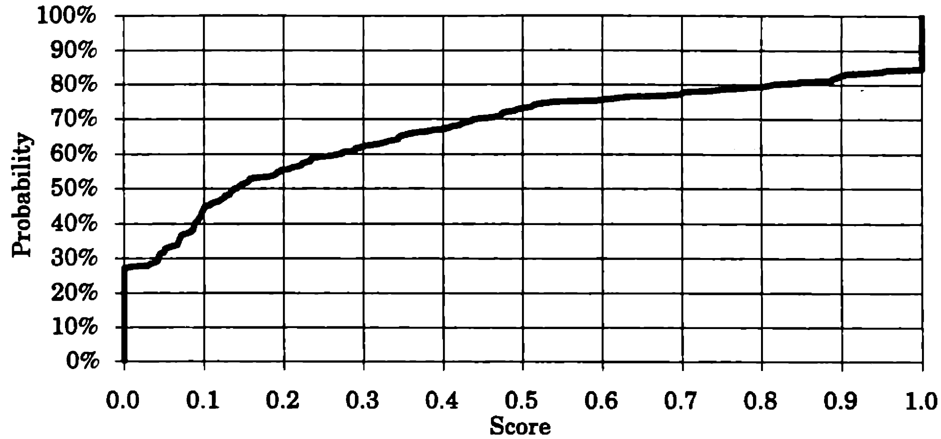

Figure F-1: CDF For License Scoreing Function.

$$\widetilde{S_i} = \min \left[1, \sum_{t=1}^{j} \alpha_t \sqrt{R_{i,t}} \right]. \tag{F.2}$$

In addition to the models of equation F.2 we also tested models where we did not fix the exponent for the income at 0.5, but estimated the best fitting parameter for that too. While these models gave a better fit, the improvement was very small and we chose to focus our analysis on the models of equation F.2.

The approximation model estimates are:

$$\widetilde{S_i} = \min \left[1, 0.112\sqrt{R_{i,1}}\right] \tag{F.3}$$

$$\widetilde{S_i} = \min \left[1, 0.080\sqrt{R_{i,1}} + 0.130\sqrt{R_{i,2}}\right] \tag{F.4}$$

$$\widetilde{S_i} = \min \left[1, 0.057\sqrt{R_{i,1}} + 0.085\sqrt{R_{i,2}} + 0.101\sqrt{R_{i,3}}\right] \tag{F.5}$$

$$\widetilde{S_i} = \min \left[1, 0.036\sqrt{R_{i,1}} + 0.046\sqrt{R_{i,2}} + 0.092\sqrt{R_{i,3}} + 0.117\sqrt{R_{i,4}}\right] \tag{F.6}$$

The sum of the squared errors for these four models are 30.4, 18.2, 12.5, and 7.8 respectively. We see there is a fast decline in the sum of the squared errors—the fit of the model using two years of data is almost twice as good as the model that only uses one year of data. We will use the second model (equation F.4) to approximate the score for the licenses.

When we look at how the average score has varied since 1986, we find that the average has not decreased. For the five universities which we have data on more than 20 licenses,

Fiscal Year	Harvard	MIT	U. Missouri	Vanderbilt	Yale
1986	n/a	0.31	n/a	n/a	0.16
1987	n/a	0.35	0.05	n/a	0.22
1988	n/a	0.36	0.22	0.41	0.24
1989	0.13	0.48	0.06	0.15	0.26
1990	0.17	0.38	0.11	0.12	0.38
1991	0.16	0.40	0.25	0.19	0.27
1992	0.16	0.41	0.11	0.44	0.24
1993	0.16	0.41	0.21	0.23	0.43
1994	0.21	0.43	0.18	0.32	0.39

Table F.2: The Average License Score Approximation.

we have listed the average approximation in table F.2, and in figures F-2 to F-6 we have plotted the approximation for all four models of equations F.3 through F.6. Notice that when we use a model that uses the income for the first two years after license execution, we do not have the averages for fiscal years 1995 or 1996.

We see that at Harvard the license score is close to 0.16 until it jumps up to 0.21 in 1994. At MIT the average score is increasing until 1989, and it then settles at about 0.40. At the University of Missouri and Vanderbilt there is a lot of variation in the average score, but we do not see a downwards trend. There is an upwards trend at Yale University, but there are also large jumps up and down. When we use the other models in equations F.3 through F.6 to approximate the average license scores, we see the same patterns as above for the five universities.

F.1.3 Conclusion

In this section we first argued that the only feasible way to determine the importance of licenses is to use income data. Based on income data from seven universities we built a scoring function for licenses. The goal of this scoring function is to replicate as well as possible the importance of a license. The importance of a licenses is determined by how much further research is induced by the licensed technology; how much product development and marketing is induced; and most importantly, by the increase in the well-being of the general public. It is not an easy task to determine the importance of a license, but we argue that our scoring function does as good a job as possible at capturing these effects. In order to predict the score of licenses where we do not have the full eight required years of data, we build an approximation for the scoring function. This approximation uses only information about the income in the first two years after license execution to predict the importance of the license. Based on this approximation we show that the average importance of a license has not deteriorated in the last ten years.

The primary goal of this section is to show that using license counts is a **reason-**

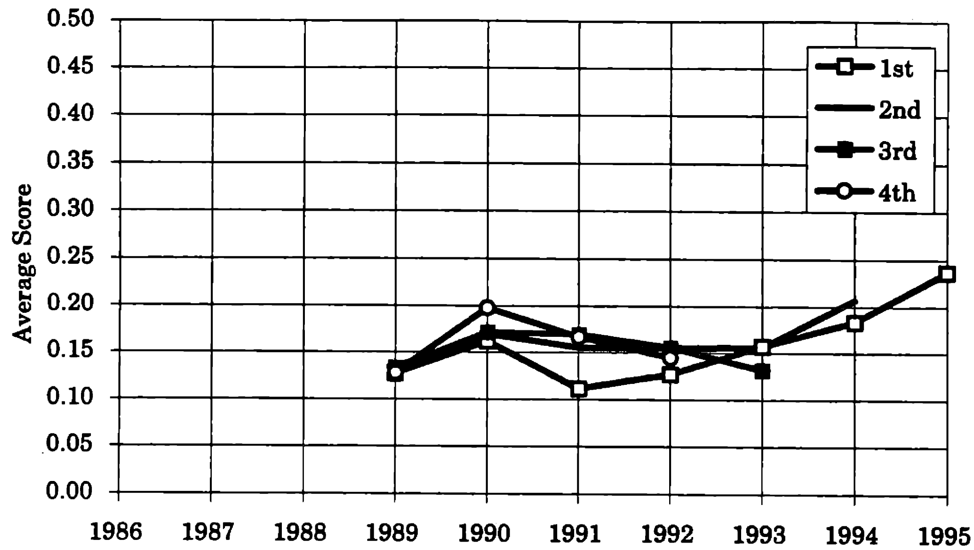

Figure F-2: Harvard University: Average Approximation of License Score.

able way to measure how much technology is transferred from a university. Ideally, we analyze the impact of each licenses, and from its success determine the effectiveness of the licensing activities. It is, however, not possible to go into this level of detail, and the best we can do is to use license counts. We can, however, check to see if the license agreements that were executed in recent years have on average the same "potential" as license agreements executed many years ago when the TTOs did not seek applications for university inventions as aggressively as today.

We do not find evidence of deterioration in the average license quality. We find, on the contrary, that if there is any change in the average license quality in the last few years, the average license executed today has a higher potential than the average license executed in the late eighties. We must conclude that using license counts is a reasonable way to measure how much technology is transferred from a university.

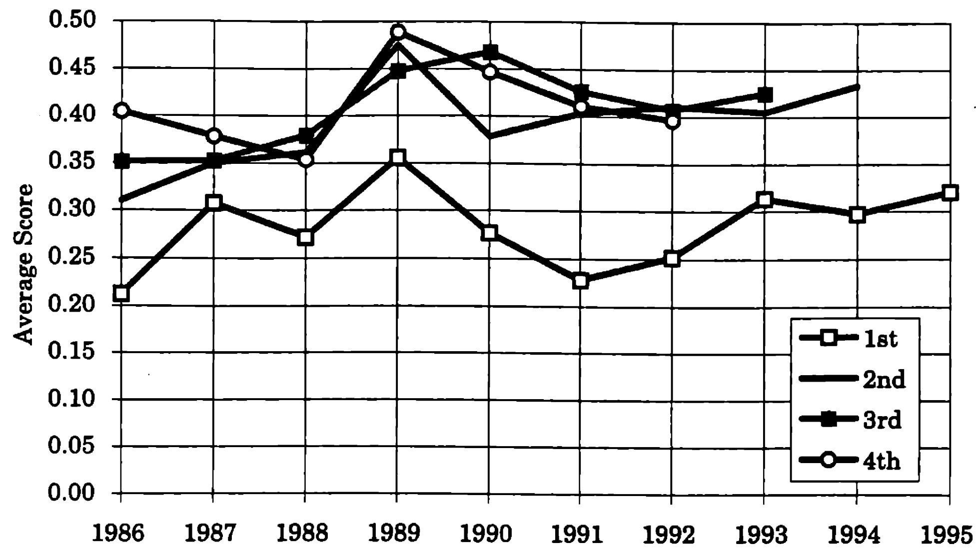

Figure F-3: MIT: Average Approximation of License Score.

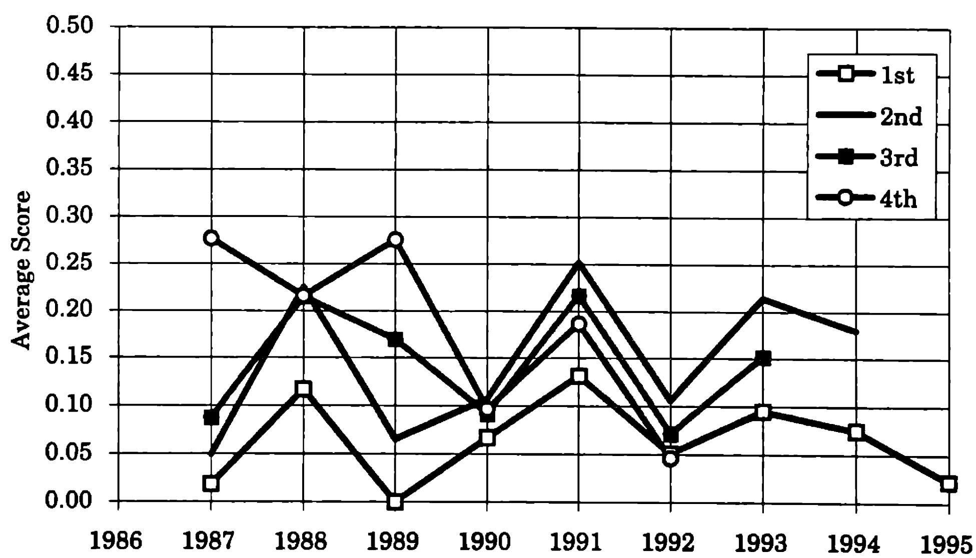

Figure F-4: University of Missouri: Average Approximation of License Score.

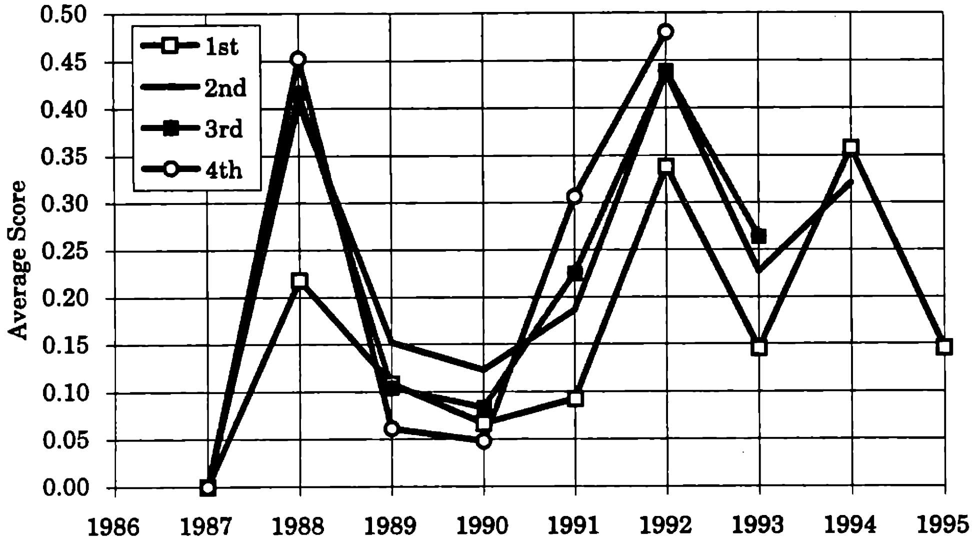

Figure F-5: Vanderbilt University: Average Approximation of License Score.

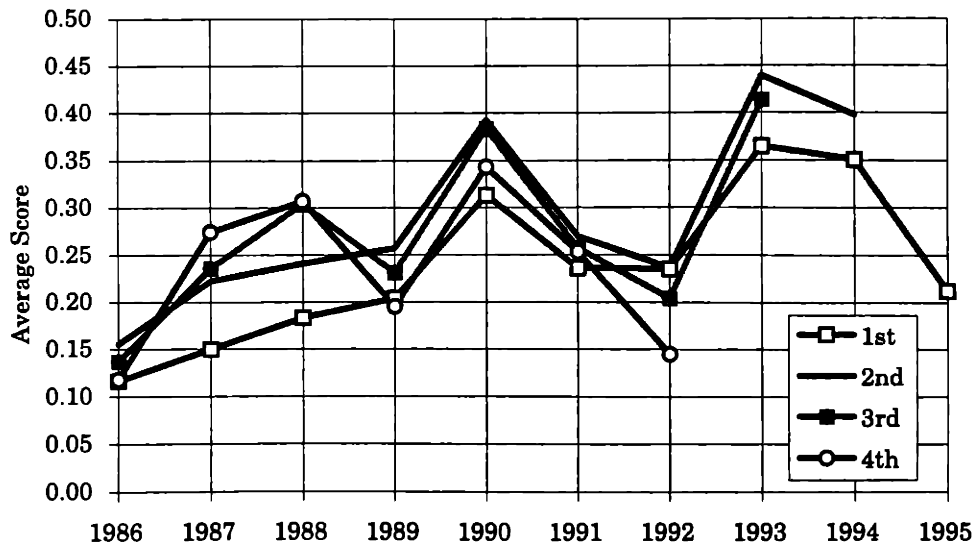

Figure F-6: Yale University: Average Approximation of License Score.

F.2 Net Present Value Estimate of a Licenses

Lets work out a rough estimate for how valuable a license is. In the data collection we undertook, we asked universities to provide detailed information on license income. Table F.3 has the average income by year and net present value using a 10% discount rate.

Year	Average Income (1994-dollars)	Number of Observations	Net Present Value of Revenue Stream Upto and Including Year (1994-dollars)
First Year	$13,400	1,427	$12,800
Second Year	$9,200	1,280	$20,800
Third Year	$9,400	1,076	$28,200
Fourth Year	$6,400	880	$32,800
Fifth Year	$20,600	687	$46,200
Sixth Year	$7,000	533	$50,400
Seventh Year	$6,100	394	$53,600
Eighth Year	$11,300	270	$59,100
Nineth Year	$32,200	174	$73,500
Tenth Year	$2,700	93	$74,600
Eleventh Year	$3,100	42	$75,700
Twelveth Year	$1,100	19	$76,000

Table F.3: Average License Income by Year and Net Present Value.

We find that the net present value of the income in the first ten years is about $75,000. This does not suggest that ten years after entering a license agreement, we should expect in most cases to have received about $75,000 in royalty income. There is a very large variation in the license income, and as an example about one-third of the licenses do not yield **any** income in the first ten years.

Often a license is based on a patented technology, so lets also factor in the patenting cost. The number of patent applications American universities have filed in the last four years is a little higher than the number of license agreements, and in Chapter 5 we found that the average cost of a patent is about $31,000. Usually the licensee reimburses some of cost of the patent prosecution. The average reimbursement was about 50% in 1995. So the total patenting cost per licenses is close to $18,000.

In a survey of university technology transfer offices it is reported that the average salary of a licensing manager at a mid-size university is $49,000. Lets assume that after incorporating other indirect costs, the total variable cost of employing one professional is $100,000.

The present value of the expected license income is about $75,000. For each license, we have approximated the associated patenting cost for the university at $18,000. The expected net income for a license is thus about \$57,000. Lets assume the inventor gets 40% of this income (this is a generous estimate for the inventor), and the university the rest. The expected increase in university income from one license is thus about \$34,000. These estimates imply that if a new professional can increase the number of license agreements by at least three per year, it is a good investment for the university to hire that professional.

Our results from Chapter 5 imply that, other things being equal, a university should expect at least three more licenses as a result of hiring a professional. Our results from Chapter 3 suggest that on average we get 2.2 more licenses for each professional, but this estimate is based on cross-sectional analysis, and consequently not as reliable as the estimate from Chapter 5.

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