Bridging the Innovation Gap Through Funding: The Case of MIT Deshpande Center

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Abstract

The idea of gap-funding program, in which academic scientists are given research funding for developing proof-of-concept and prototype, has recently attracted attention as a policy measure of commercializing academic science. While the earliest programs of its kind were initiated about a decade ago, we still lack empirical evidence on its effectiveness. Using the detailed dataset of the gap-funding program at MIT, the Deshpande Center for Technological Innovation, I observe two mechanisms that gap-funding program can facilitate academic commercialization. First, by providing research funding that allows academic freedom of problem selection and mode of disclosure, gap-funding program attracts applications from junior faculty members with commercialization interests. Second, providing research funding for prototype development and networking opportunities with industry practitioners increases the likelihood that an academic invention results in start-up founding. Moreover, its positive impact is larger for inventions without intellectual property rights protection, partly because of the reduced level of uncertainty after prototype development. However, awarding gap-funding does not increase the likelihood of technology licensing to incumbent firms. Together, I argue that gap-funding program can be a useful policy toolkit for regional economic development by fostering academic entrepreneurship.

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1. Introduction

While the amount of scientific knowledge that has commercial value tends to increase consistently, our societal ability to translate it into a finished commercial product and thus realize its full economic potential is still lagging. Both academic researchers and policy makers have been deeply interested in policy measures designed to increase the likelihood of commercializing academic science, with the hope that the increased rate contributes to superior firm performance and sustainable economic growth. Arguably, the Bayh-Dole Act of 1980 is the most well known example of such policy intervention (Mowery, Nelson, Sampat, & Ziedonis, 2001). The enactment allows universities to claim intellectual property rights on the research output generated from federally funded research projects, and is expected to facilitate the commercialization of academic science by incentivizing both firms and universities to participate actively in that endeavor. Universities are incentivized to participate actively in 'selling' university inventions to industry, in expectation to create new source of financial revenue stream from royalties. By exclusive licensing agreement, firms can also achieve a monopolistic profit if the commercialization of licensed technologies is successful. This compensates for the relatively high risk related to commercializing embryonic technologies, which is an inherent characteristic of academic inventions (Colyvas et al., 2002).

Since then, the number of all university patents has increased so drastically that the proportion of university patents among all U.S. patents has also steadily increased, implying the increase of the rate of knowledge flow from academic institutions to industry (Henderson, Jaffe, & Trajtenberg, 1998). At the same time, universities have established various institutions designed to stimulate the commercial application of university inventions. A representative example of this kind is Technology Licensing Offices (TLO), or Technology Transfer Offices

(TTO), which aim to monitor, manage, and market universities inventions to for-profit and non-profit sectors. Specifically, TLO mandates all university scientists to disclose their inventions to the office, evaluates the commercialization potential of reported inventions, and files patent applications for inventions that they evaluate as commercially promising ones. At the same time, it actively advertises its pool of patents to potential licensors, and manages all the transactions related to licensing contracts and post-licensing revenue sharing. A qualitative investigation on the success of MIT as an entrepreneurial university points out that the expertise and social capital of officers at the MIT Technology Licensing Office contribute to its higher spin-off rate (Shane, 2004 Chapter 4).

Even with the increase in university patenting and universities' endeavor for its commercialization, a series of empirical evidence suggests that the degree to which academic science is commercialized is still below the socially optimal level. One of the fundamental barriers to commercializing academic science is its embryonic state, that is, lack of a proof-of-concept or prototype (Jensen & Thursby, 2001). Under the open science institutions, priority of discovery forms a basis to determine an individual's level of rewards and reputation (Dasgupta & David, 1994). Academic scientists thus do not have strong incentives to take additional steps to find out whether their scientific discoveries are technically feasible, satisfy specific functionality that its application area demands, or meet cost-performance threshold that is required for industrial use. In comparison, for-profit firms and venture capitalists respond that the embryonic characteristic that is inherent in most university inventions is a major hurdle to license or invest in university inventions. A survey of industry licensing executives shows that the main reason of not licensing university inventions is the early stage of development of university inventions (J. Thursby, Jensen, & Thursby, 2001). Similarly, venture capitalists that regularly receive investment proposals from universities also respond that they prefer to invest in inventions with proof-of-concept already developed, even if a majority of university inventions in the proposals is at the embryonic stage (Wright, Lockett, Clarysse, & Binks, 2006). In sum, there is a gap of development between university inventions that are on the shelf of commercialization and industry demands.

'Gap-funding program' has attracted much attention as an alternative policy option to fill the gap between academic invention and commercial innovation. A defining characteristic of gap-funding program is that it provides academic scientists working in universities with the research funding that can be used to develop proof-of-concept or prototype, and by doing so, fills the funding gap between federal research budget usually aimed at basic research and industrial R&D budget and venture investment for commercialization. In some sense, universities adopting gap-funding program act as an internal venture capitalist, as they play an active role in selecting and supporting commercially promising technologies while taking risks at the same time, and provide appropriate guidance for technology commercialization, including business guidance, mentoring, and networking with industry practitioners. The gap-funding program at MIT, the MIT Deshpande Center for Technological Innovation and its Ignition Grants and Innovation Grants programs, is first created in the Fall 2002 semester. Since then, it has been regarded as a role model for such program, whose practice starts to be imitated and diffused to other research-based universities across the U.S. (Gulbranson & Audretsch, 2008). It is also noteworthy that the gap-funding program at MIT model also inspired the Obama administration recently, and as a result, the National Advisory Council on Innovation and Entrepreneurship (NACIE) launched the "i6 Challenge", a grant program aiming to replicate the proof-of-concept center similar to the MIT Deshpande Center for Technological Innovation in other states.

Though gap-funding program start to receive considerable attention from policy makers and university administrators, our theoretical and empirical understanding for such practice is non-existent. This paper is the first academic effort to systematically understand the rationale, key characteristics, and expected consequences of gap-funding program, using the case of the MIT Deshpande Center as an empirical setting. I begin by reviewing existing literature on the economics and sociology of science, and provide explanations on what distinct role gap-funding program plays as compared to other prevalent university programs for technology commercialization and entrepreneurship, what are the expected effects of awarding financial and non-financial support to university inventions, and what type of academic scientists benefits the most from the establishment of gap-funding program. I then present the case study on different gap-funding programs currently being operated by many U.S. research-oriented universities, aiming to developing key variables in the design of gap-funding programs by focusing on their similarity and difference. A detailed case study on the history of the gap-funding program at MIT will be followed, which I expect will provide an intuitive summary on the profile of applicants.

The latter part of this paper is devoted to econometric analysis on the profile of academic scientists applying to the grant program, and on the difference between MIT inventions supported by the gap-funding program and other MIT inventions. The first econometric analysis allows us to identify the profile of academic scientists "interested" in technology commercialization, independent of "noises" from their current social status and available resources. In most cases faculty members apply for university gap-funding programs when they have research ideas that they believe to have commercial potential, and they actually conduct the research to prove the concept once the gap-funding is given. In contrast, patenting, licensing, or academic entrepreneurship happen when a faculty member possesses knowledge with commercial value, so they are more representative of one's "ability" of conducting applied research. Our analysis identifies faculty members more likely to be responsive to any policy measures aiming to foster technology commercialization from academe, and therefore provides more useful findings for policy-makers.

Likewise, the second econometric analysis helps us to evaluate if providing gap-funding causes any difference in terms of the likelihood of invention commercialization. Comparing the likelihood of commercialization between inventions supported by gap-funding program and other academic inventions is arguably the most obvious way to evaluate the success of gap-funding program. By interacting the treatment of receiving gap-funding with various individual-level variables on one's prior experience in commercialization, academic status etc., I further aim to identify the profile of academic scientists that are likely to receive a disproportionate benefit when the support from gap-funding program is given. Together, I hope that these analyses will enlighten practitioners who want to use this novel policy measure to maximize the level of contribution from academic science to a larger economic entity, as well as provide novel insights to social science scholars on the micro-level process of academic commercialization.

2. Literature Review

In this section I summarize prior research on patenting, licensing and entrepreneurship behavior of academic scientists that are relevant for the understanding of gap funding programs. While policy makers and university administrators begin to conceive gap-funding programs as a potentially useful policy tool to increase the rate of technology commercialization and entrepreneurship from basic research conducted in academic institutions, empirical evidence on the effectiveness of gap-funding programs is scarce. Rather than reviewing a limited number of studies explicitly discussing existing gap-funding programs, I choose to review a broader set of literature on university technology commercialization and academic entrepreneurship, which I hope provides theoretical grounds on the rationale of establishing gap-funding programs, as well as some predictions on the effect of such programs on the behavior of academic scientists and on the likelihood of technology commercialization. For that purpose, this literature review is composed of three building blocks. First, I begin by discussing that why embryonic state of academic science makes its commercialization in the market so challenging. Second, I summarize existing university institutions that are designed and implemented to increase the rate of technology transfer from academia to industry, via licensing to incumbent and start-up firms. I pay particular attention to how each program is intended to deal with a certain type of barriers to innovation, and argue why there still exists a missing link from academic science to commercial science, a gap that gap-funding program is expected to fill in. Finally, I summarize existing literature on the profile of academic scientists who have been successfully participated in academic commercialization. The final section provides a basis to conjecture what types of academic scientists receive a disproportionate benefit in the process of academic commercialization if supported by gap-funding program.

2.1 Embryonic state as a barrier to academic commercialization

Academic institutions, and particularly research-oriented universities, have several advantageous norms and cultures in positioning themselves as efficient social mechanism to produce and disclose early-stage scientific discovery. First, the priority-based rewarding system provides considerable incentives for academic scientists to disclose their novel funding to scholarly peers and general public via publications (Dasgupta & David, 1994). This practice of "open science" is instrumental in encouraging academic scientists to overcome the concern of not being able to appropriate private benefits related to knowledge production. Second, academic institutions are economically more efficient than industrial R&D sectors in conducting inherently riskier early-stage research (Aghion, Dewatripont, & Stein, 2008). Since scientists often accept lower wages if the working environment they choose allows academic freedom in terms of project selection and mode of disclosure (Stern, 2004), academic institutions are able to hire scientists more economically. Early-stage research, characterized by high likelihood of failure and diverse lines of inquiry, can be thus conducted in academia in a more efficient manner.

A number of macro and micro-level research have suggested that early-stage knowledge created in academic institutions can be an invaluable input in enhancing performance of firms absorbing the scientific knowledge and sustaining the rate of economic growth. It is generally agreed that the overall stock and flow of knowledge are major driving force for sustaining economic growth (Mokyr, 2004; Romer, 1990). On the macro level, the mere fact that research universities as academic institutions are designed to encourage rapid disclosure of novel discoveries implies that university research is one of the essential sources for knowledge production and diffusion. On the micro level, prior literature has identified several mechanisms through which scientific discoveries from university enhance the productivity of firms, and in turn, regional and national economy. At the invention level, patents citing academic publications are on average receive more forward citations than comparable group of patents that do not cite academic publications, which suggests that scientific discoveries from research-oriented universities are conducive to breakthrough commercial discovery (Fleming & Sorenson, 2004). Similarly, industry patents that result from collaborating with academic scientists turn out to have more forward citations than patents that are developed solely by industrial R&D (Zucker, Darby, & Armstrong, 2002). Regional presence of star scientists promotes the firm founding and new business areas in the nascent industry (Zucker, Darby, & undefined author, 1998).

Given the potential contribution of academic science, a natural question to ask is how scientific discovery are diffused and thus applied by entities outside the boundary of academic institutions, whether the current rate of knowledge flow can be further improved. Unfortunately, existing literature suggests that academic science, even if the discoveries are codified, tends to "trapped inside the ivory towers" (Bikard, 2012). University inventions in most cases are so embryonic that without the active engagement of inventors, the chance of successful commercialization is scarce (Agrawal, 2006; Jensen & Thursby, 2001). It is argued that licensing, when accompanied by output-based incentives such as equity, can be an effective way to increase the chance of commercialization successes (Jensen & Thursby, 2001). However, the mere fact that university inventions are embryonic is the major hurdle for them to be licensed. In fact, the survey that Jensen and Thursby conducted indicates that about 75 percent of licensed university inventions are embryonic, that is, without proof-of-concept or prototype beyond lab scale, and that not many firms are willing to licensing academic science because of the embryonic state (J. Thursby et al., 2001). Similarly, venture capitalists who regularly receive investment proposals from universities also respond that they prefer to invest in inventions with proof-of-concept already developed, even if a majority of university inventions in the proposals is at the embryonic stage (Wright et al., 2006). Similarly, a case study reports that university spinoff companies might not have any proof of concept results, prototype, and specific business plan with well-defined customer needs, competitor analysis, and product concept, but in such case receiving seed-stage funding from venture capitalists or other types of private sector would be extremely difficult, due to the huge amount of uncertainty behind the invention (Shane, 2004). The existence of possible friction in the technology transfer process from academic institutions to for-profit firms poses a serious challenge to our model of efficient societal knowledge production (Aghion et al., 2008).

2.2 Process and programs for academic commercialization

To understand the potential barriers of academic commercialization, and how existing programs attempt to deal with some of these barriers, thereby stimulating more active academic commercialization, I start by introducing a process model of academic commercialization, from basic research to commercialization, and then identify how existing programs that claim to foster academic commercialization deal with the a series of barriers for academic commercialization. The key argument here is that gap-funding program is a unique policy measure that provides a unique financial resource for developing proof-of-concept and prototype, while at the same time guarantees academic scientists' freedom in project selection and disclosure mode.

Arguably, the Bayh-Dole Act of 1980 is the first nationwide policy intervention that intends to foster the commercialization of university research by allowing universities to possess the intellectual property generated from federally funded research. Many research universities establish Technology Licensing Offices (TLO), or Technology Transfer Offices (TTO), whose tasks include making patent decisions, advertising their intellectual properties to the potential buyers, and managing licensing revenues (Shane 2004). The typical commercialization process organized by TLO is as follows. First, an academic scientist researcher thinking his novel scientific discoveries have commercialization potential should contact TLO, thereby 'disclosing' the invention. Often times, funding for basic research that comes from federal and state governments and philanthropic foundations can be a source of discoveries that have merits in terms of scientific novelty and commercialization potential at the same time, often labeled as the "Pasteur's quadrant" (Stokes, 1997). After the invention disclosure TLO examines if the invention is novel, non-obvious, and valuable technological advance, and if the expected profit from commercialization exceeds the costs for patent filing and maintenance. It then files a patent to the US Patent Office if the invention passes the internal screening process. At the same time, TLO is actively engaged in technology commercialization activity. It decides which commercialization strategy is appropriate for the invention, usually between licensing to existing companies or forming a start-up company, and license the patent to the optimal licensee.

Even after the establishment of TLO, not all university inventions with potential commercial value are commercialized in the industry, suggesting that current rate of technology transfer from academic institutions to industry is below the socially optimal level. There are mainly two factors, not necessarily mutually exclusive, that hinder the commercialization of academic science: lack of knowledge in market opportunities and business process, and the embryonic state of university inventions. Identifying entrepreneurial opportunities, that is, market opportunities based on new technology, depends on one's prior experience and information (Shane, 2000). It is beneficial for an academic scientist to interact with a wide spectrum of individuals with idiosyncratic background if he aims to find out the most promising area of application for commercializing its discovery. Additionally, academic scientists aiming to establish their own start-up firms should acquire new skills related to business development. Shane (2004) reports that the product development stage requires activities that inventers unusually have not experienced before, including detailed documentation, packaging, and support services. In sum, it requires academic scientists to expand their social network and skills beyond the boundary of academic institutions if they are to succeed as academic entrepreneurs.

Moreover, the embryonic state, or the lack of proof-of-concept or prototype, of most academic science hinders the frictionless technology transfer from academic institutions to industry. Since rewards are given to academic scientists based on their priority of discovery (Dasgupta & David, 1994), academic scientists do not have strong incentives to take additional steps to find out whether their scientific discoveries are technically feasible, satisfy specific functionality that its application area demands, or meet cost-performance threshold that is required for industrial use, that is, developing proof-of-concept and prototype. In fact, an extensive survey reveals that funding for early-stage technology development account for only about 14 percent of the national R&D spending; and most funding is from individual private-equity "angel" investors, corporations, and the federal government, and not from venture capitalists (Branscomb & Auerswald, 2002). However, both incumbent firms that consider licensing university inventions and venture capitalists interested in investing on academic science unanimously report that the main reason of not licensing or investing in university inventions is its early stage of development. A survey of industry licensing executives shows that the main reason of not licensing university inventions is the early stage of development of university inventions (J. Thursby et al., 2001). Similarly, venture capitalists that regularly receive investment proposals from universities also respond that they prefer to invest in inventions with proof-of-concept already developed, even if a majority of university inventions in the proposals is at the embryonic stage (Wright et al., 2006). In sum, there is a gap of development between university inventions that are on the shelf of commercialization and industry demands.

The key assertion of this paper is that gap-funding program is conducive to decrease the potential licensee's perceived uncertainty surrounding the commercialization potential of a university invention, so that typical funding mechanism based on market mechanisms, including industrial R&D spending or venture capital and angel investments can be followed on for technology commercialization. Under its support, academic scientists not only tackle the issue of "what an innovative technique works", but also study commercial questions, such as whether the technique works "in a way that satisfies firm-specific profit criteria, which in turn rests upon demand and supply conditions relating to the innovation's cost-performance configurations and its placement in the market" (Feller, 1990). In comparison, the focus of TLO lies in identifying potential licensees for a university invention and managing all the transactions required for licensing and royalty sharing, taking the technology as given.

Additional unique feature of gap-funding program is that it guarantees academic scientists' freedom of project selection and disclosure mode, a feature that is rare in other funding for application-oriented research. (Figure 1) Historically, the U.S. government has enacted funding programs, such as the Defense Advanced Research Projects Agency (DARPA), Advanced Research Projects Agency—Energy (ARPA-E) and Advanced Technology Program (ATP), which are intended to bridge the gap between basic academic science and industrial innovation by supporting research that would not be supported due to the high risk of success. The difference, however, is that the government agencies initially determine the area of application, be it energy, defense science, or information and communication technologies (Fuchs, 2010). While this helps the government agencies' coordinated efforts to develop technologies applicable to their specific application areas, its little merit as publishable research, mainly due to the little emphasis that government agencies on this criteria, might not be so attractive to academic scientists. Moreover, such mission-oriented research funding mostly impose limitations on the mode of disclosure, including patenting and publication (Gans & Murray, 2011).

Another interesting program for comparison is the U.S. Small Business Innovation Research (SBIR) program. Established in 1982, the SBIR aims to increase the commercialization of federally supported research by mandating federal agencies to allocate 2 percent of the total research budget of federal institutions to qualified entrepreneurial firms. As we will see later, its three-phase structure and evaluation process are similar to the gap-funding program at MIT: Phase I aims to test the feasibility of the research by providing a small amount of seed money to the awardee, and Phase II provides a larger award to the qualified firms during the Phase I that can continue and complete the commercialization of the proposed research. In order to be a legitimate recipient for SBIR funding, however, the PI commit full-time to the commercialization. Though it increases the chance of success, participating in that commercialization endeavor full-time may exert permanent negative impact on the PI's academic freedom.

Finally, it would be informative to compare gap-funding programs to university technology incubator programs. University technology incubator programs utilize university resources, including but not limited to office spaces and other physical infrastructure, knowledge from university research, business assistance and networking opportunities, so that their tenant firms at the early stage can grow successfully (Mian, 1996). Here, the direction of knowledge flow and support is the opposite of gap-funding programs: university knowledge and resources helps the growth of start-up firms. In the detailed study on the Advanced Technology Development Center (ATDC), Georgia Tech's technology incubator program, Rothaermel and Thursby (2005) reported that the technology underlying the entrepreneurial firms admitted to the ATDC need not be related to Georgia Tech.

3. Background: MIT Deshpande Center for Technological Innovation

3.1 Gap funding programs in the U.S. universities

In this section, I will investigate on the existing gap-funding programs in the U.S. universities, and particularly the gap-funding program at MIT. As gap-funding program is a recent tool for fostering academic commercialization there exist a few documentations discussing the different characteristics of various gap-funding programs, and the existing ones are published mostly in practitioner-oriented journals. This survey thus should be read as a first attempt to systematically compare and contrast using publically available qualitative and quantitative information.

As will be discussed in greater detail, our survey shows that current gap-funding programs that are being operated in various universities are idiosyncratic in terms of sources of funding, type of services provided, affiliation, structure of grant program, not to mention the size and history. To that end, the first step is to collect as many cases of gap-funding programs as possible, but unfortunately, there is no systematic database that we can access to and collect all cases of gap-funding programs. Alternatively, we began by surveying all publications, written by both academics and practitioners, and constructed a list of gap-funding programs in the U.S. universities (Johnson, Johnson; Gulbranson & Audretsch, 2008; Rick Silva, 2009; Bradley et al., 2013). For universities that are known to be active in technology commercialization, such as universities that run one of the top 15 technology transfer programs by licensing income, we manually checked whether the university has internal gap-funding program, using keywords such as “proof of concept center” or “gap-funding program”. For each identified case, we then collected as much information as we could find from sources such as its official website, template for application, university and local news, and reports. Even after laborious effort to collect as many cases as possible, we do not argue that the final list is completely exhaustive. Our hope, however, is that comparison among the cases in our sample reveals various types of components to consider in establishing gap-funding program, providing insights to readers interested in starting similar program.

Table 1, 2, and 3 show the entire gap-funding programs in our sample and their characteristics. Among universities with one of the top 15 technology transfer programs by licensing revenue, only Northwestern University does not have, and plan to establish in the near future, a kind of gap-funding program. Table 1 contains gap-funding programs whose initial funding source was from philanthropy. The von Liebig Entrepreneurism Center at the University of California, San Diego, and the MIT Deshpande Center for Technological Innovation are two most cited examples of gap-funding program (Gulbranson & Audretsch, 2008). In fact, both programs have many characteristics in common. For each program, initial funding was donated by philanthropic foundation, located in the school of engineering, provides advisory and mentoring, as well as funding for prototype development. Gulbranson & Audretsch (2008) describes that the grant program at the von Liebig Entrepreneurism Center is similar to the MIT Deshpande Center’s grant program, in that the center independently receives proposals, reviews them, and provide seed funding ranging from $15,000 to $75,000 to the ten to twelve selected projects annually. According to its website, however, the von Liebig Entrepreneurism Center now collaborates with government, foundation and industry sponsors and Technology Acceleration Programs (TAPs). TAPs are different from their predecessors in several ways. First, each TAP specifies its target technological area, such as healthcare, clean energy and wireless technology, which its sponsoring industry partner has expertise. Eligibility for application also differs by cases. Some TAPs accept proposals by inventors not affiliated with the University of California, or proposals from women students only.

Other philanthropy-funded gap-funding programs that have received less attention include the Biomedical Accelerator Fund at Harvard University, and the Coulter Translational Partnership that support gap-funding programs at 16 different departments of biomedical engineering in the U.S. universities. The Biomedical Accelerator Fund was created in 2007 based on $6 million private donation, and expanded in 2013 with $50 million donation from the Blavatnik Family Foundation. Its major difference from the two aforementioned pro- grams is the focus in biomedical areas. It is operated within the Office of Technology Development, Harvard's TLO, and plans to draw university-wide efforts, including postgraduate fellowships at Harvard Business School for further technology commercialization.

Another less-noticed foundation, the Wallace H. Coulter Foundation, has exerted significant influence on creating gap-funding programs in biomedical areas. In October 2005, the Foundation decided to provide approximately $4.5 million to ten universities with strong program in biomedical engineering so that each department establishes its own departmental-level gap-funding program. Because of the foundation's emphasis on clinical applications, a necessary condition for biomedical technologies to be commercialized, many gap-funding programs invited participation from the medical school, as well as TLO and the business school in each university. The detailed design of gap-funding program differs by each individual university, but it usually provides $1 million of grant for translational research for about 8 awardees annually. In 2011, the Foundation selected another six programs in biomedical engineering for the establishment of gap-funding program with similar structure, and particularly donated $20 million to Case Western Reserve University.

The second category is group of gap-funding programs established from university's internal financial resource. (Table 2) Unfortunately, most information on the year founded initial funding size, and the number of projects funded and commercialized are unavailable. One noticeable pattern would be the similarity of grants programs across different universities. Except the case of the University of Colorado programs, most gap-funding programs do not focus on specified technological areas. The amount of initial seed funding ranges from $25,000 to $75,000, except the case of Boston University's Launch Award, Caltech's I-Grant and Stanford University's Gap Fund. It should be noted, however, that Boston University and Stanford University also provide Ignition Award and Birdseed Fund, respectively, with the amount of grant in this range.

Gap-funding program in the third category was established from the support of federal and state governments. (Table 3). The fact that programs in this category were established recently indicates the federal and state government's interest in gap-funding program as a policy measure to foster innovation and entrepreneurship. A common feature is that all pro- grams specify the target area, such as biomedical, defense, and clean energy industry. These target areas are aligned with economic growth strategy in each region. Maryland Proof of Concept Alliance program is unique, in that the university collaborates with the U.S. Army Research Laboratory, a federal research institution in the defense area, to identify technology with potential use in defense area, and commercial potential in areas outside defense in the long run. The U.S. Army

Research Laboratory jointly participates in selecting promising proposals among the submitted ones, along with the University's experts in technology commercialization.

The i6 Challenge, a prize competition administered by the U.S. Department of Commerce and award up to $1 million to winning teams with the most innovative ideas to foster technology commercialization and entrepreneurship in their regions, is likely to create more gap-funding programs across the nation. While not mandated, many proposals include the idea of establishing gap-funding program in the universities as a way to accelerate the technology commercialization from early-stage research. Table 4 shows a list of i6 Challenge winners since 2010. Our analysis tells us that at least three winners (Global Center for Medical Innovation, iGreen New England Partnership, Energy Storage Proof of Concept Center) include a plan to establish gap-funding programs.

In addition to the university gap-funding programs mentioned above, we would like to introduce several gap-funding programs by state governments that aim to facilitate technology transfer from local non-profit research institutions to industry. Compared to previous gap-funding programs, this type is different as the operational entity that receives proposals and decides awardees is not universities, but independent state government programs. Usually, academic scientists in universities and researchers in non-for-profit research institutions in the region are eligible for application. Below is the list of state-government- initiated gap-funding programs:

- Ohio Third Frontier (Ohio): Technology Validation and Start-Up Fund
- Science Center (Greater Philadelphia): QED Proof-of-Concept Program
- Massachusetts Technology Transfer Center (Massachusetts): The Massachusetts Clean Energy Center (MassCEC) Catalyst Program Awards

- Michigan Economic Development Corporation (Michigan): Michigan Initiative for Innovation and Entrepreneurship Technology Commercialization Fund
- Advanced Technology Development Center (Georgia): Georgia Tech Edison Fund
- Technology Commercialization & Innovation Program (Utah)

3.2 MIT Deshpande Center for Technological Innovation

Program Structure

The Deshpande Center for Technological Innovation (hereafter Deshpande Center) has been regarded as one of the key components of the MIT's entrepreneurial ecosystem since the founding in 2002. Established through a generous gift of $20 million from Jaishree and Desh Deshpande, the co-founder and chairman of Sycamore Networks Inc., the Deshpande Center aims to stimulate technology commercialization and entrepreneurship from novel discoveries at MIT laboratories. That the program focuses on supporting the commercialization of cutting-edge academic research is clearly demonstrated by the Dr. Deshpande's remark:

> *"MIT has always provided a fertile ground where its students and faculty can break through technology barriers, fuel new areas of research and development, and fundamentally transform whole industries. We can think of no better place to begin this work."*

Professor Charles Cooney, a Professor of Chemical and Biochemical Engineering, has served the role of Faculty Director since the beginning. In May 2006, Leon Sandler has been appointed as new Executive Director, following the first Executive Director Krisztina Holly. With his extensive experience as executives in management, finance, marketing and business development, he and his team in the Deshpande Center involve in selecting promising projects and offering intensive guidance to bring academic discoveries to marketplace. Between its beginning in 2002 through the end of 2011, the Deshpande Center has received about 480 proposals submitted by MIT faculty members and affiliated research scientists and provided approximately $11.6 million of seed funding to 100 selected projects. It has been reported that the amount of follow-up research funding exceeds $50 million, and 23 spinoffs have attracted more than $220 million investments and employed over 250 people. Though located at the MIT School of Engineering, the Deshpande Center has supported academic faculty members and research scientists from a wider range of disciplines and departments.

The Deshpande Center achieves its mission through four complementary programs: the Grant Program, Catalyst Program, Innovation Teams (i-Teams), and IdeaStream. The Grant Program is the centerpiece of the whole programs. It provides seed funding ranging from $50,000 to $250,000 to leading edge technologies with commercial potential, so that investigators test and demonstrate the feasibility of proposed concepts. Specifically, the Deshpande Center awards two types of grants: Ignition Grants (up to $50,000) and Innovation Grants (up to $250,000). Ignition Grants are provided to more early-stage research, that is, conceptually promising but unproven ideas, and expected to be used to demonstrate the feasibility by exploratory experimentation and proof-of-concept development. In contrast, Innovation Grant is awarded to relatively more matured-stage research. The research at this stage typically involves refining and further developing an innovation to satisfy specific market and customer needs, with clearer commercialization strategies. The Deshpande Center's expectation is that inventions finishing the stage of Innovation Grants should be ready to attract investments from outside investors so as to launch a spinout company, and/or license the invention to existing companies. The Deshpande Center receives applications to the Grant Program in each spring and fall. Interested scientists can apply by submitting 2-3 pages long pre-proposal. Researchers whose proposals pass the initial screening stage are assigned mentor, and together with them, develop and submit a full grant proposal to the Deshpande Center. The final awardees are determined approximately 8-10 weeks after the initial submission. (For the fall semester submission timeline, see Figure 2.)

As briefly mentioned above, the participation of external mentors, or Catalysts, is critical in the Deshpande Center's efforts for commercializing science. Catalysts are a group of volunteers experienced as venture investors, entrepreneurs, or executives in technology- based firms, and are expected to bring in their experience and insight on market needs and commercialization process. They participate in the grant selection process of the Grants Program, and in particular work together with potential grantees to develop their full grant proposal. After the final selection of grantees, each grantee is highly recommended to have a regular monthly meeting with an assigned Catalyst. Catalysts also attend various socialization events, including IdeaStream, Open House and the Catalyst Party, to share their expertise with as many grantees as possible.

The third component, Innovation Teams (hereafter i-Teams) is a unique entrepreneurship course at MIT, provided jointly by the Deshpande Center and the Martin Trust Center for MIT Entrepreneurship. Unlike typical entrepreneurship courses, i-Teams teaches the process of technology commercialization using real cases of early-stage technologies, that is, the recent funded projects by the Deshpande Center. Principal Investigators (PIs) of funded projects who are interested in developing well-defined commercialization strategies of their technology voluntarily apply that their technology be used as course materials. The success of this course requires active participation of PIs and selected researchers from his/her group. During the first weeks of the semester, each PI or selected researcher from each research project briefly introduces the technology to its students. Once student teams from cross-disciplinary majors are assembled and assigned to technologies, each student team interacts with the researchers in the laboratories, as well as outside experts and potential customers to develop appropriate commercialization strategies. This approach has been mutually beneficial for students taking this course and grantees working together with the students. For instance, about 80% of spinoffs from the Deshpande Center Grant Programs have gone through the i-Team course, including Lantos Technologies and Myomo (Roberts, 2011).

Finally, the Deshpande Center hosts a number of events for socialization and showcasing, including the IdeaStream, Open House and the Catalyst Party. While Open House and the Catalyst Party are internal, informal events among grantees and mentors, the IdeaStream symposium is a formal gathering of grantees, mentors, and invited guests including venture capitalists and successful entrepreneurs. A typical agenda for this event includes poster session, presentation by Deshpande grantees on their experience, and networking opportunities.

It should be emphasized that the Deshpande Center is tightly linked with other programs consisting MIT entrepreneurial ecosystem. We have already mentioned that the Deshpande Center is collaborating with the Martin Trust Center for MIT Entrepreneurship to provide an entrepreneurship course tailored to the Deshpande grantees' needs. Also, it is not uncommon that projects funded by the Deshpande Center receive additional resources and guidance for business incubating. In 2004, for instance, the Active Joint Brace team won the Top Prize at the prestigious MIT $50K Entrepreneurship Competition, a student-run business plan competition.

3.3 Descriptive statistics on the gap-funding program applicants

As a preliminary analysis, I present the profile of faculty members at MIT who have been applied to the gap-funding grant provided by the Deshpande Center from academic year 2002-03 to 2010-11, focusing on the variance in the demographic factors such as gender, academic rank, and departments between applicants and non-applicants. In most analyses, I do not differentiate between Ignition Grant and Innovation Grant, and aggregate applicants/awardees to either ignition grants or innovation grants as applicants/awardees.

Table 5 shows the number of applicants and awardees to the Deshpande Center grant program since the beginning in 2002. During this 10-year period, 478 new proposals have been submitted to the Center, and 99 proposals are selected as winners of the grant. Since 2008, the number of applicants to both Ignition Grant and Innovation Grant seems to be diminishing. It is difficult, however, to interpret this as academic scientists' shrinking interest in academic commercialization. The decreasing number of applicants might be because of the reduced marketing effort by the Center, or because of the availability of other funding sources for application-oriented research and commercialization.

In terms of gender, about 10% of the all applicants and 15% of the all awardees were women faculty. (Table 8 and Figure 3) The faculty gender ratio in the MIT School of Engineering at the same period was about 13-14%, which can be used as a benchmark. Though the small sample size and relatively short period of observations make it difficult to draw any robust conclusion, we can observe two interesting patterns. First, while women faculty members' application rate was less than their counterparts, they are more likely to be selected as grant awardees. The percentages of women faculty among the awardees for the 2002 – 2010 period are in many cases higher than those among the applicants, as shown in the Figure 4. Women faculty members' low application rate confirms prior study on the gender gap in academic commercialization (Ding, Murray, & Stuart, 2006). That said, however, the application rate of women faculty members seems to increase as time goes, particularly between 2005 and 2008. Though our small sample size prevents us to conduct any statistical test on this pattern, it might be interesting if any changes in institutional factor lie under the phenomenon.

Next, I analyze the distribution of academic rank among all the Deshpande Grants applicants. (Table 7 and Figure 6) During the 2002 – 2010 period, the majority group was (full) professor, which comprise of approximately 46% of the entire applicants. About 18% of the applicants were associate professors, 16% of the applicants assistant professors, and 20% of the applicants non-professors. The non-professors group includes research scientists, visiting professors, affiliates, and emeriti.

A more interesting question related to academic rank is which group of professor has participated most actively. To answer this question, I discard non-professors and limit the sample of study to only the faculty. During our study period, 57% of the faculty applicants were professors, 22% were associate professors, and 20% were assistant professors. For the same period, about 70% of the faculty members in the MIT School of Engineering were professors, 18% were associate professors, and 13% were assistant professors. Even though this benchmark might not be perfect, we can infer that associate and assistant professors are more willing to apply for the Deshpande Grants than professors.

Regarding department, the first observation is the dominance of engineering faculty among applicants. For the 2002 – 2010 period, about 74% of all applicants were from the School of Engineering. Only 8% of applicants were from the School of Science, and 3% of applicants from other departments, including Architecture, the Media Lab, and the Sloan School of Management. In 2011, the number of faculty in the School of Engineering is 37% of the all MIT faculty members, and the number of faculty in the School of Science is 27%. So even counting the faculty from the School of Engineering and School of Science, we can conclude that most faculty members interested in technology commercialization is from the School of Engineering. Table 6 shows the distribution of department among applicants and awardees.

From now on I focus on the applicants from the School of Engineering. For the period 2002 – 2010, professors of Mechanical Engineering comprise of 29% of all applicants from the School of Engineering, EECS 27%, Material Science and Engineering 14%, and 10% Chemical Engineering. (Figure 9) Taken together, these "top four" departments consist of 80% of all submitted proposals from the School of Engineering. Among the top four departments, the likelihood of submitting an application at a given round is approximately 10% for the faculty members in Mechanical Engineering, Material Science and Engineering, and Chemical Engineering. (Figure 14) In contrast, the application rate from EECS is relatively low, about 5%.

From the descriptive statistics above, I observe three main patterns. Overall, the number of grant proposals submitted to the Deshpande Center decreases over time. In terms of academic rank, junior faculty members are more likely to apply for the grant than senor faculty members. Women faculty members are less likely to submit proposals, but once they submit, the likelihood of receiving grant is at least as comparable, if not higher, as the success rate of other male faculty members. It is still difficult to establish systematic explanations under these patterns, because as mentioned before, the decision to apply for the gap-funding program is the complex function of variables including, but not limited to, recent academic research performance, available funding for application-oriented research, perceived business opportunity, individual-level taste for academic and commercial science, and peer effect from other faculty members in the department and larger community. In the following section, I employ econometric techniques to capture some correlations that allow us to predict one's likelihood to participate in this university-wide endeavor for technology commercialization.

4. Econometric Analysis on the Profile of Applicants

4.1 Sample definition

One of the primary research questions in this study is to understand the profile of applicants to the gap-funding program, compared to that of faculty members who have not applied. Not only does this question provides policy-makers considering the establishment of similar programs with rough estimate on group of individuals who are likely to be affected by such program, we believe understanding the characteristics of applicants in our setting will make a theoretical contribution. Gap-funding program is one of few available opportunities for academic scientists to secure necessary resources for commercialization, and the burden for application is relatively minimal. In the MIT's case, for instance, the only requirement is to submit 3-4 pages of proposal, and awardees can publish the research findings from the funded projects in academic journals. In a sense, this is a unique opportunity to identify a group of academic scientists who are interested in application-oriented research and commercialization.

To describe the characteristics of academic scientists in every possibly observable dimension, we collected data on their background and performance from many sources. As illustrated in Figure 11, the observed dimensions include scientists' publication, patenting, commercialization, funding and their demographic information, as well as their experience with the gap-funding program.

We began by constructing dataset of faculty members who have worked in the MIT School of Science or School of Engineering between academic year 2002-03 and 2010-11 for at least one year. As the Deshpande Center for Technological Innovation established in fall 2002, faculty members in this period were "at risk" of applying to the gap-funding program. Even though any MIT-affiliated professors and researchers are eligible for application, including faculty members in non-science or non-engineering disciplines and research scientists, we decided to focus on academic scientists in the School of Science or School of Engineering for two reasons: first, the primary objective of the Deshpande Center is to translate research output generated in science and engineering laboratory into innovative product and technology, and second, detailed information about faculty members, including their demographic information, work history at MIT and prior experience in research, patenting and commercialization, helps us examine various factors that potentially affect the likelihood of applying to the gap-funding program, as well as of commercialization success if funding is provided.[1] Our previous description on the Deshpande center confirms that our sample covers 82% of all submitted proposals, and 80% of funded proposals.

The Institutional Research section of the Office of Provost at MIT generously provided demographic information of all professors who have worked at MIT for at least one year from 1981. This dataset provides information on faculty name, school and departmental affiliation, gender, PhD degree year, PhD granting institution, year of employment, and rank in each year. It also contains faculty members' patenting experience through MIT, including inventor name, patent application number, patent file and issue date. While it does not document faculty

[1] According to MIT news archive, faculty members outside of the School of Engineering and other research scientists became eligible for application from the Spring 2005 round. It is unlikely, however, that this eligibility condition was enforced, as there are applications from outside the School of Engineering in the early period. (Source: http://web.mit.edu/newsoffice/2004/deshpande-fac.html)

patenting activity without the involvement of MIT, which can be non-trivial according to Thursby et al. (J. Thursby, Fuller, & Thursby, 2009), it also helps avoid "who is who" problem, that is, counting patents invented by different inventors with the same name as if they were invented by single inventor (Trajtenberg, Shiff, & Melamed, 2006). From this dataset we identified 846 faculty members in the MIT School of Science and School of Engineering who have worked at least one year between academic year 2002-03 and 2010-11.

For each person in the dataset, we counted each faculty's annual publication record between 1981 and 2011 by searching the ISI's *web of science* database. We decided to count the number of publication from 1981 in order to measure each faculty member's accumulated knowledge stock. The resulting number of total publications was 61,335. Because we used author name, university and departmental information to extract publication records, these publications are published while faculty members are working at MIT. We believe that this approach minimizes the risk of "Type II error", that is, counting publications by non-MIT affiliated researchers as publications by MIT faculty members. We also admit, however, that the collected publication record omits publications that MIT faculty members have published before joining MIT. This might lead to systematic under-representation of knowledge stock that professors who joined MIT as senior faculty have accumulated.[2] In addition to simple count of publication numbers, we also calculated journal-impact-factor (JIF) weighted count of journal publications. The 5-year average JIF was obtained from the *web of science*, and then matched to our publication data by journal name. Some publications in out data did not have matched JIF, for instance when the type of publication is conference proceeding or journal was established less than 5 years ago. Discarding those publications without JIF resulted in 38,889 publications.

[2] One way to mitigate this issue would be including the "rank at hire" information as a control variable in the following econometric analysis.

For both publication counts and JIF-weighed publication counts, we created annual publication variables from 1981 to 2011, which we will later use to calculate annual knowledge stock and flow between academic year 2002-03 and 2010-11.

We also constructed variables describing faculty members' commercialization experience: specifically, their prior experience in technology licensing, firm founding, and industry funding experience. The MIT Technology Licensing Office (TLO) generously provided detailed information on all 8,400 inventions disclosed to the office between January 1992 and October 2012. The dataset contains inventor names, including non-MIT affiliated inventors, date of invention disclosure, sponsor of research, date of patent application and grant. If an invention is licensed, the TLO also documented licensee name, whether the licensee is start-up, established firm or non-profit organizations, license effective date, and whether the license agreement is exclusive. However, we should be cautious in interpreting license effective date. When an existing licensee wants to license newly disclosed invention with similar contractual terms, the TLO sometimes simply extends the coverage of existing licensing agreement to include the new invention, in which case the license effective date for the new invention is the same as the license effective date for the existing inventions in the same agreement. In other words, the license effective date for a newly disclosed invention can precede its invention disclosure date when the invention is licensed by extending existing licensing agreement. This unique business practice inside the MIT TLO limits our inference from license effective days in several ways. For instance, we can observe whether an invention is licensed but cannot observe the exact date of licensing deal if the invention is added to an existing licensing agreement. Additionally, we can also infer when the "new licensing contract" is made, but it is not clear how "new licensing contracts" differ substantially from licensing that updates existing contracts. Interestingly, we also found 37 cases (0.4% of the total inventions) in which the date of invention disclosure is the same the date of licensing. We further compared the sources of research and licensee, and observed that in most cases, the funder and licensee are identical. We suspect this is due to the binding conditions on the ownership of inventions that the funders attached when providing research funding.

The TLO also pays special attention to the inventions related to the Deshpande Center grant program. Every time the Deshpande Center announces awardees of that round, the TLO reviews all inventions that have been disclosed, identifies inventions that belong to the same technological domain as each funded proposal and reported by the same awardee, and classified them as "Deshpande-funded" inventions. When the research output from Deshpande-funded projects is reported, the TLO also classifies it as "Deshpande-funded" invention. Therefore, it is possible that inventions classified as "Deshpande-funded" are disclosed before the related proposal to the gap-funding program is submitted. This information might be useful to further classify Deshpande-funded inventions as 1) technologies that are first developed by Deshpande-funded projects, and 2) technologies that are discovered by prior research projects, but further developed, including proof-of-concept and prototype development, by the Deshpande funding. In the latter case, the TLO might not keep track of further development of "Deshpande-funded" technologies if the inventors think that technologies they are further developing are already disclosed and protected by existing patents, if any, and thus decide not to report any new invention.

The first variable we constructed from the TLO dataset is annual licensing experience. Similar to variables on publication, we counted the number of inventions licensed to at least one for-profit firm in a given year between 1992 and 2011. After manually checking the licensee name, we discarded licensing contracts with non-profit organizations, such as university, hospital, and non-profit research institution. We used the licensing effective date recoded in the TLO dataset to count the number of licensed inventions in a given year, but as mentioned before, one caveat is that this number does not perfectly reflect the number of licensing deals if the invention is added to existing licensing agreement. Our modest defense is that since we use annual licensing experience to construct one's prior experience in any given time, counting this year's licensing deal as previous year's deal does not affect measuring accumulated experience. Following Shane and Khurana (2003), we recorded the number of licensed inventions to start-ups in a given year between 1992 and 2011 in order to measure each faculty member's career experience on new firm founding. We then generated for each year between 1992 and 2011 a dummy variable indicating whether a faculty member has any invention disclosure resulting from industry-funded research projects in a given year. It has been reported that sources of research funding are related with the characteristics of research and mode of disclosure (Gans & Murray, 2011). Industry-funded research is generally more applied, and is preceded by public funded work (Mansfield, 1995). Experience with industry funding also helps alleviate faculty members' concern on limited autonomy in research areas and mode of disclosure that are expected to come with industry funding (Gulbrandsen & Smeby, 2005). In our sample, 672 unique sources of research funding are identified. Based on the taxonomy in Gans and Murray (2011), we manually classified government agencies and foundations as public funders, examples of which include National Science Foundation (NSF), National Institutes of Health (NIH), Department of Defense (DOD) and Department of Energy (DOE), and remaining commercial entities as private funders.3 We chose to construct dummy variable, rather than a

[3] Universities, hospitals, and other research institutions also take a significant portion of funders in our sample of funders, but their type is not explicitly defined in Gans and Murray (2011). We classify them as public funders.

variable counting the total number of invention disclosures backed by private funders, as we could not separate out the cases in which multiple inventions are generated from a single research project. Between 1992 and 2011, 237 among 846 faculty members reported at least one invention disclosure generated from industry-funded research projects. We should be cautious, however, that faculty members' industry funding experience is not observed if the research output is not reported to TLO.

As a final step, we created an unbalanced panel data composed of 6,399 person-year observations by recoding years in which one is employed as assistant, associate, or (full) professor. This person-year data structure allows us to observe changing characteristics of each faculty member, for instance his/her publication, patenting, commercialization experience, and academic rank. For each variable on publication, patenting and commercialization, we created three types of measures: flow, stock, and average. "Flow" variable measures the annual experience and research output, "stock" the accumulated experience and research output during one's career at MIT, and "average" the averaged annual number of output measure, which we calculated by dividing "stock" by the number of years each faculty member has worked at MIT. We then added to each 6,399 person-year observations dummy variables indicating whether each person applied to the gap-funding program as a PI, and as a result received either Ignition Grant or Innovation Grant in a given year. Given that our primary interest lies in individual-level predictors for applying to the gap-funding program, we discarded the cases that previous awardees submitted proposals to renew currently funded project. We also did not count faculty members' participation as Co-PI.

4.2 Summary statistics

We present the summary descriptive statistics for individual-level variables. Table 9 shows the distribution of schools and departments to which individuals in our sample are affiliated. When counting one's primary affiliated department only, Electrical Engineering-Computer Science (EESC) turns out to be the largest department at MIT. Table 2 presents time-varying time-invariant characteristics of scientists in our sample.

Table 10 illustrates key characteristics of MIT-affiliated academic scientists in science and engineering disciplines. About two thirds faculty members are tenured, full professors, and women scientists consist of only 14% of entire population. In terms of number, faculty members are of order of magnitude more productive in publishing journal articles than patenting: average professor in our sample publishes 2.5 publications annually, but only 0.25 patents. Other measures on faculty members' relationship with industry or commercialization suggest that not many academic scientists are actively engaged in businesses outside the boundary of academic institutions. For instance, 32% of scientists in our sample have never reported inventions developed from industry-funded research project between academic year 2002-03 and 2010-11. As we discussed, we should be cautious that actual number of faculty members who have conducted industry-funded projects is likely to be higher, as we could observe sources of research funding only in the case of invention disclosure. For each faculty member, annual average of inventions licensed to for-profit firms is 0.14, and 0.04 cases are licensed to start-up firms. Finally 5% of faculty members eligible for application in fact have applied to the gap-funding program, and one fifth received the funding.

In Table 11, we compared the profile of faculty members with experience in the gap-funding application (Applicants) and faculty members without such experience (Non-applicants).

For this purpose we only focused on 644 faculty members working in the academic year 2001-2012, and measured every time-varying variables as of 2011. 150 faculty members have applied to the gap-funding for at least one time while working at MIT. Table 12 compares the two groups by their time-invariant characteristics. The most notable difference comes from the distribution of departments between the two groups. Obviously, academic scientists in the School of Engineering are more likely to apply to the gap-funding than scientists in the School of Science. Given the emergence of life science and biotechnology industry in the past decades, it comes as surprise that faculty members in biology department are not as active as other faculty members in engineering disciplines. Departments in which affiliated faculty members have shown interests in the gap-funding programs are EECS, mechanical engineering, material engineering and chemical engineering. No faculty member in the nuclear engineering applied to the program.

Table 12 tells that faculty members in the "applicants" group are more experienced, productive in academic publication and as commercialization, and involved with industry funders. About 80 percent of faculty members in the "applicants" group are now full professor, while the proportion of assistant professors are only 8 percent. Given this seniority, it might be obvious that faculty members in the "applicants" group have accumulated higher stocks in publication, patent, licensing and industry funding experience. However, their annual averaged productivity in those dimensions is also significantly than that of "non-applicants" group. The only exception is the comparison based on JIF-weighted publication count. We believe this is because of the tendency that science journals usually have considerably higher journal impact factors than engineering journals.

One might challenge the previous argument in two ways. Obviously faculty members in the higher rank have on average worked at MIT longer than junior faculty members, and thus have had more opportunity to apply to the gap-funding program. Therefore, the high proportion of full professors in the "applicants" group might indicate not that full professors have higher tendency of applying to the gap-funding program, but that they have been given more opportunities to apply to the program. Regarding various measures of individual scientist's productivity, the biggest caveat comes from the fact that we cannot explain whether the higher productivity of scientists in the "applicants" group is the cause or effects of applying and receiving the gap-funding. The time dimension that might allow us to separate them out is lost in the current comparison, as we only observed academic scientists' productivity in 2011.

To control for the confounding as much as we can in this comparison, we focused on the sub-sample consisting of 245 full professors in the School of Engineering. Table 13 presents the comparison of academic and commercialization productivity between the two groups. It confirms our prior conjecture that faculty members in the "applicants" group are on average more productive.

5.3 Methods and results

In this section, we revisit the question of understanding differences between faculty members with the gap-funding application experience and faculty members without such experience. We already attempted to tackle this issue by comparing average academic productivity, patenting productivity, industry funding experience, commercialization experience, and other demographic factors between the two groups. We inferred from the comparison that faculty members in the "applicants" group are mostly from engineering disciplines, academically more productive, and more experienced in commercialization and industry funding. However, there exist several confounders that make this conclusion less reliable. In our view, the most serious confounder comes from disciplines. We all know that different disciplines have different expectation on faculty members' productivity and commercial orientation, and not controlling for this would make the relationship spurious. It might be the case that many faculty members from engineering disciplines applied to the gap-funding program because of the applicability of their research, but the higher number of average number of patents that they granted led us to believe that higher productivity in patenting is a determinant of application behavior. Controlling for "unobservable" proclivity related to each discipline, and hopefully, each individual is the key to identify the relationship between scientists' productivity and experience, and their application likelihood.

We rely on two econometric analyses here. First, the individual fixed-effect logit model is applied to relate individual-level characteristics, including individual-level productivity, knowledge flow and experience, to his/her decision for application. Figure 4 shows that more than 50% of applicants have applied to the gap-funding multiple times, with new proposals, and Professor Alexander Slocum (mechanical engineering) has applied to the gap-funding 12 times. Given the prevalence of multiple applications from single researcher across time, we think that conducting event history analysis is not ideal for our purpose, that is, counting the duration between one started his/her career at MIT and the first occurrence of application behavior.

We used a (unbalanced) panel dataset of MIT faculty members in the School of Science and Engineering between the period of 2002 and 2011. For each period t (year), the likelihood that each individual i applies to the gap-funding program depends on 1) his/her unobserved, time-invariant proclivity to commercialization and 2) observable time-varying characteristics X_{it}. Intuitively, this model tracks each individual's career while he/she is observed in the sample, and measures how the changes in one's time-varying characteristics within his career affect his application likelihood. Since the focus is within variation in each scientist's career, we can control for each individual i's unobserved proclivity to commercialization, but faculty members who have never applied to the gap-funding program have to be dropped out in this analysis. Mathematically, it can be specified as:

$$\mathbb{P}(Application_{it} = 1 \,|X_{it}, \beta, \alpha_i) = f(\alpha_i + X_{it}'\beta)$$

We tested whether each individual's recent publication flow in the last three years $(PUBFLOW_{t-1}, PUBFLOW_{t-2}, PUBFLOW_{t-3})$, measured by the number of total publications in each year, last year's patenting behavior (PAT_{t-1}), experience in industry funded research (IND_{t-1}), recent licensing experience (LIC_{t-1}), as well as their academic ranks predict one's application behavior. Since patenting, industry funded research and licensing are all less frequent events than publishing in peer-reviewed journals, we also tested whether using dummy variables measuring one's prior experience in different category change our estimation results. Table 14 and 15 show the estimation results. Since faculty members who have never applied to the gap-funding program are dropped out in this analysis, the remaining number of observations in this analysis is 1,592. Surprisingly, all specifications that we have estimated deliver the consistent message that the likelihood of application increases significantly when one is junior faculty member. This might be counterintuitive, especially given the comparison that we have made in Table 19, which tells us that the proportion of full professors is significantly higher in the "applicants" group. However, the estimated results suggest different implications. That is, professors in the "applicants" group have applied to the gap-funding program early in their career, which suggest some possibilities. First, not-tenured, junior professors have difficulties securing financial resources for research, especially application-oriented research, so receiving additional funding from gap-funding program comes as significant incentive. Moreover, the opportunity to build networks with industry practitioners and investors is scarce for less-experienced faculty member. However, we cannot rule out the possibility that resources for commercialization were much more scarce in the early 2000s than now, and so most people with application experience are applied during the early history of the program, which coincides with their relatively lower academic rank. A decreasing rate of applicants to the gap-funding program seems to support this hypothesis. We will discuss these possible interpretations later in this section.

As we have seen, the disadvantage of using individual fixed-effect model is that observations without application experience are all dropped out. It might be useful to understand the individual-level variation, but since the frequency of application is low, mostly one time or two, one might argue that it does not give us sufficient within variation to find any significant relationship. Moreover, using individual-level fixed effect model does not allow us to estimate the effect of time-invariant factors, such as PhD year, gender and department, on the likelihood of application.

As an alternative, we also adopted the mixed effect model. The intuition behind it is that different department in a given year has different "threshold" of the propensity to application, above which one has higher likelihood of application. Also, we posit that male and women academic scientists have different threshold to determine whether he or she wants to actively engage in commercialization activity. (Ding et al., 2006) By allowing different intercept estimate for each group of unique time, gender, and department profile, we aim to understand what factors determine individual-level decision to apply for the gap-funding in each department in a given year. Note that the variance of intercept estimate also varies across each sub-group.

$$\mathbb{P}(Application_{it} = 1\,|X_{it}, \beta, \alpha_{department_i,time_i,gender_i}) = f(\alpha_{department_i,time_i,gender_i} + X_{it}'\beta)$$

Table 16 and 17 show the estimates from mixed-model logit analysis. First, it also confirms that non-tenured professors are more likely to apply for the gap-funding than senior professors, which confirms our previous finding from individual-level fixed-effect logit analysis. The most important finding from this analysis is that academic scientists with recent experience in industry-funded research and/or licensing are significantly more likely to apply for the gap-funding program. We think that this relationship was not shown in the individual-level fixed effect models because unobserved individual fixed-effect absorbs all the difference related to industry funding and commercialization experience. We have seen from Table 10 that experience in industry-funded research and licensing varies across individual. A similar pattern of variation exists even among faculty members in the same department. Our results suggest that academic scientists without such experience are reluctant to apply to the gap-funding. Extending this finding a little further, we could argue that gap-funding is a useful vehicle to provide more commercialization opportunities to academic scientists with interests and prior experience in commercialization or application-oriented research, but it might not be effective to convert professors without commercialization intent into active participants in commercialization activity. Contrary to the results in Table 14 and 15, the mixed model analysis shows that associate professors without tenure are more likely to apply to the funding than assistant professors, holding other variables constant.

Combining the descriptive analysis and results from individual fixed-effect logit analysis and mixed-effect logit analysis that controls for time, gender, and department provides a nuanced view on the profile of applicants. As expected, there exists a significant heterogeneity across disciplines. In each department, relatively young (non-tenured) professors with past experience in industry-funded research and/or technology licensing are most likely to apply for the gap-funding program. On individual level, professors in the "applicants" group are likely to someone who actively engages in commercialization activity. Since unobserved individual fixed-effect absorbs the proclivity, the only significant predictor for individual's decision for application in each round is academic rank. That is, junior professors aspiring to participate in commercialization, but without sufficient financial and non-financial resources resort to apply to the gap-funding to secure those necessary resources. It also suggests that gap-funding program might not be able to convert professors without inherent interests in commercialization into academic entrepreneurs.

Our results provides a few interesting observations for scholars in the economics of innovation area. First, our results question whether the traditional life cycle theory on academic scientists' participation in commercialization is valid. While Thursby and her coauthors (2007) argue that academic scientists put their resources in commercialization activity later in their life cycle, Lacetera (2009) posits that academic scientists participate in application-oriented research with commercialization potential at any time, if they believe its expected monetary reward compensates for rewards from academic reputation. Our evidence supports the latter perspective, in that junior faculty members are also equally, if not more, likely to apply for the gap-funding program. Second, it is interesting to discuss why junior faculty members are more interested in applying to gap-funding programs than senior faculty members. To secure their status within academic institutions, junior faculty members devote most of their time conducting basic science research for publications in peer-reviewed journals. In contrast, senior faculty members with already established reputations tend more to diversity their interests in industry. Junior faculty members are more likely to be attracted to research funding that allows academic publications, that is, freedom in the mode of disclosure. With the academic freedom in problem selection, junior faculty members are willing to identify problems that are located in the "Pasteur's quadrant," that is, research questions with both academic and industrial merits. Senior faculty members with established reputations, in contrast, can negotiate with potential funders on research areas, mode of disclosure, and expected deliverables to their interests. For them, he relatively small amount of grant that most gap-funding program provides will be less attractive.

5. Econometric Analysis on the Impact of Gap-funding

5.1 Sample definition

Another main purpose of this study is to evaluate if providing gap-funding causes any difference in terms of the likelihood of invention commercialization. As we have observed before, most gap-funding programs state explicitly that its mission is to help inventions from university laboratories progress on a commercial path. Comparing the likelihood of commercialization between inventions supported by gap-funding program and other academic inventions is arguably the most obvious way to evaluate the success of gap-funding program. Moreover, this relates to the sustainability of gap-funding program in the long run. Recent trends indicate that a number of philanthropic foundations, corporations, non-profit organizations, as well as federal and state government programs, are interested in providing financial resources to establish and sustain gap-funding programs. This does not guarantee, however, that such financial stream continues in the future, and the only way to sustain the program is that the higher success rate in commercialization justifies additional investments in conducting proof-of-concept research. NYU's gap-funding program specifies this pre-condition for sustainability as follows:

> *"The Fund will recycle investment returns from the successful sale of portfolio companies back into the University to finance further research and spinout ventures. In time, recycling these proceeds could provide a self-financing means to enable NYU to continue these activities into the future."*[4]

To understand the impact of receiving the gap-funding on the characteristics of research output, particularly its likelihood of commercialization, we shift our unit of analysis from individual to invention, and compare invention funded by the Deshpande Center and other MIT inventions. We started from the dataset of 4,650 invention disclosures that were reported between 2003 and 2012 to the MIT Technology Licensing Office (TLO), which is the same dataset we used to construct each scientist's experience in commercialization. As the first awardees from the gap-funding program were selected in Fall 2002, we think observing inventions reported from 2003 is appropriate to evaluate the impact of gap-funding. For each invention in the dataset, we recoded how many patents are filed and issued, along with each corresponding date. Non-US patent applications are discarded in this process for two reasons: first, it increases the risk of double-counting the same invention, and second, we believe that IP rights in the US seem to have direct impact on the licensing probability. The detailed explanation on the constructs we developed will be provided in later section.

It should be noted that our sample consists of invention disclosures, not patent. Most prior literature on licensing and university start-up solely focuses on patented inventions (Agrawal, 2006; Gans, Hsu, & Stern, 2008; Shane & Khurana, 2003). However, we observed

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[4] Excerpted from the official website (http://www.nyu.edu/about/university-initiatives/entrepreneurship/innovation-venture-fund.html)

that many inventions that are not patented are licensed to incumbent firms or start-ups. Omitting those observations might bias our understanding on academic commercialization.

Several issues make unbiased comparison between inventions funded by gap-funding program and other university inventions extremely challenging. The most obvious challenge arises from selection bias: gap-funding program has strong incentives to select most commercially promising projects, and those funded projects would have been successful in commercialization without receiving funding. Measuring and thus controlling for "commercialization potential" for each invention is impossible. Given the lack of ideal natural experiment that would allow us to construct comparable group of funded inventions and non-funded inventions, we resort to a "less ideal" alternative of including control variables that are known to relate to the propensity of invention commercialization *ex ante*. After reviewing reported empirical patterns we identified the following factors, all of which we include as independent variables in the our econometric specification:

- *Funding source*: Academic scientists have reported that research funds from industry are used to extend research findings that they have developed from government-backed basic research (Mansfield, 1995). This applied nature of industry-funded research may possess similar commercialization potential to inventions funded by gap-funding program. Moreover, industry-backed research is sometimes bound to mandatory disclosure policy to funder, and it is not uncommon that such research output is licensed to funder on the same date that the invention is disclosed to TLO. In this research, we define $IND_i = 1$ if the invention is funded by for-profit firms, and 0 otherwise.

- *Number of patents issued*: Patent grant reduces uncertainty in the invention's market value and the degree of appropriation, and thereby increases the likelihood of technology licensing (Gans et al., 2008). While not adopted in this paper, prior literature uses the maximum number of forward citation to patents from invention as a proxy of quality or importance of the invention (Agrawal, 2006). We define $PATENTt_i$ as the number of US patents granted to each invention i.
- *Firm founding experience*: Analyzing the cases of new firm spawning from the patented inventions at MIT, Shane and Khurana (2003) demonstrates that inventors' prior experience in new firm founding predicts the likelihood that their new invention is licensed to start-up firms. We constructed two variables to measure the inventors' prior experience in firm founding: $FEX, FEX5$. The first variable counts the total number of incidences that each member in the group of inventors has experience prior inventions are licensed to start-up firms. The second variable only counts such incidence in the recent five years before the invention disclosure.
- *Academic rank*: Following Elfenbein (2007), if there are multiple inventors we recorded the highest academic rank in the group of inventors for each invention as $RANK_i$. There are five possible categories: 1) professor, 2) associate professor with tenure, 3) associate professor without tenure, 4) assistant professor, and 5) no professor.

Additionally, we include as control variables the disclosure year, department, the number of MIT non-professor inventors, such as graduate students and MIT-affiliated researchers, and the number of outside inventors. In many cases, there are multiple inventors that are affiliated with different departments, which makes controlling for department a little tricky. Based on the inventions reported between 1992 and 2002, we created a department index ($DEPT_k$), which shows the relative contribution of each department to the number of inventions licensed to start-ups firms. Finally we developed a dummy variable ($DESHPANDE$) indicating whether an invention is originated from the research projects funded by the gap-funding program at MIT.

5.2 Summary statistics

The descriptive statistics of 4,650 inventions that are disclosed between Jan 1, 2003 to Nov 1, 2012 are presented in Table 18. About 700 inventions are licensed to incumbent firms, and 460 inventions are licensed to start-up firms. As we discussed before, there are several cases in which one invention is licensed to multiple licensees, even if the contract is exclusive. An invention of "One Step Synthesis of a Diverse Library of Lipids," invented by Professor Robert Langer and four other MIT researchers and disclosed on Nov 2004, has the maximum number of licensing agreements from one invention, 18.

164 among 4,650 inventions in our sample are funded by the Deshpande Center; 20% of inventions are funded by industry partners. It is also interesting that only 12% of inventions disclosed are in fact patented. This number is underestimated, however, as it usually takes years for patent filing and issuing, and inventions disclosed in 2011 and 2012 are too early to tell whether they will be patent protected.

5.3 Method and Result

In the following analysis, we will use logit analysis to understand the determinants of technology licensing to incumbent firms, and new firm founding by licensing inventions to start-up firms. To justify our choice of binary outcome model as an appropriate econometric method, we first describe the measurement issue related to our outcome variable.

First and foremost, we decided to recode the cases in which inventions are licensed to incumbent firms and start-ups separately. Even if many mentions licensing and start-up founding as two representative cases of academic commercialization, prior literature alludes that mechanisms in which academic inventions are licensed to incumbent firms and start-up firms are different. This issue is also critical for policy makers' perspective. As we have seen, some gap-funding program specifies that its goal is to spawn start-up firms around its geographic region, thereby contributing to regional economic development. For them, it would be of first order importance to understand factors affecting more start-up firms spawning, but less interested in promoting licensing to incumbent firms. Finally, the MIT TLO documents cases in which inventions are licensed to incumbent firms and start-up firms. It might be ideal if we treat the outcome as mutually exclusive ones, and apply discrete outcome models, for instance multinomial logit analysis. However, there are several inventions that are licensed to both incumbent firms and start-up firms, in which case coding them as different category outcome variables is not well suited.

Second, there are many ways in which our measurement of duration from invention disclosure to technology commercialization can be inaccurate. At first we were interested in conducting event history analysis to understand factors affecting the rate of technology commercialization. Additional advantage of using event history analysis is that it takes into account the existence of right-censoring observations, that is, observations that recently added in the risk-set and therefore does not experience "event" even if its potential of experiencing "event" is sufficient. Given the relatively short history of the Deshpande Center, controlling for such potential bias in a systematic way comes as not negligible benefit. However, we later found out that there are many cases in which the duration can be biased. First, when an existing licensee wants to license newly disclosed invention with similar contractual terms, the TLO sometimes simply extends the coverage of existing licensing agreement to include the new invention, in which case the license effective date for the new invention is the same as the license effective date for the existing inventions in the same agreement. Second, we feel that the date of invention disclosure is rather arbitrary. A good example to explain this point is Brontes Technologies, a start-up firm from Deshpande-funded inventions.[5] The first invention related to this company is disclosed on June 8th, 2004, and it takes only a week for the invention to be licensed. According to its history, however, its inventor already initiated a series of actions to commercialize their invention in Autumn 2002. As invention disclosure is simply a recommended action for inventors, and particularly inventors considering commercializing their technologies by establishing start-up firm do have different incentives about disclosing their technologies to the TLO early on, we think that calculating duration between invention disclosure date and first commercialization deal might be inaccurate.

Given these complications, the most reliable output measure that we can construct is whether an invention is licensed to either for-profit firms or start-ups. After creating dummy variables of 1) licensing to incumbent firms, and 2) licensing to start-up firms separately, we will conduct logit analysis to identify factors affecting success in each commercialization path. We will also compare the two results to see different mechanisms governing each commercialization path.

[5] Its brief history can be found here. (http://en.wikipedia.org/wiki/Brontes_Technologies)

5.3 Method and results

Impact of gap-funding on licensing to incumbent firms

Table 19 and 20 show the results of logit analysis. The departmental level measure of its past exposure to licensing (*DEPT*) turns out to be a strongest predictor of licensing success. Receiving research funding from industry partners (*IND*) significantly increase the likelihood of licensing. There might be two sources for the differential. Usually industry-funded research aims more application-oriented research, and research questions are motivated by industry needs. This will lead industry-funded research output to be utilized more actively by incumbent firms. Alternatively, some industry funders mandate that the research output generated from their funding should be disclosed to them first, and if they want, they can exclusively license the inventions. Without detailed documentation on funding conditions, however, we cannot rule out any hypothesis. The number of patents granted from each invention (*PATENT*) turns out to be highly correlated to the likelihood of licensing. This is as expected, as prior literature has adopted the notion that the number of patents granted from a single invention is correlated with its commercial value. The number of student inventors is statistically positive significant to the likelihood of licensing.

Surprisingly, receiving funding from the Deshpande Center (*DESHPANDE)* does not increase invention's likelihood to be licensed to incumbent firms. Existing literature posits that developing a proof-of-concept and prototype can be a way to reduce potential licensees' concern on its technological and market uncertainty. At least on licensing, however, our result shows that this conjecture might not be a case. Similarly, faculty members' prior experience related to start-up founding (*FEX)* is not correlated with the likelihood of licensing.

Another surprising factor is that the likelihood that an invention by regular faculty member is licensed is much lower than the likelihood that an invention by non-faculty research scientist is licensed. In our analysis, the baseline dummy for academic rank is the group of non-faculty research scientists. Our estimated coefficients on academic rank dummies are all negative, indicating that the likelihood that faculty members' invention is licensed is significantly lower than that of non-faculty research scientists. Given that little is known on the behavior of university-affiliated academic scientists, this interesting phenomenon calls for follow-up research on their characteristics, including their motivation and incentive systems. Among faculty members, the likelihood that tenured professors' inventions are licensed is lower than untenured professors' inventions. In my view, this pattern also support the hypothesis that academic scientists under the pressure of reputation building through academic publication only choose to conduct application-oriented research when its commercial potential is significant. (Lacetera, 2009) In other words, untenured professors participate in research with commercial value, and this selection process might explain the superior performance of their inventions relative to that of tenured professors. Moreover, it might suggest that the social and knowledge capital related to commercialization, which tenured professors seem to have advantage, play lesser role in technology licensing. It should be also noted, however, that our sample consists of academic scientists in a highly reputable academic institutions, and therefore should not be generalized to describe the pattern of technology licensing of all university inventions.

Impact of gap-funding on new firm founding

Table 20 and 21 show our estimates on the predictor of start-up founding. Interestingly, I can observe a stark difference among predictors for licensing success (to incumbent firms) and predictors for new firm founding (licensing to start-up firms). In the case of new firm founding, Deshpande-funded inventions (*DESHPANDE)* are significantly more likely to result in new start-up firms than other MIT inventions. The commercial potential of an invention, as measured by the number of patents granted from the single invention (*PATENT),* was also significantly correlated with new firm founding. . In Model 3 and 6, we also found out that the coefficient on the interaction term of number of patents granted (*PATENT)* and gap-funding support (*DESHPANDE)* is negative. Similar to prior research, inventors' past experience in new firm founding also predicts that their subsequent inventions have a higher likelihood of resulting in new firm founding (Shane & Khurana, 2003).

In contrast to the previous analysis on licensing, inventions by faculty members are more likely to result in new firm founding than inventions by non-faculty research scientists, except inventions by assistant professors. We are also interested in whether the support from the Deshpande Center compensates for one's lower rank as an academic scientist. However, the interaction terms between our treatment variable (*DESHPANDE)* and levels of academic rank are all statistically not significant, implying that the positive impact of receiving gap-funding on start-up founding is not different across academic ranks.

Finally, it is interesting to observe that the number of students participating in the research is correlated with the chance of new firm founding based on that invention. From qualitative investigations on the start-up firms emerged from MIT inventions, I also observed that students involved in the research project actually decide to establish and join the firm that their discovery is being commercialized.

Overall, my findings suggest that the processes for licensing to incumbent firms and start-up firms (new firm founding) are different. Prior research tends to describe the two events together under the term "academic commercialization," however, the fact that different predictors exist for these distinct events indicates that by aggregating those two distinct events, scholars have missed the opportunity of studying micro-level mechanism of how scientific discoveries are transferred and commercialized in the market. Our key result is that the support from gap-funding programs exerts different level of positive influence for the process of licensing (to incumbent firms) and new firm founding (licensing to start-up firms). It implies that for inventions that are developed in a highly renowned research-oriented university like MIT, the lack of proof-of-concept and prototype matters less for technology licensing. However, providing research funding for prototype development and networking opportunities with industry practitioners increases the likelihood that an academic invention results in start-up founding. It is also noteworthy that its positive impact is larger for inventions without intellectual property rights protection. As IPR has been pointed out as a formal mechanism to reduce various uncertainties in the ability of appropriation and technological value (Gans, Hsu & Stern, 2008), our result might suggest that developing proof-of-concept and prototype is another effective way to reduce such uncertainties to the mind of investors and inventors.

Our interpretation is not without limitations. In particular, our further work should address the source of differential effects that gap-funding provides to technology licensing and start-up founding. Our previous explanation assumes that the role of prototype is less important for highly reputable academic institutions like MIT. Another interesting avenue of thinking is the possible positive confidence that proof-of-type and prototype would bring to the mind of inventors themselves. Prior research argues that developing proof-of-type and prototype resolves the concern of technological and market uncertainty by potential licensees and venture capitalists. If somehow the support from gap-funding programs only increases the likelihood of new firm founding, but not the likelihood of licensing to incumbent firms, the existing theory does not provide sufficient explanation for the difference. I believe that one missing part in the existing literature is the potential impact of gap-funding on the side of inventors, and subsequent research should follow-up to explain the different path of academic commercialization.

6. Conclusion

In this study, I attempt to provide theoretical ground of gap-funding program by reviewing existing literature on academic commercialization, describe key constructs that determine the type of gap-funding program by surveying currently active gap-funding programs at U.S. universities, and analyze the antecedents and consequences of establishing gap-funding programs using detailed information on the MIT Deshpande Center gap-funding program. From a practitioner's perspective, I believe our results provide two interesting observations. First, gap-funding program can be a policy measure to provide opportunities of technology commercialization for junior faculty members, that is, assistant or not tenured associate professors. Existing resources for technology commercialization, such as venture capital investment and industry funding have been available for senior faculty members whose academic reputation has been well established. Gap-funding program is an ideal platform for junior faculty members interested in technology commercialization. Its competing ground for securing necessary resources is expected to be relatively fair to junior faculty members. At the same time, the fact that it provides academic freedom for problem selection and disclosure mode allows junior faculty members to pursue the type of inventions located in the "Pasteur's quadrant", which are scientifically and commercially valuable and can be disclosed via publications and patents at the same time. Secondly, gap-funding program is more likely to increase the rate of new firm founding via licensing contracts to start-up firms, rather than licensing to incumbent firms. This suggests that gap-funding program can be a useful policy toolkit for regional economic development by fostering academic entrepreneurship. Economically, new firm founding has a more direct positive impact on the creation of jobs and the development of regional economy in general. From a perspective of knowledge creation, entrepreneurial firms are the major agents to bring in disruptive innovation in the marketplace (Klepper, 1996), and at the same time, tend to form a robust link between industry and academic science by providing social and financial capital. (Murray, 2004; Shane, 2004) Our finding tells us that gap-funding program has a disproportionate positive impact to the technology transfer from academic intuitions to industry via start-up spawning, and I believe many practitioners have neglected this point.

From the perspective of scholar interested in innovation, our descriptive efforts have pointed out many missing links that exist in the prior literature. For instance, our understanding on the micro-level mechanism for technology commercialization is still limited. Our results particularly show that different predictors exist for the success of licensing to incumbent firms and new firm founding as measured by licensing to start-up firms. In addition, the canonical view of life-cycle model of scientists, in which scientists focus on academic publications in the early stage of the career and gradually participate in commercialization later on, misses the empirical evidence that junior faculty members are also willing to participate in the academic commercialization if appropriate supporting programs exist. Given the prevalence of technologies on the "Pasteur's quadrant", it would be timely to rebuild our conceptual model on the knowledge production and diffusion function of academic scientists. Finally, this research calls for the scholarly community's attention that the types of funding program for academic and commercial research is increasing dramatically, and traditional dichotomy between public and private R&D funding model cannot capture all characteristics of this hybrid program.

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Table

Table 1: Examples of gap-funding programs (philanthropy)

Program	University	Year Founded	Funding Source ($000,000)	Affiliation	Services	Target Area	Grant ($000)	Projects Funded	Output
von Liebig Entrepreneurism Center	UCSD	2001	10	School of Engineering	Funding; Advisory and mentoring; Education	Defined by partners	Technology Acceleration Program (15 - 75)	82	37 spinout
Deshpande Center	MIT	2002	17.5	School of Engineering	Funding; Advisory and mentoring; Education	General	Ignition (50); Innovation (250)	99	21 spinout
Biomedical Accelerator Fund	Harvard	2007	6 (2007); 50 (2013)	TLO	Funding; Education	Biomedical	Pilot (25); 150-200	27	N/A
Coulter Translational Partnership	Boston, Case Western Reserve, Drexel, Duke, Georgia Tech (Joint with Emory), Stanford, Michigan, Virginia, Washington, Wisconsin	2006	4.5	Dept. of Biomedical Eng.	Varying	Biomedical	100	6-8 (annual)	Varying
Coulter Translational Partnership	Columbia, Johns Hopkins, Louisville, Missouri, Pittsburgh, Southern California	2011	N/A	Dept. of Biomedical Eng.	N/A	Biomedical	N/A	N/A	N/A

Table 2: Examples of gap-funding programs (university)

Program	University	Year Founded	Funding Source ($000,000)	Affiliation	Target Area	Grant ($000)	Projects Funded	Output
Ignition Awards / Launch Awards	Boston University	N/A		TLO	General	50-200 (launch)	37; 2-3 launch (annual)	2-3 (Launch)
Internal Innovation Funding Programs	Caltech	N/A		TLO	General	125		
NYU Innovation Venture Fund	NYU	2010	3	University	General			
Purdue Research Foundation-managed Trask Innovation Fund (TIF)	Purdue University	N/A		TLO	General			
Proof of Concept Funds for Technology Commercialization Program	Rutgers	N/A		University	General	50		
Gap Fund	Stanford University	2000		TLO	General	250		
Birdseed Fund	Stanford University	N/A		TLO	General	25		
Proof of Concept Fund	University of California	N/A		N/A	General			
Proof of Concept Grant (POCg)	University of Colorado	2005		TLO	Biomedical	10-25	58	17 spinout; 24 licensing
POC Grant Program (POCg) for Renewable Energ	University of Colorado	2011		TLO	Cleantech	50		
UIC OTM Proof of Concept Gap Funding Initiative	University of Illinois, Chicago	2012		TLO	General	25-75		
Commercial Ventures and Intellectual Property (CVIP) Technology Fund	University of Massachusetts	2004	0.05 (FY 2004)	TLO	General	25	66	
The Engineering Translational Research Fund	University of Michigan	N/A		TLO	General	Max 50		
Commercialization Gap Fund (CGF)	University of Washington	N/A	1 (annual)	TLO	General	50		
Innovation & Economic Development Research Program (IEDR)	University of Wisconsin	1973		University	General	40-50	15 (annual)	15
Robert Draper Technology Innovation Fund (TIF) Grants	University of Wisconsin	1991		University	General	50		
Ideas Empowered Program	USC	2010		TLO	General		9 (annual)	9

Table 3: Examples of gap-funding program (government)

Program	University	Year Founded	Funding Source ($000,000)	Sponsor	Affiliation	Target Area	Grant ($000)	Projects Funded	Output
Bioscience Discovery and Evaluation Grant Program (BDEG , POCsb)	University of Colorado	2006	N/A	State	TLO	Biomedical	50-200	34	7 spinout; 8 licensing
Maryland Proof of Concept Alliance	University of Maryland	2010	5.1	U.S. Army Research Laboratory (ARL)	University	Defence	15	11 (annual)	
U-M MTRAC for Life Sciences	University of Michigan	2013	7.5	Michigan Economic Development Corporation (State); University	Medical School	Life Science			
TBD	Columbia University	2013	5	New York State Energy Research and Development Authority (State)		Clean Energy			
TBD	Polytechnic Institute of New York University	2013	5	New York State Energy Research and Development Authority (State)		Clean Energy			

Table 4: List of i6 challenge winners

Round	Name	Participants	Region	Area
2010	Global Center for Medical Innovation	Georgia Institute of Technology, Saint Joseph Translational Research Institute (SJTRI), Piedmont Healthcare and the Georgia Research Alliance (GRA)	Atlanta	Medical
2010	New Mexico Technology Ventures Corporation	Arrowhead Center, Air Force Research Lab, Los Alamos National Lab, National Center for Genome Resources, New Mexico State University, New Mexico Tech University, Sandia National Laboratories, University of New Mexico, White Sands Missile Range	Austin	N/A
2010	Innovative Solutions for Invention Xceleration	University of Akron Research Foundation and Austen BioInnovation Institute in Akron	Chicago	Biomedical; Polymer science
2010	Coalition for Plant and Life Sciences, BioGenerator	BioGenerator, Washington University in St. Louis, Saint Louis University, the University of Missouri at St. Louis, Donald Danforth Plant Science Center, St. Louis County Economic Council, and the St. Louis Development Corporation	Denver	Bioscience
2010	Agile Innovation System	Innovation Works, Inc. and Carnegie Mellon Universit		N/A
2010	Oregon Innovation Cluster	Oregon Translational Research & Drug Development Institute, the Oregon Nanoscience & Microtechnologies Institute, and the Oregon Built Environment & Sustainable Technologies Center	Oregon	N/A
2011	Iowa Innovation Network i6 Green Project	Iowa Innovation Council and Iowa State University	Iowa	Clean Energy
2011	Proof of Concept Center for Green Chemistry Scale-up	Michigan State University, Lakeshore Advantage, Prima Civitas Foundation, and the NewNorth Center	Michigan	Clean Energy
2011	iGreen New England Partnership	New England Clean Energy Foundation (NECEF) with Maine partners including the Maine Technology Institute (MTI), E2Tech, the Maine Regional Redevelopment Authority (MRRA) and the University of Maine.	New England	Clean Energy
2011	Igniting Innovation (I2) Cleantech Acceleration Network	University of Central Florida, the University of Florida, and the Technological Research and Development Authority	Florida	Clean Energy
2011	Louisiana Tech Proof of Concept Center	Louisiana Tech University	Louisiana	Clean Energy
2011	Washington Clean Energy Partnership Project	Puget Sound Regional Council, South Seattle Community College, Cleantech Open, and InnovateWashington	Washington State	Clean Energy
2012	The Arrowhead Center	New Mexico State University	New Mexico	N/A
2012	FirstWaVE Venture Center	Tampa Bay WaVE, University of South Florida	Tampa	N/A
2012	Energy Storage Proof of Concept Center	Southern Indiana Development Commission and the Battery Innovation Center Inc.	Indiana	Energy
2012	Wisconsin Innovates for Success Proof of Concept Center	University of Wisconsin - Madison	Madison	N/A
2012	Digital Sandbox Proof of Concept Center	corporate (Sprint, Hallmark, UMB, VML, Cerner, RareWire, SparkLabKC), academic (UMKC, University of Kansas), nonprofit (Enterprise Center of Johnson County; Kansas City Area Life Sciences Institute; Union Station, Inc.; KCNext), public (Missouri Technology Corporation, Mayors' Bistate Innovation Team, Economic Development Corp. of KC) and philanthropic (Ewing Marion Kauffman Foundation)	Kansas City	IT
2012	Virginia Innovation Project	University of Virginia, Virginia Tech, and SRI International	Virginia	N/A
2012	Proof of Concept Center	University of California, Davis and the Sacramento Area Regional Technology Alliance (SARTA)	Sacramento	Agriculture

Table 5: Number of applicants and awardees

	Ignition Grant			Innovation Grant			Total		
	Applicants	Awardess	(%)	Applicants	Awardess	(%)	Applicants	Awardess	(%)
2002 Fall	30	6	20	18	4	22	48	10	21
2003 Spring	20	8	40	12	0	0	32	8	25
2003 Fall	22	7	32	20	4	20	42	11	26
2004 Spring	15	4	27	21	3	14	36	7	19
2004 Fall	16	3	19	16	1	6	32	4	13
2005 Spring	22	3	14	19	3	16	41	6	15
2005 Fall	13	2	15	10	1	10	23	3	13
2006 Spring	16	3	19	11	1	9	27	4	15
2006 Fall	23	4	17	14	1	7	37	5	14
2007 Spring	22	5	23	12	1	8	34	6	18
2007 Fall	24	5	21	12	3	25	36	8	22
2008 Spring	9	5	56	3	0	0	12	5	42
2008 Fall	16	4	25	11	1	9	27	5	19
2009 Spring	0	0	-	1	0	0	1	0	0
2009 Fall	11	4	36	8	2	25	19	6	32
2010 Fall	8	3	38	10	4	40	18	7	39
2011 Fall	6	2	33	7	2	29	13	4	31
Mean	16.06	4.00	-	12.06	1.82	-	28.12	5.82	-
Total	273	68	25	205	31	15	478	99	21

Note: Proposals for renewal are not counted. % indicates the percentage of awardees from applicants.

Table 6: Distribution of applicants and awardees by department, 2002-2011

	Number of applicants	Number of awardees	(%)
Mechanical Engineering	100	24	24
Electrical Engineering-Computer Science	94	18	19
Materials Science and Engineering	44	14	32
Chemical Engineering	27	12	44
Biological Engineering	20	1	5
Aeronautics and Astronautics	15	3	20
Chemistry	14	4	29
Civil and Environmental Engineering	13	0	0
Media Lab	13	1	8
Brain & Cognitive Sciences	13	0	0
Biology	11	3	27
HST	10	4	40
Engineering Systems Division	3	0	0
Nuclear Science and Engineering	3	0	0
Physics	2	0	0
Earth, Atmospheric & Planetary Sciences	1	0	0
Mathematics	1	0	0
Other Professors	24	5	21
Non-Professors	70	10	14
Total	478	99	21

Note: Proposals for renewal are not counted. Only PIs are included. Dual-appointed department is not counted. % indicates the percentage of awardees from applicants for each department. "Other professors" include professors not from School of Science, School of Engineering, and the Whitaker College of Health Sciences and Technology. Examples of "non-professors" are research scientists, visiting professors, and MIT affiliate.

Table 7: Distribution of applicants by rank, 2002-2011

		Assisant	Associate (without tenure)	Associate (with tenure)	Professor	Emeritus	Total
	Mechanical Engineering	18	5	19	53	5	100
	Electrical Engineering-Computer Science	24	10	11	44	5	94
	Materials Science and Engineering	8	4	3	29	0	44
	Chemical Engineering	0	2	5	20	0	27
Engineering	Biological Engineering	10	1	0	9	0	20
	Aeronautics and Astronautics	1	2	6	5	1	15
	Civil and Environmental Engineering	2	0	1	10	0	13
	Engineering Systems Division	2	0	0	1	0	3
	Nuclear Science and Engineering	0	1	0	2	0	3
	Chemistry	4	1	0	9	0	14
	Brain & Cognitive Sciences	1	2	2	8	0	13
Science	Biology	0	0	0	11	0	11
	Physics	1	0	0	1	0	2
	Earth, Atmospheric & Planetary Sciences	0	0	0	1	0	1
	Mathematics	0	0	0	1	0	1
	%	20	8	13	67	3	100
	Total	71	28	47	204	11	361

Note: Proposals for renewal are not counted. Only PIs are included. Dual-appointed department is not counted. Professors from "School of Science" and "School of Engineering" are counted.

Table 8: Number of women applicants, 2002-2011

	Ignition			Innovation			Total		
	Applicants	Women Applicants	(%)	Applicants	Women Applicants	(%)	Applicants	Women Applicants	(%)
2002 Fall	30	2	7	18	1	6	48	3	6
2003 Spring	20	1	5	12	0	0	32	1	3
2003 Fall	22	2	9	20	0	0	42	2	5
2004 Spring	15	0	0	21	1	5	36	1	3
2004 Fall	16	2	13	16	2	13	32	4	13
2005 Spring	22	4	18	19	1	5	41	5	12
2005 Fall	13	3	23	10	2	20	23	5	22
2006 Spring	16	0	0	11	2	18	27	2	7
2006 Fall	23	3	13	14	1	7	37	4	11
2007 Spring	22	2	9	12	2	17	34	4	12
2007 Fall	24	3	13	12	2	17	36	5	14
2008 Spring	9	1	11	3	1	33	12	2	17
2008 Fall	16	2	13	11	0	0	27	2	7
2009 Spring	0	0	0	1	0	0	1	0	0
2009 Fall	11	1	9	8	1	13	19	2	11
2010 Fall	8	2	25	10	1	10	18	3	17
2011 Fall	6	1	17	7	0	0	13	1	8
Total	273	29	11	205	17	8	478	46	10

Note: Proposals for renewal are not counted. Only PIs are included. % indicates the percentage of awardees from applicants for each department.

Table 9: Schools and Departments of MIT Professors
(N=846)

School	Department	Number	%
Engineering	Electrical Engineering-Computer Science	148	17.5
Science	Physics	97	11.5
Engineering	Mechanical Engineering	88	10.4
Science	Mathematics	79	9.3
Science	Biology	68	8.0
Science	Earth, Atmospheric & Planetary Sciences	48	5.7
Science	Brain & Cognitive Sciences	46	5.4
Engineering	Civil and Environmental Engineering	46	5.4
Engineering	Aeronautics and Astronautics	45	5.3
Engineering	Materials Science and Engineering	42	5.0
Engineering	Chemical Engineering	41	4.8
Science	Chemistry	38	4.5
Engineering	Nuclear Science and Engineering	25	3.0
Engineering	Biological Engineering	24	2.8
Engineering	Engineering Systems Division	11	1.3

Table 10: Descriptive statistics for individual-level variables

	Mean	Std. Dev.	Min.	Max.	N
Time-varying (6,399 person-year observations)					
Experience at MIT (year)	16.21	9.66	1	31.00	6399
% Assistant professor	0.18	0.38	0	1.00	6399
% Associate professor (without tenure)	0.04	0.21	0	1.00	6399
% Associate professor (with tenure)	0.09	0.29	0	1.00	6399
% Full professor	0.68	0.47	0	1.00	6399
Patent flow (year)	0.25	1.03	0	22.00	6399
Patent stock	3.20	13.06	0	308.00	6399
Publication flow (year)	2.50	3.73	0	47.00	6399
Publication stock	33.48	53.99	0	652.00	6399
JIF-weighted publication flow (year)	17.31	35.25	0	433.11	6399
JIF-weighted publication stock	222.58	505.94	0	5135.00	6399
Industry funding flow (year)	0.08	0.27	0	1.00	6399
Industry funding experience	0.68	1.72	0	17.00	6399
Licensing flow (year)	0.14	0.60	0	17.00	6399
Licensing experience	1.36	4.36	0	106.00	6399
Start-up flow (year)	0.04	0.24	0	4.00	6399
Start-up experience	0.44	1.52	0	29.00	6399
% Deshpande application	0.05	0.22	0	1.00	6399
% Deshpande funding	0.01	0.11	0	1.00	6399
Time-invariant (846 observations)					
% Female	0.15	0.36	0	1.00	846
PhD degree year	1986.39	14.44	1949	2011.00	846
Year of hire	1990.57	14.55	1954	2011.00	846
% Hired as assistant professor	0.76	0.43	0	1.00	846
% Hired as associate professor (w/o tenure)	0.09	0.29	0	1.00	846
% Hired as associate professor (w/ tenure)	0.03	0.18	0	1.00	846
% Hired as full professor	0.10	0.30	0	1.00	846

Table 11: Summary statistics for applicants and non-applicants
(Time-variant variables; N=644; All faculty members working in the academic year 2011-2012)

	Applicants (N=150)	Non-applicants (N=494)	t-stat.	p-value
Demographic				
% Female	0.14	0.18	−1.207	0.229
	(0.348)	(0.385)		
PhD degree year	1987.4	1988.004	−0.520	0.604
	(11.929)	(14.096)		
Experience at MIT (year)	19.02	17.227	1.965	0.050
	(9.239)	(11.415)		
Department				
% Engineering faculty	0.827	0.496	8.629	0.000
	(0.38)	(0.5)		
% Aero	0.033	0.061	−1.504	0.134
	(0.18)	(0.239)		
% Bio-eng	0.04	0.028	0.658	0.511
	(0.197)	(0.166)		
% Biology	0.047	0.103	−2.565	0.011
	(0.212)	(0.305)		
% Brain	0.033	0.067	−1.808	0.072
	(0.18)	(0.25)		
% Chem-eng	0.087	0.034	2.136	0.034
	(0.282)	(0.182)		
% Chemistry	0.067	0.034	1.465	0.145
	(0.25)	(0.182)		
% Civil	0.06	0.055	0.243	0.808
	(0.238)	(0.228)		
% Earth	0.007	0.065	−4.492	0.000
	(0.082)	(0.246)		
% EECS	0.3	0.164	3.312	0.001
	(0.46)	(0.371)		
% ESD	0.013	0.014	−0.077	0.938
	(0.115)	(0.118)		
% Material	0.107	0.028	2.970	0.003
	(0.31)	(0.166)		
% Math	0.007	0.097	−6.069	0.000
	(0.082)	(0.296)		
% Mech-eng	0.187	0.081	3.090	0.002
	(0.391)	(0.273)		
% Nuclear	0	0.03	−3.929	0.000
	(0)	(0.172)		
% Physics	0.013	0.138	−6.853	0.000
	(0.115)	(0.345)		

Table 12: Summary statistics for applicants and non-applicants
(Time-varying variables; N=644; All faculty members working in the academic year 2011-2012)

	Applicants (N=150)	Non-applicants (N=494)	t-stat.	p-value
Rank				
% Assistant professor	0.08	0.229	−5.096	0.000
	(0.272)	(0.42)		
% Associate professor (without tenure)	0.007	0.022	−1.657	0.098
	(0.082)	(0.148)		
% Associate professor (with tenure)	0.127	0.097	0.972	0.332
	(0.334)	(0.296)		
% Full professor	0.787	0.652	3.385	0.001
	(0.411)	(0.477)		
Academic productivity				
Patent stock	10.333	1.998	3.511	0.001
	(28.89)	(5.986)		
Average annual patent number	0.462	0.087	4.403	0.000
	(1.032)	(0.285)		
Publication stock	58.333	35.472	3.106	0.002
	(85.067)	(54.219)		
Average annual publication count	3.085	1.994	3.586	0.000
	(3.5)	(2.322)		
JIF-weighted publication stock	350.807	264.403	1.433	0.153
	(665.105)	(583.299)		
Average annual JIF-weighted publication count	19.48	14.972	1.662	0.098
	(30.136)	(25.363)		
Commercialization productivity				
Industry funding experience	2.753	0.457	8.220	0.000
	(3.336)	(1.377)		
Average annual industry funding experience	0.166	0.031	8.718	0.000
	(0.183)	(0.092)		
Licensing experience	4.727	0.986	4.436	0.000
	(10.204)	(2.911)		
Average annual licensing experience	0.236	0.048	5.829	0.000
	(0.387)	(0.133)		
Start-up experience	1.647	0.269	5.204	0.000
	(3.205)	(0.884)		
Average annual start-up experience	0.087	0.013	6.375	0.000
	(0.139)	(0.046)		

Table 13: Summary statistics for applicants and non-applicants
(Time-varying variables; N=245; Engineering professors working in the academic year 2011-2012)

	Applicants (N=149)	Non-applicants (N=96)	t-stat.	p-value
Academic productivity				
Patent stock	9.074	3.834	3.176	0.002
	(14.833)	(7.589)		
Average annual patent number	0.436	0.156	3.615	0.000
	(0.694)	(0.36)		
Publication stock	48.819	33.318	2.427	0.016
	(50.65)	(45.145)		
Average annual publication count	2.403	1.494	3.011	0.003
	(2.469)	(1.991)		
JIF-weighted publication stock	195.564	141.709	1.577	0.116
	(255.64)	(266.735)		
Average annual JIF-weighted publication count	10.226	6.872	1.864	0.064
	(13.829)	(13.469)		
Commercialization productivity				
Industry funding experience	3.043	1.02	5.216	0.000
	(3.331)	(2.21)		
Average annual industry funding experience	0.161	0.044	5.885	0.000
	(0.179)	(0.093)		
Licensing experience	4.202	1.364	4.085	0.000
	(6.309)	(2.992)		
Average annual licensing experience	0.205	0.059	4.585	0.000
	(0.29)	(0.133)		
Start-up experience	1.553	0.49	3.894	0.000
	(2.452)	(1.264)		
Average annual start-up experience	0.079	0.02	4.517	0.000
	(0.119)	(0.054)		

Table 14: Fixed-effect logit analysis

	Model 1	Model 2	Model 3	Model 4
Pub. flow in (t-1) year	0.00968	0.0184	0.0197	0.0266
	(0.0247)	(0.0279)	(0.0233)	(0.0238)
Pub. flow in (t-2) year		-0.0316	-0.0275	-0.0215
		(0.0271)	(0.0310)	(0.0350)
Pub. flow in (t-3) year			-0.0134	0.00607
			(0.0267)	(0.0318)
Pat. flow in (t-1) year	-0.111	-0.114	-0.113	-0.0779
	(0.0834)	(0.0930)	(0.0745)	(0.0831)
Ind. fund. flow in (t-1) year	0.275	0.285	0.289	0.361^{*}
	(0.180)	(0.166)	(0.199)	(0.163)
Lic. flow in (t-1) year	-0.0339	-0.0217	-0.0224	-0.00142
	(0.123)	(0.0947)	(0.0924)	(0.101)
Assistant prof.	2.617^{***}	2.530^{***}	2.508^{***}	
	(0.511)	(0.586)	(0.456)	
Associate prof. (w/o tenure)	1.977^{***}	1.931^{***}	1.921^{***}	
	(0.583)	(0.539)	(0.437)	
Associate prof. (w/ tenure)	1.152^{**}	1.135^{***}	1.132^{**}	
	(0.360)	(0.292)	(0.351)	
Years after PhD				-0.180^{***}
				(0.0246)
Observations	1592	1592	1592	1592
Log lik.	-511.8	-511.2	-511.1	-503.4

Standard errors in parentheses

Cluster-robust standard errors for the individual fixed effects estimated by bootstrapping.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Fixed-effect logit analysis (cont'd)

	Model 5	Model 6	Model 6	Model 8
Pub. flow in (t-1) year	0.0132	0.0199	0.0207	0.0273
	(0.0298)	(0.0299)	(0.0274)	(0.0303)
Pub. flow in (t-2) year		-0.0244	-0.0218	-0.0175
		(0.0279)	(0.0325)	(0.0297)
Pub. flow in (t-3) year			-0.00852	0.00869
			(0.0286)	(0.0400)
Pat. exp. until (t-1) year	-0.402	-0.396	-0.391	-0.332
	(0.290)	(0.310)	(0.321)	(0.353)
Ind. fund. exp. until (t-1) year	-0.149	-0.141	-0.136	0.133
	(0.351)	(0.314)	(0.331)	(0.297)
Lic. exp. until (t-1) year	-0.105	-0.0882	-0.0857	-0.0108
	(0.318)	(0.355)	(0.284)	(0.289)
Assistant prof.	2.272^{***}	2.219^{***}	2.210^{***}	
	(0.556)	(0.518)	(0.509)	
Associate prof. (w/o tenure)	1.757^{***}	1.731^{***}	1.728^{***}	
	(0.488)	(0.394)	(0.496)	
Associate prof. (w/ tenure)	1.023^{***}	1.015^{***}	1.016^{**}	
	(0.304)	(0.271)	(0.311)	
Years after PhD				-0.173^{***}
				(0.0219)
Observations	1592	1592	1592	1592
Log lik.	-512.7	-512.3	-512.3	-505.1

Standard errors in parentheses

Cluster-robust standard errors for the individual fixed effects estimated by bootstrapping.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Mixed-effect logit analysis

	Model 1	Model 2	Model 3	Model 4
Pub. flow in (t-1) year	−0.006	0.028	0.028	−0.002
	(0.018)	(0.026)	(0.027)	(0.027)
Pub. flow in (t-2) year		−0.050	−0.048	−0.049
		(0.028)	(0.031)	(0.032)
Pub. flow in (t-3) year			−0.003	0.029
			(0.030)	(0.030)
Patent flow in (t-1) year	0.025	0.030	0.030	0.055
	(0.047)	(0.046)	(0.046)	(0.046)
Ind. fund. flow in (t-1) year	1.081^{***}	1.095^{***}	1.095^{***}	1.012^{***}
	(0.167)	(0.167)	(0.167)	(0.169)
Lic. flow in (t-1) year	0.161^{*}	0.186^{*}	0.186^{*}	0.209^{**}
	(0.077)	(0.079)	(0.079)	(0.080)
Assistant prof.	0.400^{*}	0.359^{*}	0.357^{*}	
	(0.161)	(0.162)	(0.164)	
Associate prof. (w/o tenure)	0.547^{*}	0.526^{*}	0.524^{*}	
	(0.234)	(0.234)	(0.235)	
Associate prof. (w tenure)	0.228	0.222	0.221	
	(0.191)	(0.191)	(0.191)	
years.after.phd				-0.066^{***}
				(0.006)
Observations	6399	6399	6399	6399
Log llk.	−1434.679	−1433.075	−1433.071	−1376.227

Table 17: Mixed-effect logit analysis (cont'd)

	Model 5	Model 6	Model 7	Model 8
Pub. flow in (t-1) year	0.011	0.011	0.036	0.007
	(0.016)	(0.016)	(0.026)	(0.027)
Pub. flow in (t-2) year			−0.033	−0.032
			(0.031)	(0.031)
Pub. flow in (t-3) year			−0.001	0.027
			(0.029)	(0.029)
Patent exp. until (t-1) year	−0.323	−0.323	−0.326	0.138
	(0.172)	(0.172)	(0.172)	(0.176)
Ind. fund. exp. until (t-1) year	0.784***	0.784***	0.796***	0.604***
	(0.159)	(0.159)	(0.160)	(0.161)
Lic. exp. until (t-1) year	0.386*	0.386*	0.390*	0.328
	(0.169)	(0.169)	(0.169)	(0.174)
Assistant prof.	0.521**	0.521**	0.491**	
	(0.172)	(0.172)	(0.174)	
Associate prof. (w/o tenure)	0.558*	0.558*	0.538*	
	(0.242)	(0.242)	(0.243)	
Associate prof. (w tenure)	0.188	0.188	0.179	
	(0.193)	(0.193)	(0.194)	
years.after.phd				−0.073***
				(0.006)
Observations	6399	6399	6399	6399
Log llk.	−1438.142	−1438.142	−1437.369	−1379.057

Table 18: Descriptive statistics for MIT inventions, 2003-2012

	Mean	Std. Dev.	Min.	Max.	N
Outcome variables					
Number of licensing agreements with incumbent firms	0.21	0.68	0	18.00	4650
% Licensed to incumbent firms	0.15	0.36	0	1.00	4650
Number of licensing agreements with start-up firms	0.13	0.43	0	5.00	4650
% Licensed to start-up firms	0.10	0.30	0	1.00	4650
Predictor variables					
% Deshpande-funded	0.03	0.17	0	1.00	4650
% Industry-funded	0.21	0.41	0	1.00	4650
Number of patents granted	0.12	0.35	0	5.00	4650
Prior experience in firm-founding	4.70	11.91	0	80.17	4650
Prior experience in firm-founding (in the last five years)	1.87	4.34	0	28.50	4650
% No professor	0.33	0.47	0	1.00	4650
% Assistant professor	0.06	0.24	0	1.00	4650
% Associate professor (without tenure)	0.03	0.18	0	1.00	4650
% Associate professor (with tenure)	0.07	0.26	0	1.00	4650
% Full professor	0.50	0.50	0	1.00	4650
Control variables					
Department rank in firm founding	0.07	0.06	0	0.17	4650
Number of student inventors	2.02	1.51	0	16.00	4650
Number of outsider inventors	0.41	1.04	0	16.00	4650
% Invented in 2003	0.09	0.29	0	1.00	4650
% Invented in 2004	0.09	0.29	0	1.00	4650
% Invented in 2005	0.11	0.31	0	1.00	4650
% Invented in 2006	0.09	0.29	0	1.00	4650
% Invented in 2007	0.09	0.29	0	1.00	4650
% Invented in 2008	0.10	0.30	0	1.00	4650
% Invented in 2009	0.09	0.29	0	1.00	4650
% Invented in 2010	0.10	0.30	0	1.00	4650
% Invented in 2011	0.12	0.33	0	1.00	4650
% Invented in 2012	0.11	0.31	0	1.00	4650

Table 19: Logit analysis (outcome: licensing to incumbent firms)

	Model 1	Model 2	Model 3
(Intercept)	-1.524^{***}	-1.515^{***}	-1.531^{***}
	(0.148)	(0.148)	(0.149)
deshpande	−0.029	−0.425	0.111
	(0.249)	(0.798)	(0.284)
ind	0.750^{***}	0.750^{***}	0.751^{***}
	(0.100)	(0.100)	(0.100)
patent	0.812^{***}	0.809^{***}	0.842^{***}
	(0.106)	(0.106)	(0.111)
log(fex)	−0.023	−0.023	−0.022
	(0.049)	(0.049)	(0.049)
assistant prof.	-0.767^{***}	-0.736^{**}	-0.767^{***}
	(0.227)	(0.235)	(0.227)
associate prof. (w/o tenure)	-0.561^{*}	-0.671^{*}	-0.559^{*}
	(0.255)	(0.267)	(0.255)
associate prof. (w/ tenure)	-1.065^{***}	-1.054^{***}	-1.069^{***}
	(0.233)	(0.238)	(0.234)
full prof.	-0.762^{***}	-0.756^{***}	-0.762^{***}
	(0.165)	(0.166)	(0.165)
dept	3.326^{**}	3.272^{**}	3.308^{**}
	(1.179)	(1.180)	(1.179)
nstudent	0.083^{**}	0.084^{**}	0.083^{**}
	(0.027)	(0.027)	(0.027)
noutsider	0.026	0.025	0.025
	(0.039)	(0.039)	(0.039)
deshpande * assistant prof.		0.162	
		(0.994)	
deshpande * associate prof. (w/o tenure)		1.891	
		(1.143)	
deshpande * associate prof. (w/ tenure)		0.276	
		(1.125)	
deshpande * full prof.		0.331	
		(0.872)	
deshpande * patent			−0.322
			(0.344)
Log-likelihood	−1814.405	−1812.516	−1813.983
McFadden R-sq.	0.081	0.082	0.081
N	4650	4650	4650

Table 19: Logit analysis (outcome: licensing to incumbent firms) (cont'd)

	Model 4	Model 5	Model 6
(Intercept)	-1.538^{***}	-1.529^{***}	-1.544^{***}
	(0.148)	(0.148)	(0.148)
deshpande	−0.027	−0.427	0.107
	(0.249)	(0.798)	(0.285)
ind	0.740^{***}	0.740^{***}	0.741^{***}
	(0.100)	(0.100)	(0.100)
patent	0.810^{***}	0.807^{***}	0.839^{***}
	(0.106)	(0.106)	(0.111)
log(fex5)	−0.110	−0.110	−0.108
	(0.062)	(0.062)	(0.062)
assistant prof.	-0.780^{***}	-0.750^{**}	-0.781^{***}
	(0.227)	(0.235)	(0.227)
associate prof. (w/o tenure)	-0.569^{*}	-0.679^{*}	-0.567^{*}
	(0.255)	(0.267)	(0.255)
associate prof. (w/ tenure)	-1.064^{***}	-1.055^{***}	-1.068^{***}
	(0.234)	(0.238)	(0.234)
full prof.	-0.729^{***}	-0.722^{***}	-0.729^{***}
	(0.163)	(0.163)	(0.163)
dept	3.656^{**}	3.603^{**}	3.637^{**}
	(1.176)	(1.177)	(1.176)
nstudent	0.088^{***}	0.089^{***}	0.088^{***}
	(0.027)	(0.027)	(0.027)
noutsider	0.025	0.024	0.024
	(0.039)	(0.039)	(0.039)
deshpande * assistant prof.		0.162	
		(0.994)	
deshpande * associate prof. (w/o tenure)		1.894	
		(1.142)	
deshpande * associate prof. (w/ tenure)		0.300	
		(1.125)	
deshpande * full prof.		0.334	
		(0.872)	
deshpande * patent			−0.306
			(0.344)
Log-likelihood	−1812.903	−1811.005	−1812.517
McFadden R-sq.	0.081	0.082	0.082
N	4650	4650	4650

Table 19: Logit analysis (outcome: licensing to start-up firms)

	Model 1	Model 2	Model 3
(Intercept)	-3.185^{***}	-3.204^{***}	-3.205^{***}
	(0.207)	(0.209)	(0.207)
deshpande	1.192^{***}	1.888^{**}	1.398^{***}
	(0.204)	(0.646)	(0.225)
ind	−0.133	−0.128	−0.128
	(0.132)	(0.133)	(0.132)
patent	0.818^{***}	0.831^{***}	0.891^{***}
	(0.123)	(0.124)	(0.128)
log(fex)	0.271^{***}	0.271^{***}	0.272^{***}
	(0.051)	(0.051)	(0.051)
assistant prof.	0.100	0.315	0.106
	(0.311)	(0.326)	(0.311)
associate prof. (w/o tenure)	1.467^{***}	1.564^{***}	1.477^{***}
	(0.265)	(0.267)	(0.264)
associate prof. (w/ tenure)	1.333^{***}	1.311^{***}	1.323^{***}
	(0.231)	(0.240)	(0.232)
full prof.	0.602^{**}	0.611^{**}	0.599^{**}
	(0.204)	(0.207)	(0.204)
dept	0.102	0.145	0.098
	(1.294)	(1.295)	(1.294)
nstudent	0.150^{***}	0.150^{***}	0.151^{***}
	(0.031)	(0.031)	(0.031)
noutsider	−0.002	−0.002	−0.003
	(0.052)	(0.052)	(0.052)
deshpande * assistant prof.		−1.595	
		(0.938)	
deshpande * associate prof. (w/o tenure)		−1.995	
		(1.094)	
deshpande * associate prof. (w/ tenure)		−0.355	
		(0.820)	
deshpande * full prof.		−0.593	
		(0.699)	
deshpande * patent			-0.685^{*}
			(0.336)
Log-likelihood	−1328.795	−1325.739	−1327.017
McFadden R-sq.	0.118	0.120	0.120
N	4650	4650	4650

Table 20: Logit analysis (outcome: licensing to start-up firms) (cont'd)

	Model 4	Model 5	Model 6
(Intercept)	−3.214***	−3.233***	−3.233***
	(0.207)	(0.209)	(0.207)
deshpande	1.206***	1.887**	1.416***
	(0.205)	(0.646)	(0.226)
ind	−0.131	−0.127	−0.126
	(0.133)	(0.133)	(0.133)
patent	0.818***	0.831***	0.889***
	(0.123)	(0.123)	(0.127)
log(fex5)	0.347***	0.348***	0.348***
	(0.061)	(0.061)	(0.061)
assistant prof.	0.081	0.300	0.086
	(0.311)	(0.326)	(0.311)
associate prof. (w/o tenure)	1.446***	1.544***	1.457***
	(0.264)	(0.267)	(0.264)
associate prof. (w/ tenure)	1.308***	1.287***	1.298***
	(0.231)	(0.240)	(0.232)
full prof.	0.640**	0.648**	0.637**
	(0.202)	(0.204)	(0.202)
dept	0.183	0.224	0.177
	(1.283)	(1.284)	(1.284)
nstudent	0.150***	0.150***	0.151***
	(0.031)	(0.031)	(0.031)
noutsider	−0.003	−0.004	−0.004
	(0.052)	(0.052)	(0.052)
deshpande * assistant prof.		−1.594	
		(0.937)	
deshpande * associate prof. (w/o tenure)		−1.997	
		(1.094)	
deshpande * associate prof. (w/ tenure)		−0.356	
		(0.820)	
deshpande * full prof.		−0.567	
		(0.698)	
deshpande * patent			−0.705*
			(0.340)
Log-likelihood	−1326.841	−1323.751	−1325.015
McFadden R-sq.	0.120	0.122	0.121
N	4650	4650	4650

Figure

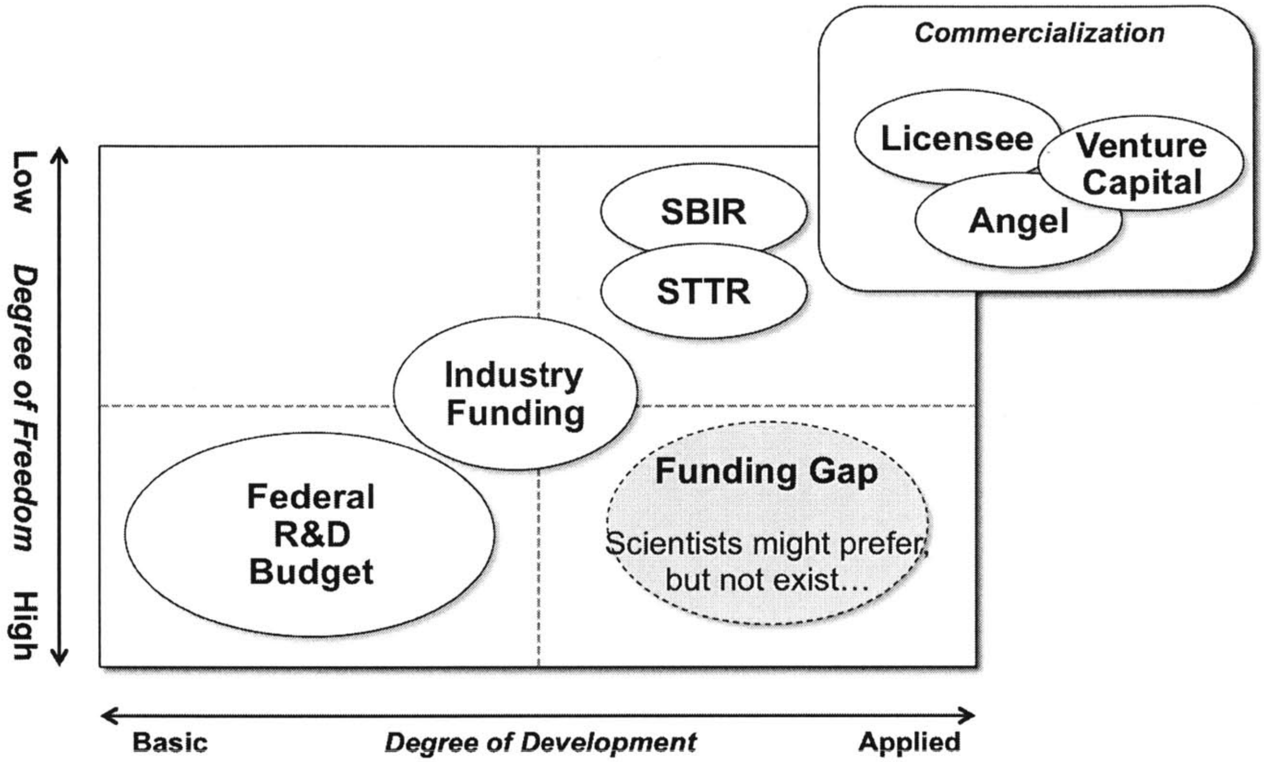

Figure 1: Funding sources in academic institutions

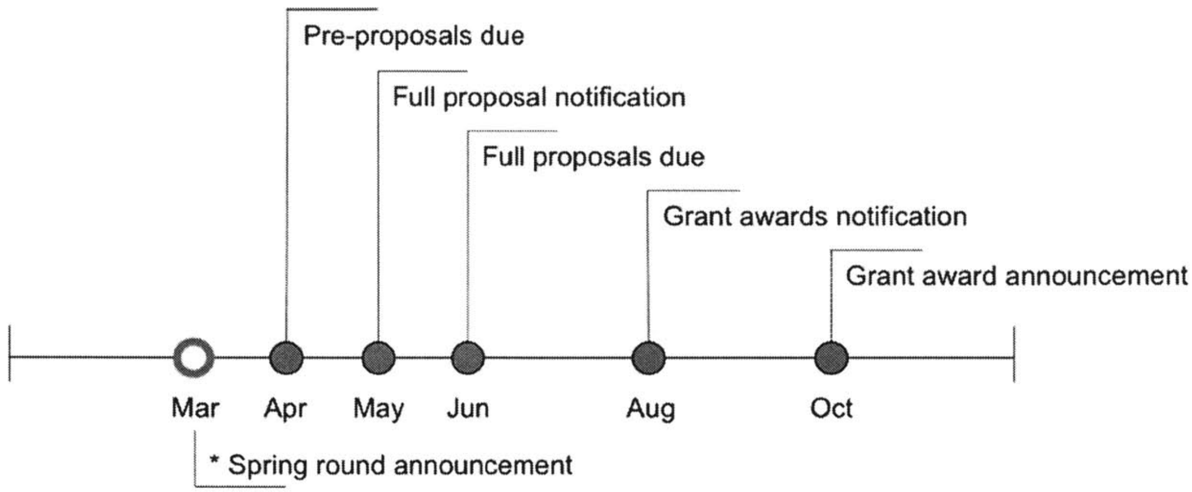

Figure 2: Timeline for the Fall submission

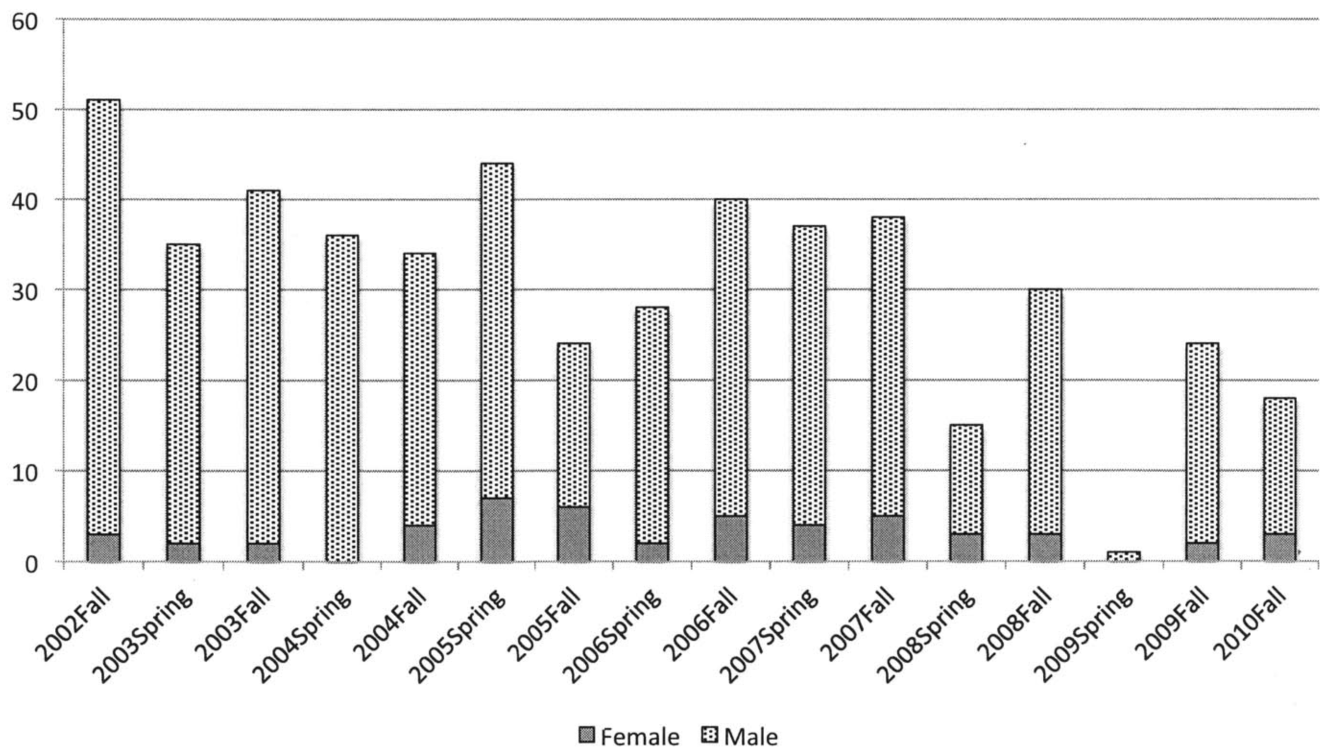

Figure 3: Number of the Deshpande grants applicants (2002 – 2010)

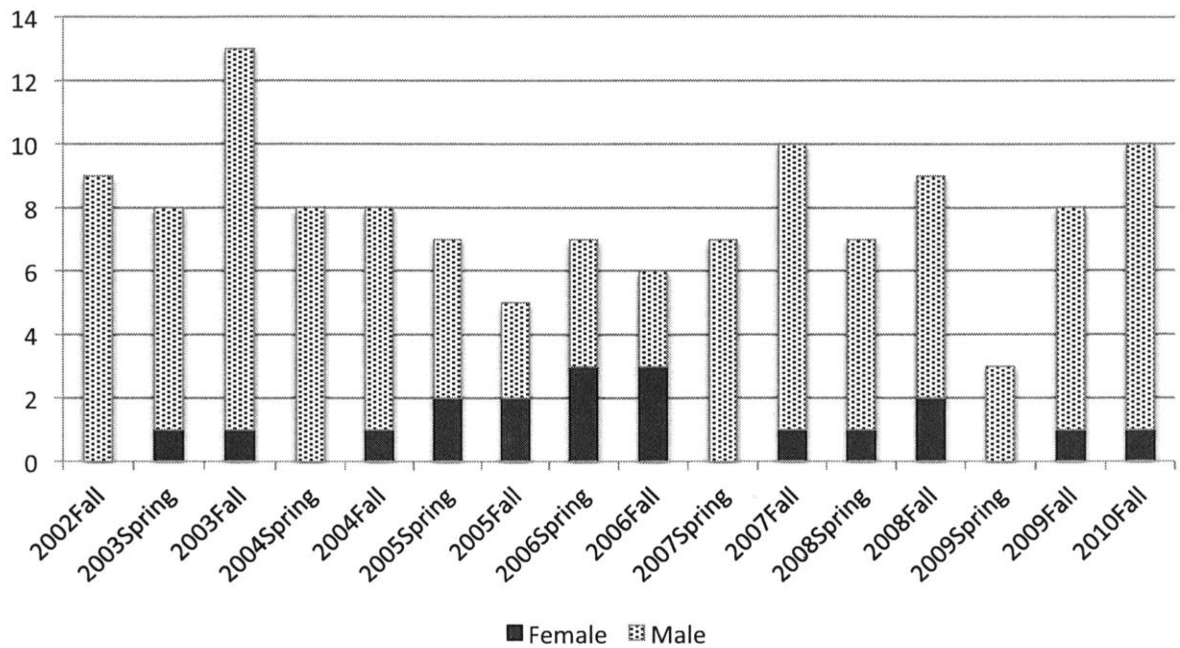

Figure 4: Number of the Deshpande grant awardees (2002 – 2010)

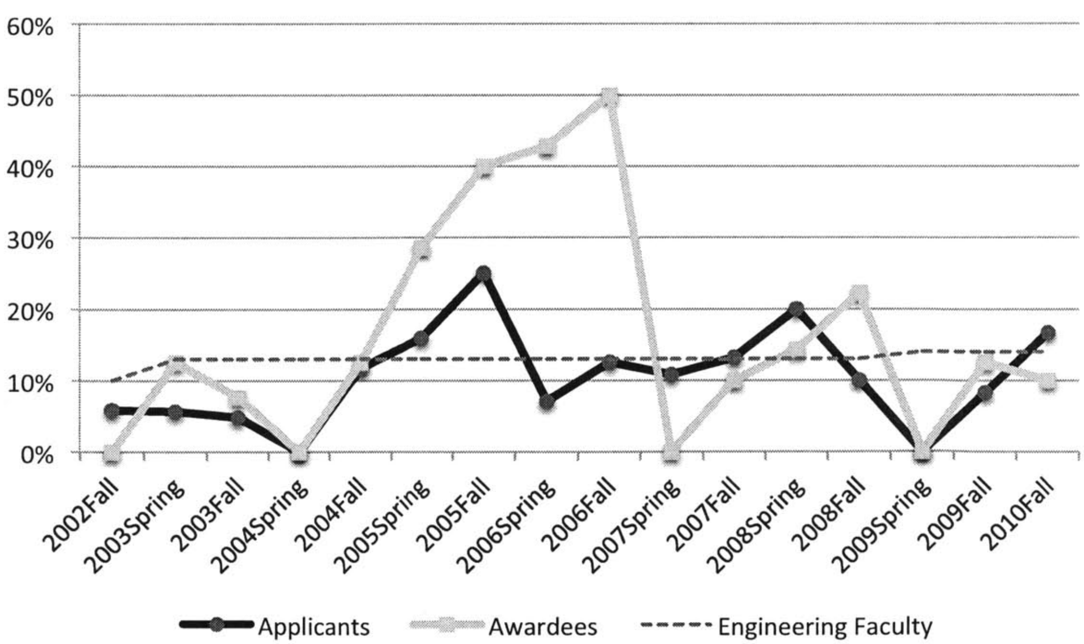

Figure 5: Percentage of women faculty applicants and awardees

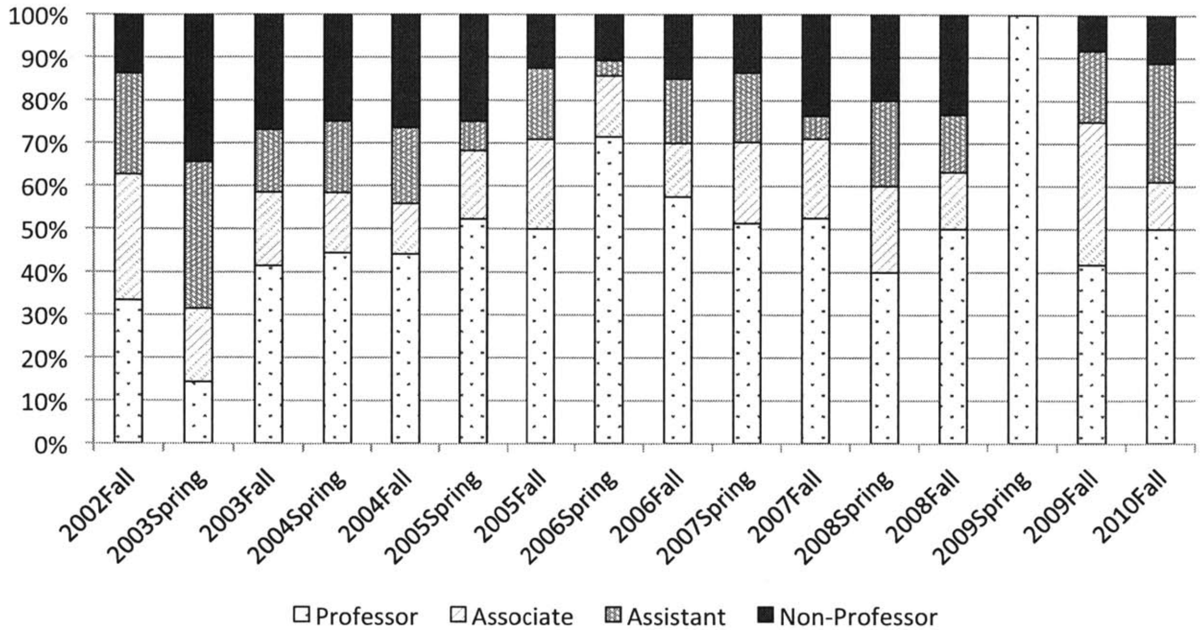

Figure 6: Distribution of academic rank among the Deshpande grants applicants

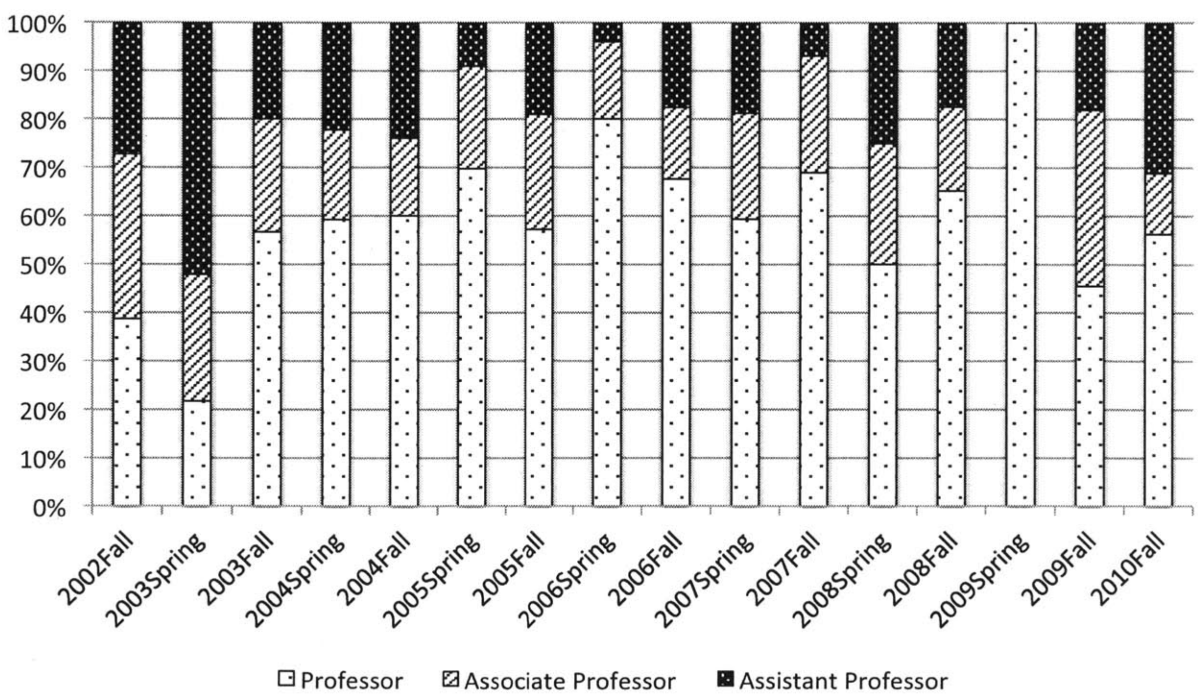

Figure 7: Share of academic rank among the Deshpande grants applicants

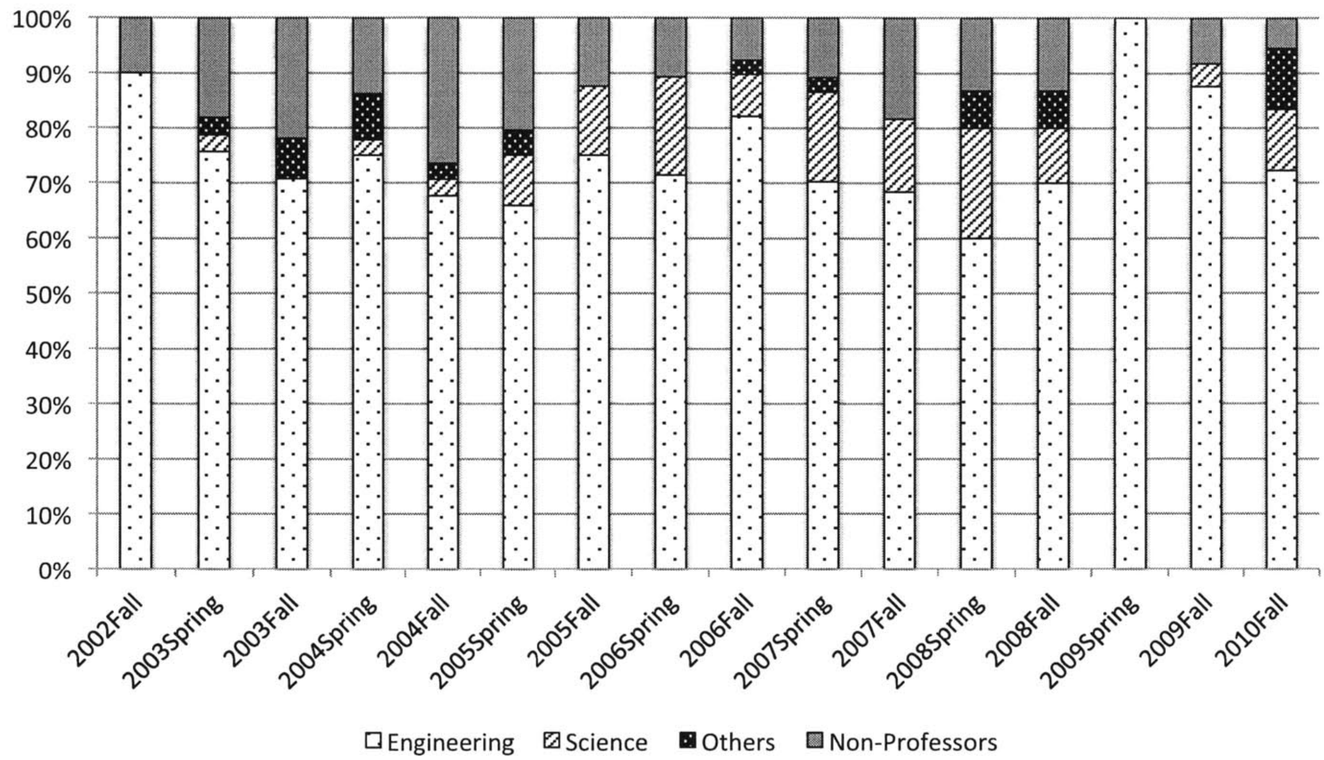

Figure 8: School of the Deshpande grants applicants, by year

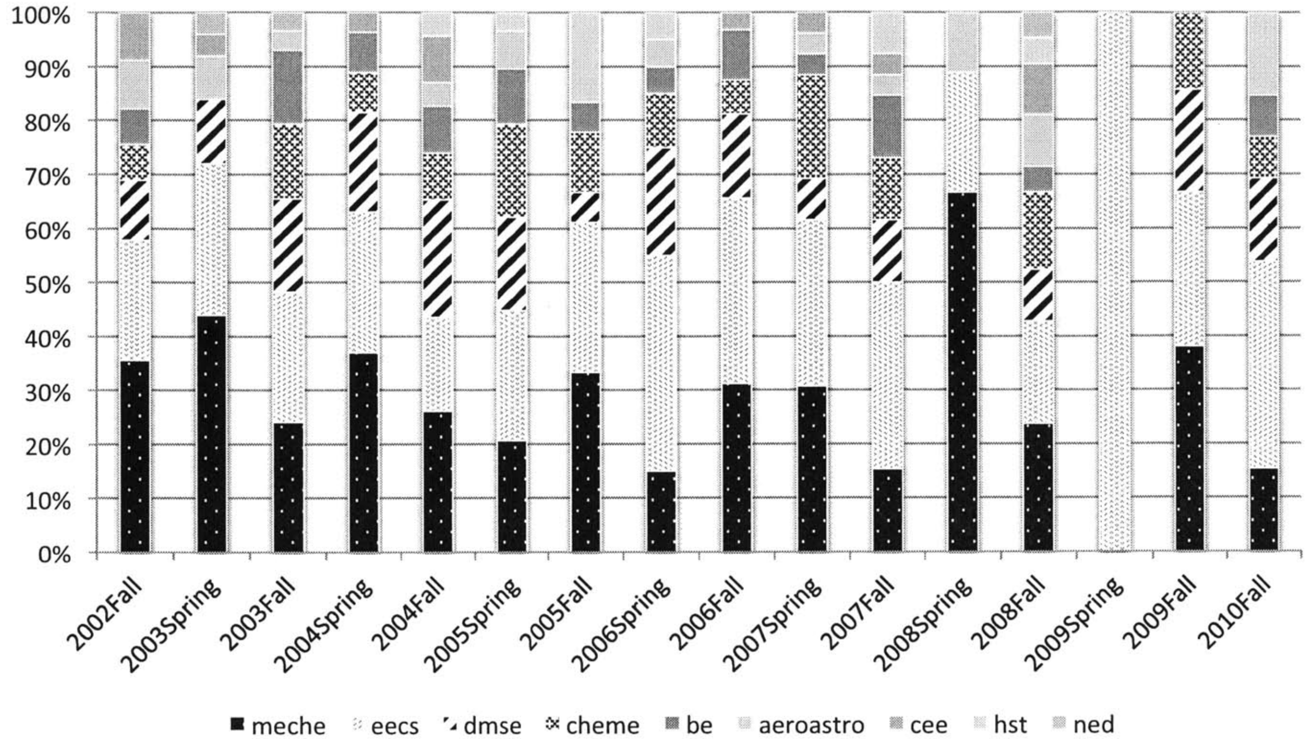

Figure 9: Applicants from the MIT School of Engineering

(Note: meche – Mechanical Engineering. eecs – Electrical Engineering & Computer Science. dmse – Material Science & Engineering. cheme – Chemical Engineering. be – Biological Engineering. aeroastro - Aeronautics and Astronautics. cee - Civil and Environmental Engineering. hst - Health Sciences and Technology. ned - Nuclear Science and Engineering.)

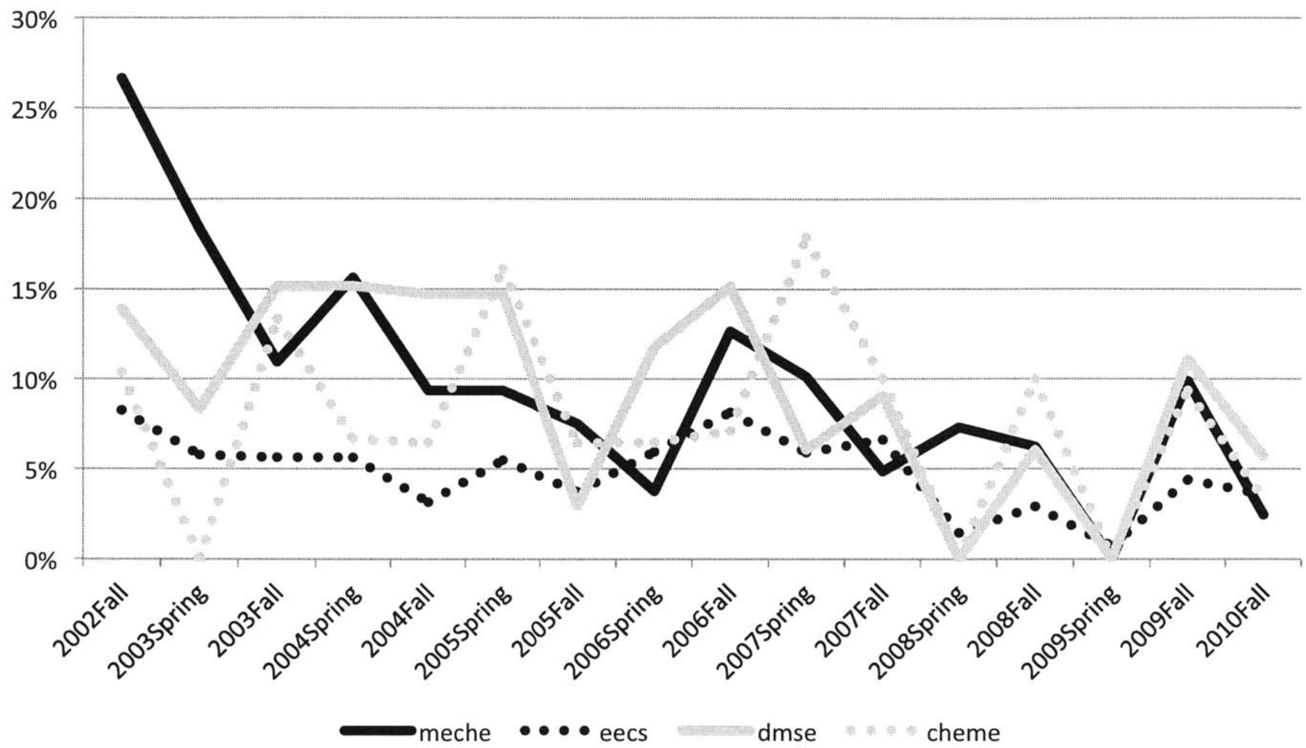

Figure 10: Application rate from the top four departments

(Note: meche – Mechanical Engineering. eecs – Electrical Engineering & Computer Science. dmse – Material Science & Engineering. cheme – Chemical Engineering.)

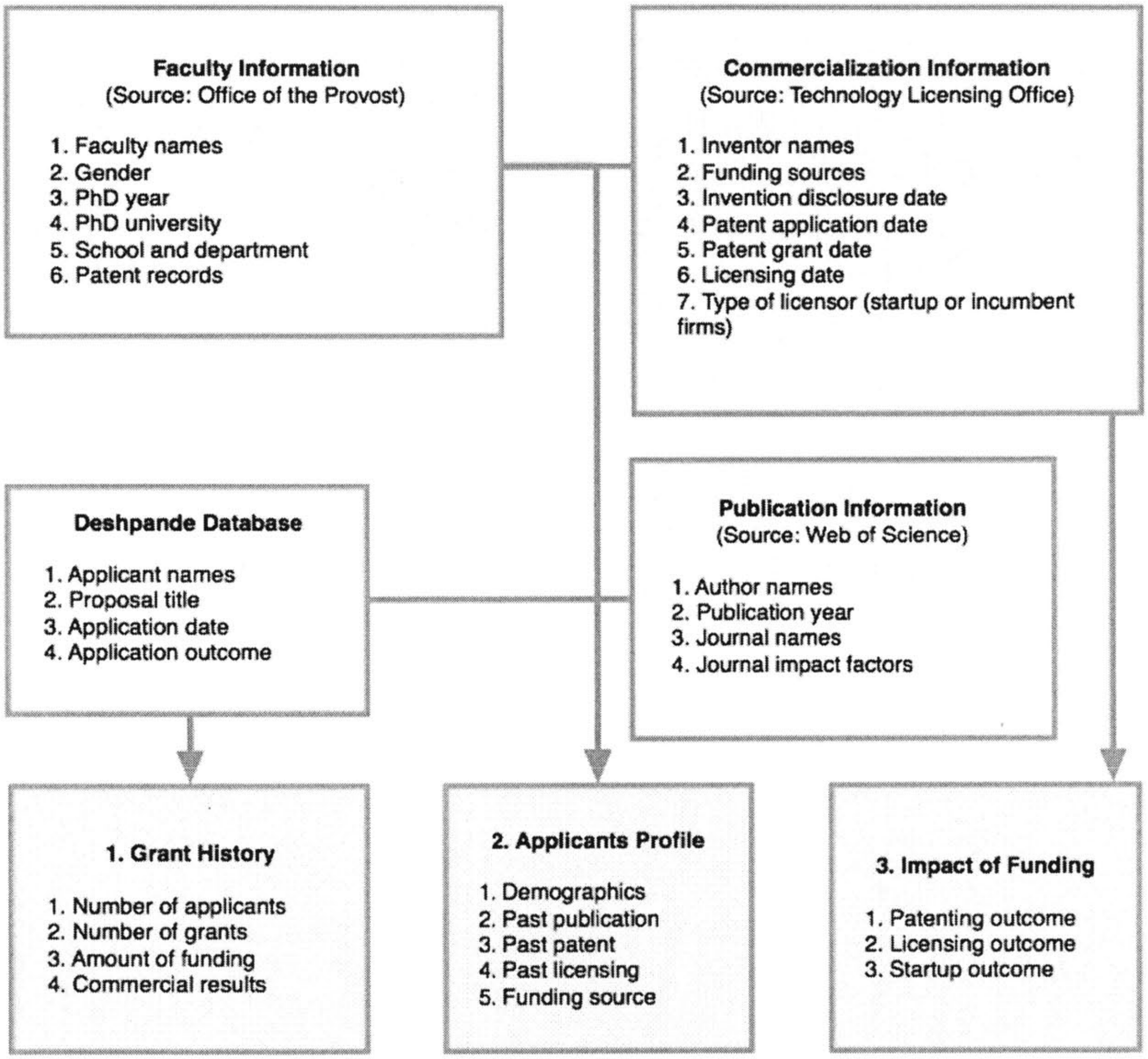

Figure 11: Data source and variable construction

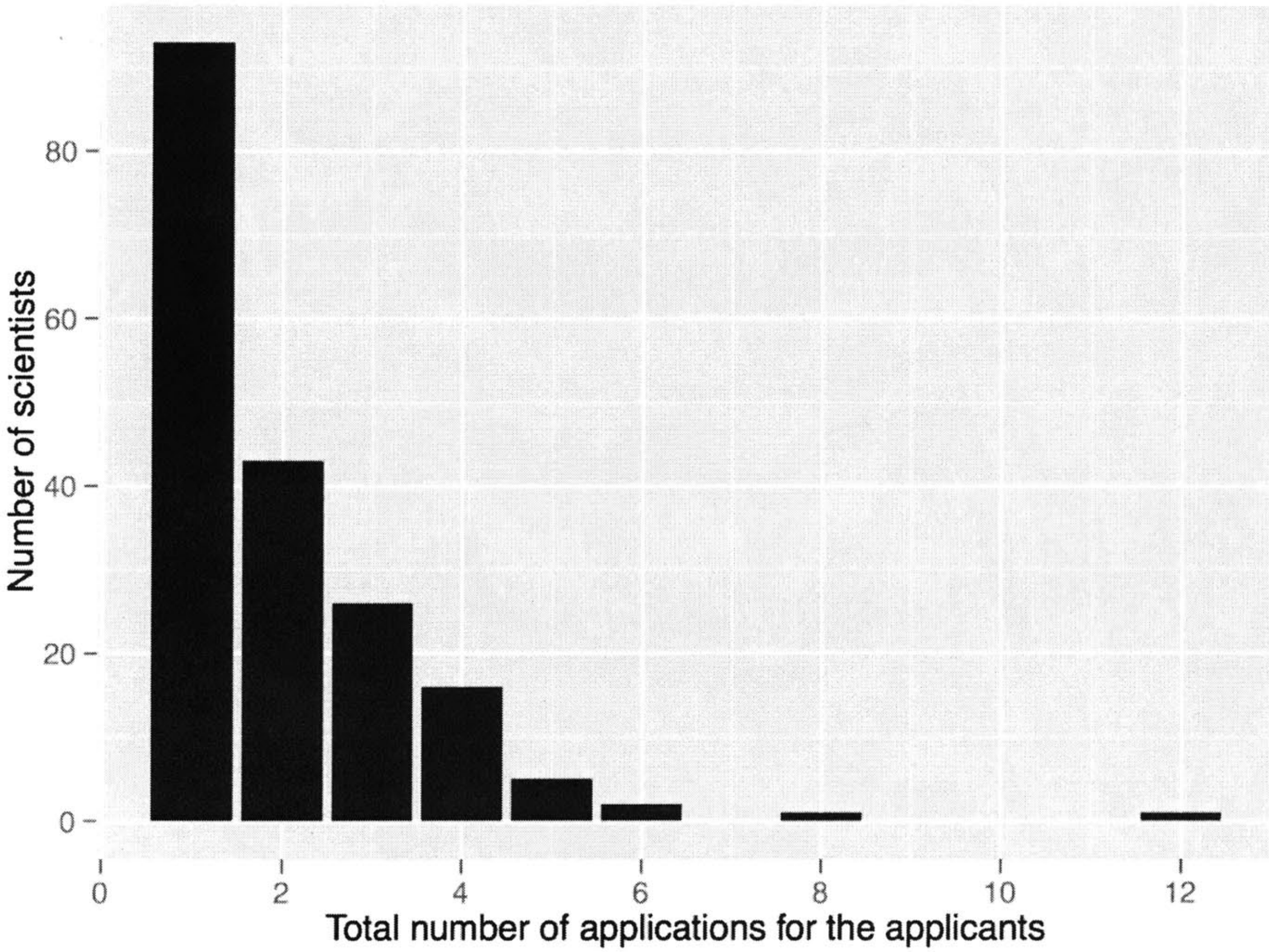

Figure 12: Frequency of applications among applicants