University Science Faculty Ventures into Entrepreneurship

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Executive Summary

Most of the studies measuring and analyzing technology transfer and knowledge spillovers from universities turn to the databases collected by the universities which report the activities of the Offices of Technology Transfer. This paper instead examines university scientist entrepreneurship not by asking the University Technology Transfer Offices what they do in terms of entrepreneurial activities, but rather university scientists directly what they do in terms of entrepreneurial activities. The results from this study are as startling and novel as they are revealing. While the Offices of Technology Transfer databases suggest that new firm startups by university scientists are not particularly a frequent occurrence, this study instead finds exactly the opposite. Most striking is that using a large database of scientists funded by grants from the United States National Science Foundation, this study finds that around 13 percent of the scientists have started a new firm. These findings would suggest that university scientist entrepreneurship is considerably more prevalent that would be indicated by the data collected by the Offices of Technology Transfer and compiled by the Association of University Technology Managers (AUTM).

In addition, the propensity for a university scientist to be engaged in entrepreneurial activity apparently varies considerably across scientific fields. In certain fields, such as computer and network systems, the prevalence of entrepreneurship is remarkably high, 23.8 percent. Similarly, in civil, mechanical, and manufacturing innovation, over one in five of the university scientists report starting a new business.

By contrast, in other scientific fields, the prevalence of entrepreneurship is considerably more subdued. For example, in environmental biology, only 4.6 percent of the university scientists report having started a new business. Similarly, in particle and nuclear astrophysics 6.2 percent of the scientists have started a new firm, and in biological infrastructure 8.2 percent of the scientists have started a new firm.

There is also considerable evidence that university scientist entrepreneurship mirrors the entrepreneurial activity for the more general population in certain important ways, while in other ways scientist entrepreneurship clearly differs from more general entrepreneurial activity. In sharp contrast to what has been found in the entrepreneurship literature for the general population, certain personal characteristics of university scientists, such as age and experience, do not seem to influence the likelihood of a scientist becoming an entrepreneur. However, gender influences the entrepreneurial decision of university scientists in much the same way it does for the general population. Males have a greater likelihood of starting a new business, both for university scientists as well as for the more general population. Similarly, access to resources and high social capital, in the form of linkages to private companies, encourages entrepreneurial activity among university scientists, just as it does for the overall population.

The empirical evidence from this study indicates that the determinants of university scientist entrepreneurship apparently are not constant across scientific fields. Rather, what is important in influencing scientific entrepreneurship in some scientific fields is less important in other scientific fields. For example, the extent of social capital has no statistically significant impact on the entrepreneurial activity of university scientists in scientific fields such as environmental biology, while it has a positive and statistically significant impact on entrepreneurial activity in civil, mechanical, and manufacturing innovation, as well as in computer and network systems.

While the age of the university scientist generally does not play an important role, the empirical evidence does point to a negative relationship between age and entrepreneurial activity that is more radical and less innovative in nature. In particular, those university scientists starting a new business for products that are highly innovative tend to be younger.

Thus, the findings of this paper based on asking university scientists about their entrepreneurial activities suggest that entrepreneurship is considerably more prevalent among a broad spectrum of university scientists than had been previously identified using databases reporting what Offices of Technology Transfer are doing in terms of entrepreneurship. The results from this study would suggest that the spillover of knowledge from universities for commercialization, innovation and ultimately economic growth, employment creation and global competitiveness is substantially more robust than had been previously thought.

1. Introduction

Bolstering innovation has emerged as the widely recognized key to re-igniting economic growth, employment creation and global competitiveness in the United States. In February 2011, President Obama released his vision and plan for *A Strategy for American Innovation: Securing Our Economic Growth and Prosperity*. [1] Similarly, in his 2011 State of the Union Address to the United States Congress, President Obama emphasized, "America's economic growth and competitiveness depend on its people's capacity to innovate. We can create the jobs and industries of the future by doing what America does best – investing in the creativity and imagination of our people. To win the future, the U.S. must out-innovate, out-educate, and out-build the rest of the world. We have to make America the best place on earth to do business."[2]

The strategy of promoting innovative activity as an engine of economic growth is not new. In fact, the era of stagflation, or the twin burdens of inflation combined with high unemployment triggered by the 1973 OPEC oil embargo, ushered in a policy turn towards innovation as a source of reinvigorating economic growth, creating jobs and enhancing competitiveness. The early 1980s witnessed a series of new legislation enacted by the United States Congress to spur American innovative activity. The United States Congress enacted the Small Business Innovation Research (SBIR) program in 1982 into law with an explicit goal of reinvigorating jobs and growth through enhancing the innovative performance of the United States.[3] In particular, the explicit mandate created by the Congress was to promote technological innovation, enhance the commercialization of new ideas emanating from scientific research, increase the role of small business in meeting the needs of federal research and development, and expand the involvement of minority and disadvantaged persons in innovative activity.

Similarly, in an effort to increase the amount of knowledge spilling over from the universities for commercialized innovative activity, the Congress enacted the *Bayh-Dole Act* in 1980.[4] The explicit goal of the Bayh-Dole Act was to foster the commercialization of university science (Kenney & Patton, 2009).

[1] "A Strategy for American Innovation: Securing Our Economic Growth and Prosperity," National Economic Council, Council of Economic Advisers, and Office of Science and Technology Policy, Washington, D.C.: The White House, February 2011, http://www.whitehouse.gov/sites/default/files/uploads/InnovationStrategy.pdf

[2] "Obama's Innovation Agenda," *Forbes*, January 25, 2011, http://www.forbes.com/sites/brianwingfield/2011/01/25/obamas-innovation-agenda/.

[3] Testimony of David B. Audretsch to the House of Representatives, Committee on Small Business, March 16, 2011, http://smallbusiness.house.gov/uploadedfiles/david_audretsch_sbir_testimony.pdf.

[4] Public Law 98-620

Thus, the investment in research at universities has been viewed by both scholars and public policy as a key component to generating innovative activity. Capitalizing upon the investment in university research and transforming it into innovative activity involves not just increasing the magnitude of scientific research but also fostering its commercialization.

Studies focusing on the commercialization of university research have generally been mixed and at best many have been critical about the paucity of innovative activity emanating from universities. In fact, the number of patents applied for and granted to universities has exploded since the Bayh-Dole was passed. Between 2000 and 2008 there were 83,988 new patent applications filed by United States universities.[5] In addition, universities entered into and signed 41, 598 license and option agreements. Studies find that only a handful of universities have generated large flows of licensing revenue (Phan & Siegal, D. S., 2006). Similarly, studies suggest that the number of officially sponsored startups spawned by universities has been remarkably low (Phan & Siegal, D. S., 2006), leading many to conclude that the transfer of technology of transfer from universities to the private sector has not been particularly effective. As *Business Week* reports, "Bayh-Dole critics postulate that universities and technology transfer offices are inefficient obstacles to the formation of startup companies."[6]

However, Aldridge and Audretsch (2010 and 2011) point out that much of the assessment of the extent and impact of the commercialization of university research is influenced by asking the universities about their activities, rather than the principle agents, the scientists. In their 2010 and 2011 studies, Aldridge and Audretsch found that entrepreneurial activity, in the form of starting a new business, was considerably more prevalent based on a database of scientist commercialization activity rather than on data reported by the universities. Perhaps the most striking result of their study was the finding that one in four scientists reported starting a business.

However, a severe limitation of the Aldridge and Audretsch (2010 and 2011) studies was that their database consisted of scientist entrepreneurial activity solely from one main scientific field – cancer research. In addition, the scientists included in their database ranked among the very top performers in science. These limitations raised the question about whether the strong propensity for scientists to become entrepreneurs identified in the Aldridge and Audretsch (2010 and 2011) studies was limited to the particular sample of high performing scientists engaged in cancer research, or whether it also extended to other scientific fields as well.

[5] "Defending the University Tech Transfer System," *Businessweek*, February 19, 2010, http://www.businessweek.com/smallbiz/content/feb2010/sb20100219_307735.htm

[6] "Defending the University Tech Transfer System," *Businessweek*, February 19, 2010, http://www.businessweek.com/smallbiz/content/feb2010/sb20100219_307735.htm

The purpose of this study is to examine university scientist entrepreneurship across a broader spectrum of scientific fields. In particular, this study seeks to identify the prevalence of university scientists in a number of scientific fields. In addition, this study seeks to identify the extent to which the determinants of such university entrepreneurship is not only homogeneous across the different scientific fields, but also mirrors that for what has already been found to drive entrepreneurial activity for the more general population.

In the following section, the role of knowledge spillovers from universities and the exact reasons for analyzing the entrepreneurial activities of individual scientists rather than that for the universities are explained. The methods used to compile a new and unique database measuring scientist entrepreneurship across a broad spectrum of scientific fields is explained in the third section. In the fourth section, the main determinants for scientific entrepreneurship are introduced and developed. The empirical results are presented in the fifth section. In section six the scientist entrepreneur incremental and radical innovation material is presented. Finally, in the last section a summary and conclusions are presented. In particular, this paper provides compelling evidence that scientist entrepreneurial activity in the form of starting a new business is considerably more prevalent and robust than is commonly thought. For the entire sample of university scientists, this paper finds that nearly 13 percent have started a new firm. In addition, the propensity for a scientist to engage in entrepreneurial activity is not homogenous but rather varies systematically across scientific fields. For example, in certain scientific fields, such as computer and network systems, the prevalence of entrepreneurship is 23.8 percent. Similarly, in civil, mechanical, and manufacturing innovation, just over one in five scientists have started a new firm. By contrast, in environmental biology, the prevalence rate of entrepreneurship is 4.6 percent, and in particle and nuclear astrophysics it is 6.2 percent.

Similarly, the determinants of university scientific entrepreneurship are apparently heterogeneous and depend crucially upon the nature of a particular scientific field. In addition, the entrepreneurial activities in certain scientific fields are more conducive to radical innovation, while in others they tend to be more closely associated with incremental innovation.

2. Knowledge Spillovers from Universities: Scientist versus University Entrepreneurship

2.1 Introduction

The purpose of this section is to explain why knowledge spillovers from universities matter for economic performance and how the role of universities and scientists working at those universities in entrepreneurial activities, has evolved over time. The following section explains the role of knowledge spillovers from universities in what has been termed as the "managed economy" or an economy where investments in the physical capital provide the engine of growth. In section 2.3 the role of knowledge spillovers from universities in what has been termed as the knowledge economy is explained, and in section 2.4 how the role of university and scientist entrepreneurship has emerged in the contemporary entrepreneurial economy (Audretsch, 2007 and Audretsch, Keilbach & Lehmann, 2006). In Section 2.5 the distinction between university entrepreneurship and scientist entrepreneurship is explained.

2.2 The Managed Economy

The managed economy characterizes a historical era when economic growth, employment creation and competitiveness were shaped by investments in physical capital such as factories, machinery and plants. According to the Nobel Prize winner, Robert Solow (1956), the driving forces underlying economic growth in what became known as the Solow model consisted of two key factors of production – physical capital and (unskilled) labor. Solow did point out that most of economic growth remained unaccounted for in his model. In fact Solow attributed to the unobserved factor of technical change, which was characterized to "fall like manna from heaven."

The neoclassical growth model was econometrically verified in a vast number of studies linking measures of economic growth to the factors of physical capital and labor. According to Nelson (1981, p. 1032), "Since the mid-1950s, considerable research has proceeded closely guided by the neoclassical formulation. Some of this work has been theoretical. Various forms of the production function have been invented. Models have been developed which assume that technological advance must be embodied in new capital…Much of the work has been empirical and guided by the growth accounting framework implicit in the neoclassical model."

There did not seem to be much of an economic contribution that a university could make in a capital-driven economy. The major activities and focus of universities – research and education – did not seem to be relevant in either generating physical capital or increasing the availability of unskilled labor for industry.

Rather, it was in the social and political realms that the universities could contribute during the era of the managed economy. The university was an institution preparing young people to think freely and independently, and where the fundamental values of western civilization and culture were passed down from generation to generation.

American universities had evolved from being extensions of religious institutions to effective independent institutions of higher learning by the twentieth century. The earliest colleges founded in the United States, such as Harvard College, were burdened with explicit ties to the church. In fact, the church played a fundamental role in creating and sustaining institutions of higher education during the early years of the country. The sponsorship and support of universities by the church was more the norm than the exception, and had been established as the norm for higher education in Europe.

The historical and institutional linkage between the church and the university was disrupted by Alexander Humboldt in Berlin during the 1800s. In particular, Humboldt triggered a new tradition for universities centering on freedom of thought, learning, intellectual exchange, research and scholarship as the salient features of the university. As the Humboldt model for the university diffused through first Europe and subsequently to the other side of the Atlantic, universities became free from parochial constraints, leading instead to the non-secular university committed to independence of thinking, learning and research.

Thus, the Humboldt tradition for the university was reinforced during the managed economy, with the emphasis on physical capital and unskilled labor as the twin factors shaping economic performance. Despite the preeminent contributions to social and political values, the economic contribution of universities was modest.

2.3 The Knowledge Economy

The stagflation characterized by the twin problems of inflation and unemployment starting in the 1970s ushered in the demise of the managed economy. Both scholars and policy makers began to turn towards a new source of economic growth, employment creation and competitiveness – knowledge. The primacy of knowledge and innovation became the salient feature of the endogenous growth models (Romer, 1986,1994, and Lucas, 1988). The main advancement of the endogenous growth models was that the factor of knowledge became explicit in the growth model. While knowledge, or technological change, entered the Solow model only as an undetermined residual, in the endogenous growth models knowledge was not only a key factor driving economic growth, but it was also explicitly included in the model. Not only did knowledge drive economic growth, it is particularly potent because of its inherent propensity to spill over from the firm or university creating that knowledge to other firms and individuals who could apply that knowledge.

In fact, some American colleges and universities were thrust in the role of directed research with specific and concrete commercial applications as the goal. In an effort to stem the tide and ultimately win the Second World War, the United States Government turned to a number of American colleges and universities to produce innovative technological based weapon systems. This partnership between the federal government and the universities was so fruitful that it contributed a significant role in the ultimate victory by the allies.

One of the engineers who had played a key role in the development of the nuclear bomb, Vannevar Bush, argued for an expanded role for universities once the peace had been won. In his 1945 book*, Science: The Endless Frontier*, Bush provided a mandate for sustained involvement and investment in science, technology and research by the United States federal government to ensure that the United States would not just win the war but also the peace.

In fact, the deviation from the traditional role afforded by the Humboldt model of the university that came about from the Second World War was supported by an even older tradition which oriented the land grant colleges and universities towards commercialization established by passage and implementation of the Morrill Act. The Morrill Act, which was more commonly known as the Land Grant Act, was signed into law by Abraham Lincoln in 1862, and granted land to each state that was to be used in perpetuity to fund agriculture and mechanical colleges benefiting the state. As they evolved, the land-grant universities developed an effective set of institutional mechanisms that enabled the commercialization of science and technology from the land grant universities that contributed to agriculture in the United States becoming the most productive in the world (Audretsch, 2007).

As the knowledge economy replaced the managed economy, or as the factor of knowledge became more important while the role of physical capital receded, the role of universities in the economy shifted from being tangential and marginal to playing a central role as a source of knowledge. Universities in the United States became not just viewed as institutions promoting social and cultural values but as key engines driving the growth of the economy. In the Solow economy, where economic growth was achieved by combining unskilled labor with physical capital, the economic contribution of universities was marginal. As the knowledge economy replaced the Solow economy, a new role for the university emerged, as an important source of economic knowledge.

2.4 The Entrepreneurial Economy

The assumption implicit in the endogenous growth models that investments in new knowledge, either by firms or universities, would automatically spill over for commercialization resulting in innovative activity and ultimately economic growth has not proven to be universally valid. In fact, new knowledge investments must penetrate what has been termed "*the knowledge filter*" in order to contribute to innovation, competitiveness and ultimately economic growth (Audretsch, Keilbach and Lehmann, 2006; and Acs *et al.*, 2010). The knowledge filter is defined as the barrier or gap between the investment in new knowledge and its commercialization. The knowledge filter poses a barrier that impedes or preempts the commercialization of investments in research and knowledge. While he did not use the phrase "knowledge filter", Senator Birch Bayh was essentially concerned about the magnitude and impact of the knowledge filter when he admonished his colleagues in Congress to beware, "A wealth of scientific talent at American colleges and universities — talent responsible for the development of numerous innovative scientific breakthroughs each year — is going to waste as a result of bureaucratic red tape and illogical government regulation."[7]

The knowledge filter can be viewed as posing a barrier or impediment between investments in new knowledge and their commercialization, which leads to innovative activity and growth of the economy. The existence of a formidable knowledge filter can actually render investments in research and science impotent in terms of their spill overs for commercialization and innovative activity. As Senator Bayh wondered, "What sense does it make to spend billions of dollars each year on government-supported research and then prevent new developments from benefiting the American people because of dumb bureaucratic red tape?"[8]

The existence of the knowledge filter suggests that investments alone in research at universities will not suffice in facilitating the spill overs that are requisite to generate innovative activity and economic growth. In order to take advantage of the massive investments in research and education, additional entrepreneurial activity was required by the universities. In particular, the universities needed to become more entrepreneurial in that they pro-actively developed mechanisms, incentives and even change their culture from that of a Humboldt University to facilitate knowledge spillovers for commercialization out of the universities.

[7] Introductory statement of Birch Bayh, September 13, 1978, cited from the Association of University Technology Managers Report (AUTM) (2004, p. 5).

[8] Statement by Birch Bayh, April 13, 1980, on the approval of S. 414 (Bayh-Dole) by the U.S. Senate on a 91-4 vote, cited from (AUTM) (2004, p. 16).

In order to spur innovative activity to re-ignite American economic growth, employment creation and competitiveness, the United States Congress enacted the Bayh-Dole Act in 1980. The Bayh-Dole Act represented an explicit policy attempt to facilitate knowledge spillovers from universities for commercialization and ultimately economic growth (Kenny and Patten, 2009; Link and Siegel, 2005; Link, Siegel and Bozeman, 2007).

Part of the response to creating the entrepreneurial university was the development of academic fields and areas of research that were not just focused on "knowledge for its own sake", which is the gold standard of scholarly inquiry under the model of the Humboldt University, but rather oriented towards knowledge for the sake of solving specific and compelling problems and challenges confronting society. Thus, relevance and applicability emerged as the key guiding values in these new, external oriented fields and areas of research, such as biochemistry, informatics, and bioengineering.

In his highly influential book on higher education in the United States, *A Larger Sense of Purpose: Higher Education and Society* (2005), the former Princeton University president Harold Shapiro laments that American universities do not actually seem to possess a larger sense of purpose. Shapiro's concern echoes a recent assessment condemning what is characterized as the selling out of American universities in the *New York Times*, which chides higher education in the United States because "colleges prostitute themselves to improve their U.S. News & World Report rankings and keep up a healthy supply of tuition-paying students, while wrapping their craven commercialism in high-minded sounding academic blather…I would keep coming up with what I thought were pretty outrageous burlesques of this stuff and then run them by one of my professor friends and he'd say, 'Oh yea, we're doing that.'"[9]

Similarly, Steve Lohr of the *New York Times* warns that "the entrepreneurial zeal of academics also raises concerns, like whether the direction of research is being overly influenced by the marketplace."[10] The eminent sociologist, Toby E. Stuart wonders whether "basic scientific questions are being neglected because there isn't a quick path to commercialization? No one really knows the answer to that question."[11]

[9] Stephen Budiansky, "Brand U.," *New York Times*, April 26, 2006, p. A23.

[10] Steve Lohr, "U.S. Research Funds Often Lead to Start-Ups, Study Says," *New York Times*, April 10, 2006

[11]Quoted from Steve Lohr, "U.S. Research Funds Often Lead to Start-Ups, Study Says," *New York Times*, April 10, 2006.

2.5 University Entrepreneurship versus Scientist Entrepreneurship

There has been wide acclaim for the impact of the Bayh-Dole Act on the innovative performance. According to the *Economist*, "Possibly the most inspired piece of legislation to be enacted in America over the past half-century was the Bayh-Dole Act of 1980. Together with amendments in 1984 and augmentation in 1986, this unlocked all the inventions and discoveries that had been made in laboratories through the United States with the help of taxpayers' money. More than anything, this single policy measure helped to reverse America's precipitous slide into industrial irrelevance. Before Bayh-Dole, the fruits of research supported by government agencies had gone strictly to the federal government. Nobody could exploit such research without tedious negotiations with a federal agency concerned. Worse, companies found it nearly impossible to acquire exclusive rights to a government owned patent. And without that, few firms were willing to invest millions more of their own money to turn a basic research idea into a marketable product."[12]

Similarly *Business Week* concludes that, "Since 1980 the Bayh-Dole Act has effectively leveraged the tremendous value of academic research to create American jobs, economic growth, and public benefit. The Act has resulted in a powerful system of knowledge transfer unrivaled in the world. One would think that the combination of public benefit and the productive, job-creating effects of the Bayh-Dole Act would be a winner in every sense."[13]

The mechanism or instrument attributed to facilitating the spillover of knowledge from university scientist research to commercialization and innovative activity is the university Technology Transfer Office (TTO). The TTO was not explicitly created or mandated by the Bayh-Dole Act, but subsequent to passage of the Act in 1980 most universities created a TTO dedicated to commercializing university based research. Virtually every research university has a TTO or similar office today.

The TTO not only oversees and directs the commercialization efforts of a university. In addition, the TTO is charged with the painstaking collection of the intellectual property disclosed by scientists to the university along with the commercialization activities achieved by the TTO. A national association of offices of technology transfer, The Association of University Technology Managers (AUTM), collects and reports a number of measures reflecting the intellectual property and commercialization of its member universities.

[12] "Innovation's Golden Goose," *The Economist*, 12 December, 2002.

[13] "Defending the University Tech Transfer System," *Businessweek*, February 19, 2010, http://www.businessweek.com/smallbiz/content/feb2010/sb20100219_307735.htm

The databases collected and assembled by AUTM have been subjected to considerable empirical scrutiny, resulting in the emergence of a large and growing body of research. These studies have been large concerned with analyzing the impact of the Bayh-Dole Act in general and the TTOs on generating innovative activity from the research and scientific activities at universities (Lockett, Wright and Franklin, 2003; Lockett, Wright and Ensley, 2005; O'Shea, 2008; Phan, Siegel and Wright, 2005; Siegel, Veugelers and Wright, 2007; Siegel, Wright and Lockett, 2007). It is important to recognize that the bulk of these studies analyze and reach conclusions about the inputs and outputs of the TTOs at universities (Mustar *et al.*, 2006; Mosey and Wright, 2007; Shane, 2004, Powers and McDougal 2005, Phan and Siegel (2006); Di Gregorio and Shane, 2003, Mowery *et al.*, 2004.) As Phan and Siegel (2006) point out, most of this literature concludes that the commercialization efforts of the TTOs have been strikingly positive.

However, most of these studies (Phan and Siegel, 2006) analyze the outputs of the TTO in terms of patents and/or licensed technology. While the conclusions based on these studies are generally remarkably positive, considerably less attention has been given to startups emanating from universities.

In fact, scientist entrepreneurship, as measured by new firms started by university scientists, is seemingly remarkably modest. The data reported by university TTOs and collected by AUTM suggests a paucity of commercialization spilling over from universities in the form of scientist entrepreneurship. For example, the number of university based startups in the United States reported by AUTM (2004) averaged 426 per year for the entire country from 1998 to 2004. When compared to the number of research universities and the dollar amount investment in scientific research at universities, this amount of university entrepreneurship does not seem to be particularly encouraging or in any sense an endorsement of a robust system of knowledge spillovers from universities.

Similarly, an examination of entrepreneurial performance of particular universities also points to a paucity of university entrepreneurship. For example, one study found that the TTO of the Massachusetts Institute of Technology (MIT) generated only 29 startups in 2001 (O'Shea, Chugh and Allen 2008). At the same time, there were only six startups facilitated by and registered at the TTO at Stanford University. Thus, however successful universities have been at generating patents and licenses, entrepreneurial activity seems to be considerably more meager and modest, leading perhaps at least some to infer that based on the TTO data measuring scientist entrepreneurship at universities compiled by AUTM, universities have not been particularly successful in commercializing research and science.

Aldridge and Audretsch (2010 and 2011) point out that there may be limitations inherent in the inferences made about university entrepreneurship and knowledge spillovers based solely upon data collected by the TTOs. In particular, using data generated and compiled by the TTOS and collected and made available by AUTM could lead to underestimating the extent to which entrepreneurial activity is being generated by universities. Aldridge and Audretsch (2010 and 2011) point out that the main task of the TTO is not to measure and document all of the intellectual property created by university research along with the subsequent commercialization. While the TTO does measure and document the creation and commercialization of intellectual property, its commercialization activities are typically a subset of the broader and more pervasive intellectual property being generated by university research and its commercialization. In fact, as Thursby and Thursby (2002 and 2005) and Mosey and Wright (2007) point out, there are considerably more commercialization activities undertaken at universities which may not interface or fall within the TTO's activities. Similarly, Shane (2004, p. 4) finds that, "Sometimes patents, copyrights and other legal mechanisms are used to protect the intellectual property that leads to spinoffs, while at other times the intellectual property that leads to a spinoff company formation takes the form of know how or trade secrets. Moreover, sometimes entrepreneurs create university spinoffs by licensing university inventions, while at other times the spinoffs are created without the intellectual property being formally licensed from the institution in which it was created. These distinctions are important for two reasons. First it is harder for researchers to measure the formation of spinoff companies created to exploit intellectual property that is not protected by legal mechanisms or that has not been disclosed by inventors to university administrators. As a result, this book likely underestimates the spin-off activity that occurs to exploit inventions that are neither patented nor protected by copyrights. This book also underestimates the spin-off activity that occurs "through the back door", that is companies founded to exploit technologies that investors fail to disclose to university administrators."

Shane's (2004) concern that relying upon data collected by the TTO could result in a systematic underestimation of the entrepreneurial activity emanating from universities has been echoed by other scholars (Thursby *et al.*, 2009, and Aldridge and Audretsch, 2010 and 2011). Placing an undervalued estimate on the extent to which university research and science is commercialized may also lead to underestimating the extent to which knowledge spills over for commercialization and innovative activity from universities.

The economic performance of the United States depends crucially upon the capacity to generate knowledge spillovers from universities. Such knowledge spillovers are essential for generating economic growth, the creation of jobs and competitiveness in global markets. Underestimating the extent to which knowledge actually spills over from the universities, and the impact of university science and research, can lead policy makers to undervalue the economic and social impact of investments in research and science.

In order to mitigate such policy distortions, Aldridge and Audretsch (2010 and 2011) proposed an alternative method for measuring and analyzing scientist entrepreneurship. Rather than asking universities what they do in terms of commercialization activities, Aldridge and Audretsch (2010 and 2011) instead went directly to university scientists and asked the scientists what they do in terms of commercialization.

Aldridge and Audretsch (2010 and 2011) surveyed university scientists who had been awarded the largest grants from the National Institute of Cancer at the National Institutes of Health. Thus, their database consisted of commercialization activities identified by the scientists themselves rather than the standard method prevalent throughout the literature of turning to the OTTs and the commercialization activities they report, which are ultimate compiled and made public by AUTM. In particular, Aldridge and Audretsch (2010 and 2011) developed alternative measures of scientist entrepreneurship and other commercialization activities on the basis of the scientists reporting their own commercialization and entrepreneurial efforts.

The Aldridge and Audretsch (2010 and 2011) studies enabled them to create a measure of scientist commercialization of university research and identify which factors are conducive to scientist entrepreneurship and which factors inhibit scientist entrepreneurship. A key finding of the Aldridge and Audretsch (2010 and 2011) studies was that, of the patenting scientists, around one in four had started a new firm to commercialize their research. A second key finding of the Aldridge and Audretsch (2010 and 2011) studies emerged from subjecting their new university scientist-based data set to empirical scrutiny to ascertain which factors influence the propensity for scientists to become an entrepreneur. This enabled a comparison of the factors conducive to scientist entrepreneurship to what has already been solidly established in the literature for the more general population. In fact, the empirical results suggested that scientist entrepreneurship does not simply mirror what has been found in the more general entrepreneurship literature (Aldrich & Martinez, M., 2010), for the entrepreneurial activities of the general population. By comparison the likelihood of becoming an entrepreneur was found to be less influenced by certain personal characteristics, such as age, gender and experience, as well as by human capital. Social capital seems to play a particularly important role in influencing which scientist becomes an entrepreneur and which scientist abstains from entrepreneurial activities.

However, there are a number of important qualifications and limitations involved in the Aldridge and Audretsch (2010 and 2011) studies. The first is the highly selective and special nature of the scientists included in the database. In fact, only exceptionally highly performing scientists within a very narrow scientific field, cancer research, were included in the database. A second restriction was that only scientists who had been granted intellectual property protection by a patent were included in the database. The entrepreneurial activities of scientists in all of the other scientific fields were not considered, just as the entrepreneurial activities of scientists not awarded a patent were not considered.

3. Creating a Scientist Entrepreneurship Database

3.1 Introduction

This section summarizes the salient findings from the scientist entrepreneurship database created using the 1899 scientist responses from an online survey administered among 9150 scientists (response rate of 20.75 percent). The survey captures the number and frequency of scientist startups, among scientists that received funding from the National Science Foundation (NSF), in one or more of the six broad fields of research, between 2005 and 2012 – Q2,b. The survey measures various modes of startup commercialization like patents, innovative products, and consulting, and the success or failure of scientist firms during this period.

Section 3.3.1 summarizes findings on scientist startups. Results indicate that, on average, one in eight scientists have commercialized their research by starting up a legally recognized company. There was also considerable degree of variation in scientist startups across various modes of startup commercialization and fields of research. Possible causal mechanisms and practical implications are discussed.

Section 3.3.2 describes scientist characteristics across gender, age, country of origin, and fields of research. It is observed that gender, age, and country of origin are strong determinants of scientist startup commercialization across and within fields of research. Practical significance of these demographic characteristics is discussed.

Section 3.3.3 describes the effect of availability and access to various sources of financial and human resources on scientist startup commercialization across the six fields of research. It is observed that financial and human resources have a strong positive effect on the scientist's likelihood to commercialize research through startups. The practical significance and analytical power of financial and human resources on the scientist commercialization decision are discussed.

Section 3.3.4 explains the relationships between scientist human capital – constructed as scientist's tenure status and experience (years of experience in tenured status) – and scientist startup commercialization decision. It is observed that there is a strong positive relationship between determinants of scientist human capital and scientist commercialization through startups.

Section 3.3.5 explains the relationships between scientist social capital – constructed as scientist's status as a board member – and scientist startup commercialization. It is observed that there is a strong positive relationship between determinants of scientist social capital and scientist commercialization through startups.

Section 3.3.6 explores the relationship between the locational and institutional factors on the scientist's startup commercialization decision. Locational factors are captured as the effect of scientist's location and field of research, and institutional factors are captured as the department head's entrepreneurial orientation, and department's overt encouragement towards research commercialization, characteristics of the Technology Transfer Office (TTO).

Results suggest that locational and institutional factors have varying effects depending on the scientist's field of research. Roughly, 25 percent of the scientists described the TTO as incompetent in understanding their area of research, and 15 percent of the scientists described TTOs as unsuccessful in commercializing research. However, the majority of the scientist responses indicated that the TTOs are of significant help in assisting scientists in overcoming the knowledge filter. Practical significance and hypothesis for future empirical research are discussed.

3.2 Survey

This section describes the scientist entrepreneurship database which was created using survey responses from an online adaptive survey administered among scientists that received funding from the National Science Foundation (NSF), conducting research in six different fields of research, between 2005 and 2012-Q2. The scientific fields of research discussed in this report are civil, mechanical, and manufacturing innovation; environmental biology; computer and network systems; physical oceanography; particle and nuclear astrophysics and; biological infrastructure.

The purpose of this section is to discuss the aggregate and annual characteristics of National Science Foundation (NSF) awards by scientific fields of research between 2005 and 2012-Q2. A total of 13,777 NSF awards to 9361 scientists, across six different fields of research, are analyzed.

This section also describes the survey instruments used in the online survey, the survey response rates, and robustness of the scientist entrepreneurship database. The online survey was administered on a sample of 9150 scientists, from six different fields of research, with 1899 scientist responses, a survey response rate of 20.75 percent.

This section discusses the aggregate and annual characteristics of National Science Foundation (NSF) awards by scientific fields of research between 2005 and 2012-Q2. In the 90 months between 2005 and 2012-Q2, a total of 13,777 NSF awards were granted to scientists in six broad scientific fields of research – civil, mechanical, and manufacturing innovation; computer and network systems; biological infrastructure; environmental biology; physical oceanography; and particle and nuclear astrophysics.

Award Instrument

The 13,777 NSF awards were made through multiple award instruments – Standard Grant, Continuing grant, Contract, Contract Interagency Agreement, Cooperative Agreement, Fellowship, Interagency Agreement, and Personnel Agreement. Table 1 below summarizes the 13,777 awards by the type of award instrument.

Table 1: Summary of NSF awards by Award Instrument

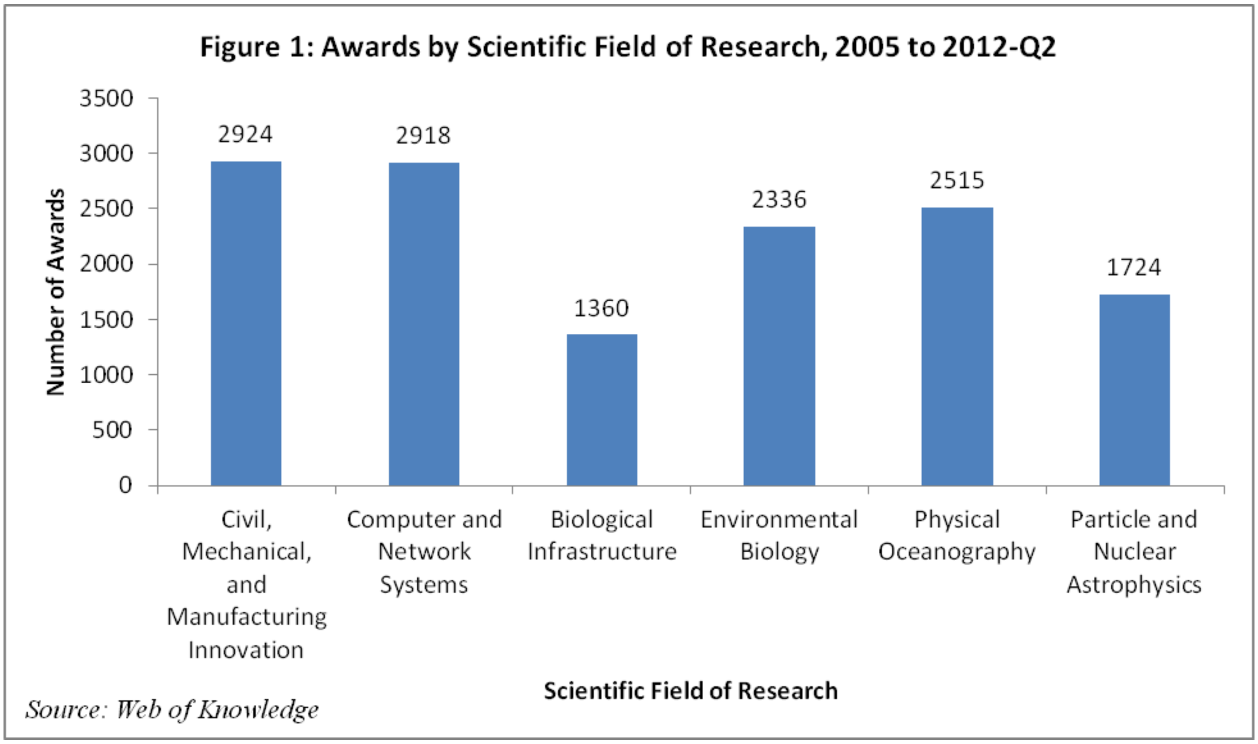
Award Instrument	Number of Awards
Standard Grant	9402
Continuing grant	4062
Fellowship	169
Cooperative Agreement	90
Interagency Agreement	45
Personnel Agreement	6
Contract Interagency Agreement	2
Contract	1
Grand Total	**13777**

Source: Web of Knowledge

These figures indicate that 9402 (65.6 percent) of the awards are standard grants, and 4062 (29.5 percent) of the awards are continuing grants issued to scientists in six different fields of research. Furthermore, these results indicate that about one in three awards are tranche (or block) payments of awards which were awarded in previous years. Since, we are primarily interested in identifying scientist that received funding from the NSF across the six fields of research; these awards represent the entire population of scientists who have funding from the NSF as of 2012-Q2.

Number of Awards

Figure 1 below shows the distribution of the 13, 777 NSF awards by scientific field of research, between 2005 and 2012-Q2. Roughly 45 percent (6211) of the awards were granted to the fields of environmental biology, physical oceanography, and biological infrastructure. These figures signify that the broader interdisciplinary academic fields of biological and environmental sciences receive the dominant share of NSF awards. Furthermore, roughly 42.5 percent (5842) of the awards were granted to the civil, mechanical, and manufacturing innovation, and computer and network systems fields of research. These figures signify that the much broader academic disciplines of engineering and computer science received the second largest share of NSF awards. About 12.5 percent (1724) of the awards were granted in the particle and nuclear astrophysics field of research.



It is important to note that one in three awards are continuing grants and hence there is a many to one relationship between NSF awards and scientist-research. Since we are primarily interested in analyzing scientist research, we shifted the unit of analysis from awards to scientists. The 13,777 awards were grouped to obtain a total of 9361 unique scientists as defined by the NSF awards' Principal Investigator (PI) and the PI's organization/university affiliation.

NSF Funding Amount

The award amounts for the 9361 unique scientists were combined to obtain the total NSF funding available to the scientist between 2005 and 2012-Q2. These 13,777 NSF awards, to 9361 scientists, aggregated to a total of 6,897,223,522USD, averaging 4,703,719USD per scientist.

Table 2 below shows the aggregate and average NSF funding amounts to scientists by their scientific field of research. The average amount awarded varies considerably between the scientific fields of research. Civil, mechanical, and manufacturing innovation has the least average award amount of 413, 053USD and physical oceanography has the highest award amount of 1,317,341USD. It is also interesting to note that the awards in the field of particle and nuclear astrophysics have an average grant amount of 1,270,744 USD signifying a considerable degree of heterogeneity among awards aimed at theoretical and application based research.

Table 2: Aggregate and Average Award Amount by Scientific Field of Research

	Number of Awards	Total Award Amount	Average Award Amount
Civil, Mechanical, and Manufacturing Innovation	2073	856,259,169	413,053
Environmental Biology	1657	792,254,675	478,126
Computer and Network Systems	1811	1,127,815,651	622,759
Physical Oceanography	1463	1,927,269,264	1,317,341
Particle and Nuclear Astrophysics	1159	1,472,792,525	1,270,744
Biological Infrastructure	1198	720,832,238	601,696
Total	**9361**	**6,897,223,522**	**4,703,719**

Source: Web of Knowledge

It is interesting to compare the average award amounts between the applied fields of civil, mechanical, and manufacturing innovation (413,053USD); Environmental biology (478,126USD); and computer and network systems (622,759USD). We would expect that the award amounts for civil, mechanical, and manufacturing innovation and environmental biology would be higher, due to the human resource intensive projects typical to these fields; however, the average grant amounts for these fields are lower than that of computer and network systems. These comparisons suggest that scientific research output in these fields is not as capital intensive as one would normally expect.

Construction of Sample

This section describes the construction of sample of scientists, survey instruments used in the online survey, and the survey response rates of the independent variable and measures for key determinants of scientist entrepreneurship.

The web of knowledge database contained email addresses of 9361 scientists that received NSF funding between 2005 and 2012-Q2. The online survey questionnaire was directed to the entire population of 9361 scientists in the first round of survey administration – we detected that 30 scientists were on sabbatical, 9 scientists were inactive, and email addresses of 172 scientists were returned since they were incorrect/incomplete. Hence, we ended up with a survey sample of 9150 scientists (97.75 percent of the population).

Survey Administration

The online survey was administered on a sample of 9150 scientists, from six different fields of research, with 1899 scientist responses, a survey response rate of 20.75 percent. The survey was administered in three rounds – the initial round of survey questionnaire was administered on the entire population of 9361 scientists in the first three weeks of May 2012, with responses from about 1600 scientists (84 percent of total responses). The second round of questionnaire was administered on the remainder of the sample, after truncating the population of 9361 scientists to a sample of 9150 scientists in the last week of May 2012, with responses from 220 scientists (11.5 percent of total responses). The final round of questionnaire was administered on the remainder of the sample in the second week of June 2012, gathering roughly 80 responses (8.5 percent of the sample).

Survey Questionnaire

The survey questionnaire was designed to capture scientist entrepreneurship through startups (our key dependent variable). The survey also captures the use of patents, innovative products, and consulting in scientist startups, for scientists who indicated that they founded a legally recognized company.

Furthermore, the survey included measures for key determinants of scientist entrepreneurship like availability of financial resources from other sources of funding, availability of human resources, scientist human capital, scientist social capital, scientist locational and institutional contexts, and scientist demographic information. The response rates of the dependent variable and measures for key determinants of scientist entrepreneurship are provided in Appendix A.

The survey instrument used to measure the key dependent variable, scientist startups, is the first question of the online survey – "Have you started a legally recognized company?" The survey respondents could either respond yes or no, to the question. This survey instrument is used to construct the key dependent variable, scientist startups, which had a survey response rate of 99.5 percent.

The survey instrument used to measure the use of patents in scientist startups – "What sort of startup have you founded?" – was administered on scientists who responded 'yes' to the question of scientist startups. This survey instrument had a survey response rate of 91.7 percent.

The survey instrument used to measure the use of innovative in scientist startups – "Does your business currently or intend to sell an innovative product?" – was administered on scientists who responded 'yes' to the question of scientist startups. This survey instrument had a survey response rate of 77.6 percent.

The survey instrument used to measure the provision of consulting services in scientist startups – "Does your business do a majority of consulting service with Industry or

Government??" – was administered on scientists who responded 'yes' to the question of scientist startups. This survey instrument had a survey response rate of 76.3 percent.

All key determinants of scientist entrepreneurship had a survey response rate of over 80 percent, except the survey instrument measuring tenure experience of the scientist – "In what year did you attain "tenure" status?" This survey instrument had a response rate of 45 percent.

The Appendix A presents the response rates all the determinants of scientist entrepreneurship. Also, please refer to Appendix B for the online survey questionnaire administered on the sample of 9150 scientists.

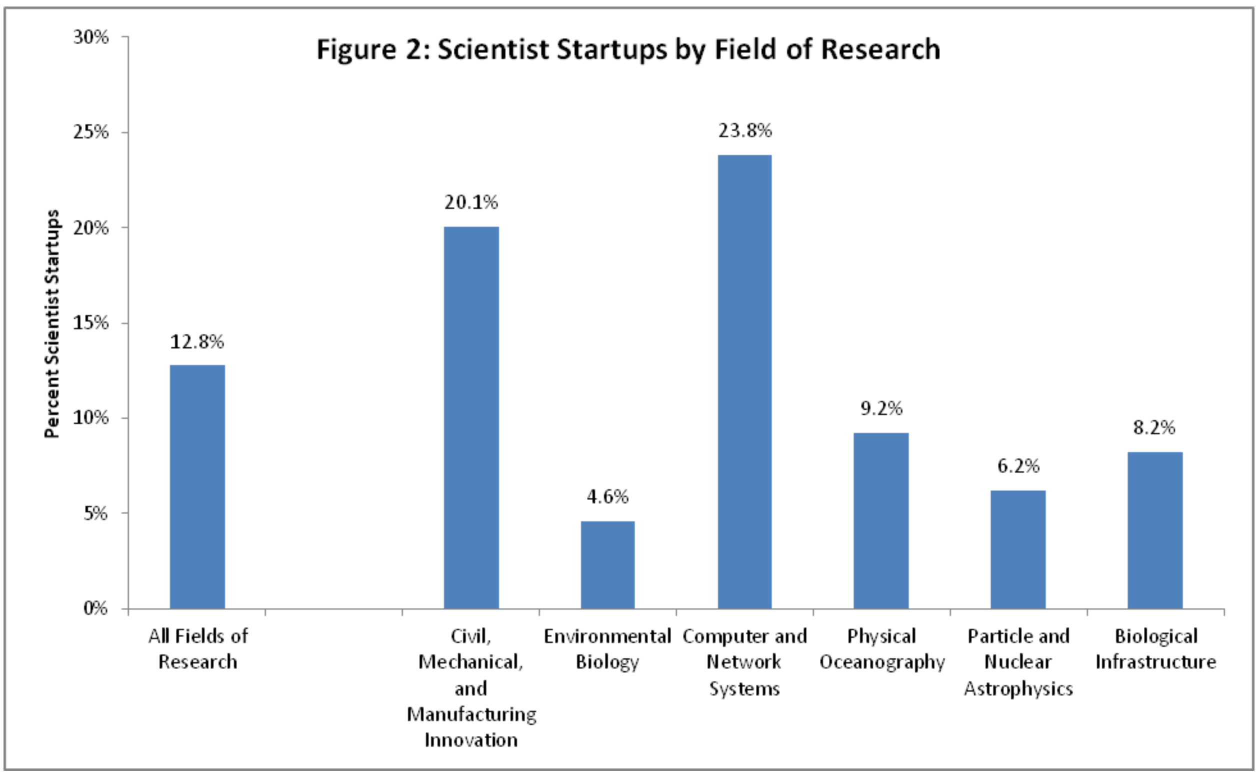
SECTION 3.3: Salient Findings

3.3.1 Scientist Startups

This section describes the likelihood of scientist commercialization through startups and compares the likelihood of various modes of startup commercialization – patents, innovative products, and consulting – across six different fields of research – civil, mechanical, and manufacturing innovation (CMMI), environmental biology (DEB), computer and network systems (CNS), physical oceanography (OCE), particle and nuclear astrophysics (PHY), biological infrastructure (DBI).

Scientist Startups

Figure 2 compares the likelihood of scientist commercialization through startups across the six field of research. 241 of the 1,889 scientist respondents, an average of 12.8 percent across six fields of research, indicated that they have commercialized their research by starting up a legally recognized company. Furthermore, there is considerable variation in the likelihood of scientist commercialization through startups, ranging from 4.6 percent in environmental biology to 23.8 percent in computer and network systems.



The figure also explains the nature of research, and the likelihood of commercialization through startups, across the fields of research. There is sufficient evidence to indicate that scientists in the fields of computer and network systems (23.8 percent, 86 out of 361 scientists), and civil, mechanical, and manufacturing innovation (20.1 percent, 73 out of 364 scientists) are more likely, and have historically been more successful, in commercializing their research over time.

On the other hand, scientists in the fields of physical oceanography (9.2 percent, 25 out of 271 scientists), biological infrastructure (8.2 percent, 26 out of 317 scientists), particle and nuclear astrophysics (6.2 percent, 13 out of 209 scientists), and environmental biology (4.6 percent, 19 out of 415 scientists) are less likely to commercialize their research through startups.

The variation in commercialization through startups can be explained in numerous ways. First, it is likely that scientists in the fields of biological, physical, and environmental sciences need greater human capital (access to large number of prior patents, collaboration from a large number of field experts) in order to commercialize their research.

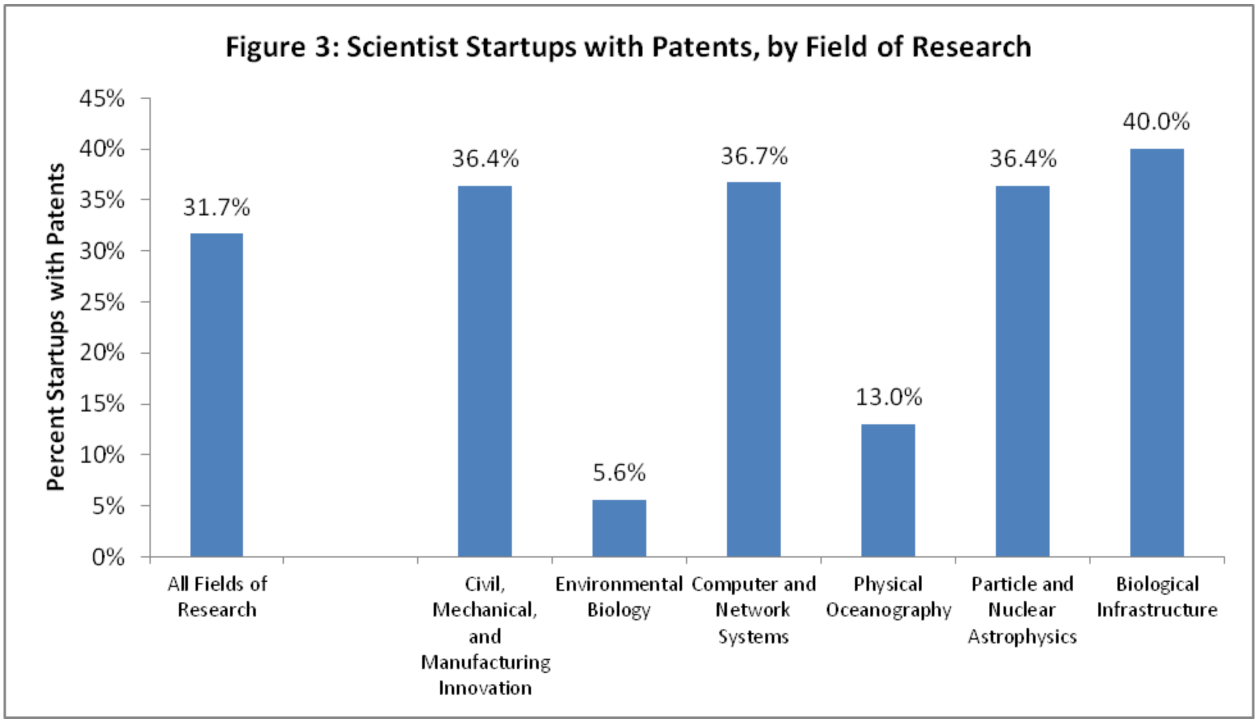
Second due to the interdisciplinary and basic nature of research, it is likely that scientists in these fields need greater access to financial (funding from sources other than the government) and institutional (location of industry; networks of suppliers and buyers) resources to commercialize their research.

Third, and most importantly, it is likely that the technology transfer offices in their universities are not competent in understanding their area of research, and hence are unsuccessful in surpassing the knowledge filter in commercializing their research through startups.

Finally as Aldridge and Audretsch (2010 and 2011) suggest, it is likely that scientists in these fields prefer to commercialize their research through other modes of commercialization like patents and licensing commitments, without founding a legally recognized company. These reasons for variation in scientist commercialization across fields of research are further explored in the empirical findings section of the report.

Patents and Scientist Startups

Figure 3 compares the likelihood of scientist startup commercialization through the use of patents across the six fields of research. 70 of the 221 scientist startups, an average of 31.7 percent across six fields of research, have indicated that their startups own patents of one or more founding members. This indicates that, in 3 out of 10 scientist startups, patents have played a significant role in commercializing scientist research through starting up a legally founded company.

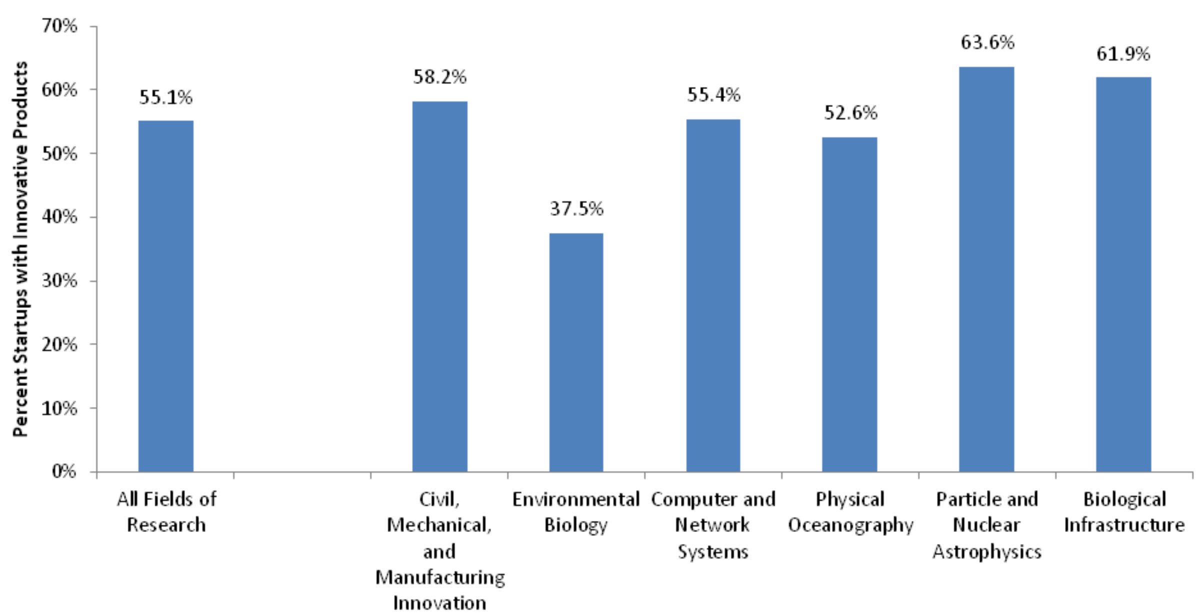


Furthermore, there is variation in the significance of scientist startup commercialization across the six fields of research, ranging from 5.6 percent (1 out of 18 startups) in environmental biology to 40 percent (29 out of 79 startups) in computer and network systems. These figures indicate that patents play a significant role in commercializing one in four startups in the fields of civil, mechanical, and manufacturing innovation, computer and network systems, particle and nuclear astrophysics, and biological infrastructure. The lack of significance of patents in startup commercialization in the fields of environmental biology, and physical oceanography can be explained in part by the basic and exploratory nature of research and in part by the patent hoarding by large corporations in these sectors. Hence, Audretsch and Aldridge (2010 and 2011) suggest, it is likely that scientists in these fields prefer to license or sell their patents in the marketplace, than commercialize them through startups.

Innovative Products and Scientist Startups

Figure 4 compares the likelihood of scientist startup commercialization through innovative product offering across the six fields of research. 103 of the 187 scientist startups, an average of 55.1 percent across six fields of research, have indicated that their startups commercialize research by offering innovative products and services. This indicates the extreme significance of innovative products in scientist startup commercialization. Furthermore, these figures provide evidence for the enormous potential, and demand, for innovative products through the scientist startup commercialization route; and the substantial role technology transfer offices can play in realizing this potential.

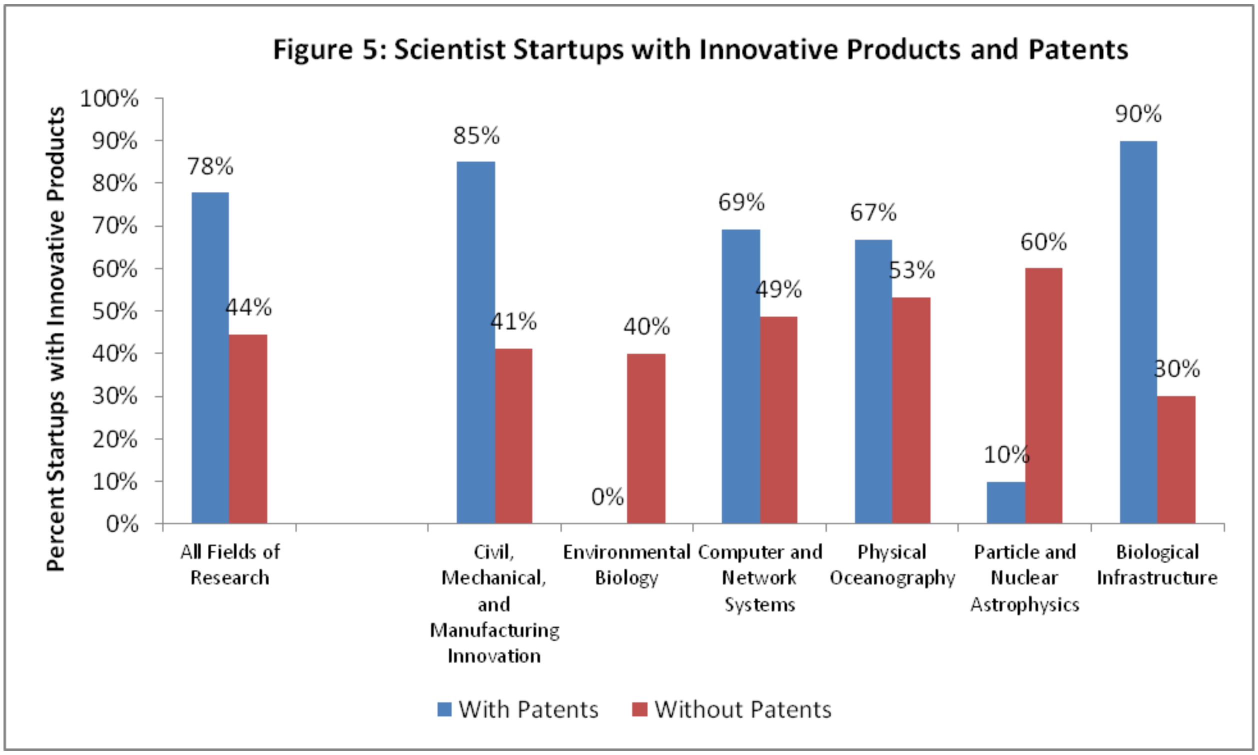
Figure 4: Scientist Startups with Innovative Products



It is interesting to note that more than half of scientist startups across all fields of research, except environmental biology, use innovative products in commercializing their research. This indicates that there is tremendous potential for product innovations from scientist research, irrespective of the field of research. The significance of patents in developing innovative products for scientist startup commercialization is explored in Figure 4 below.

Innovative Products and Patents

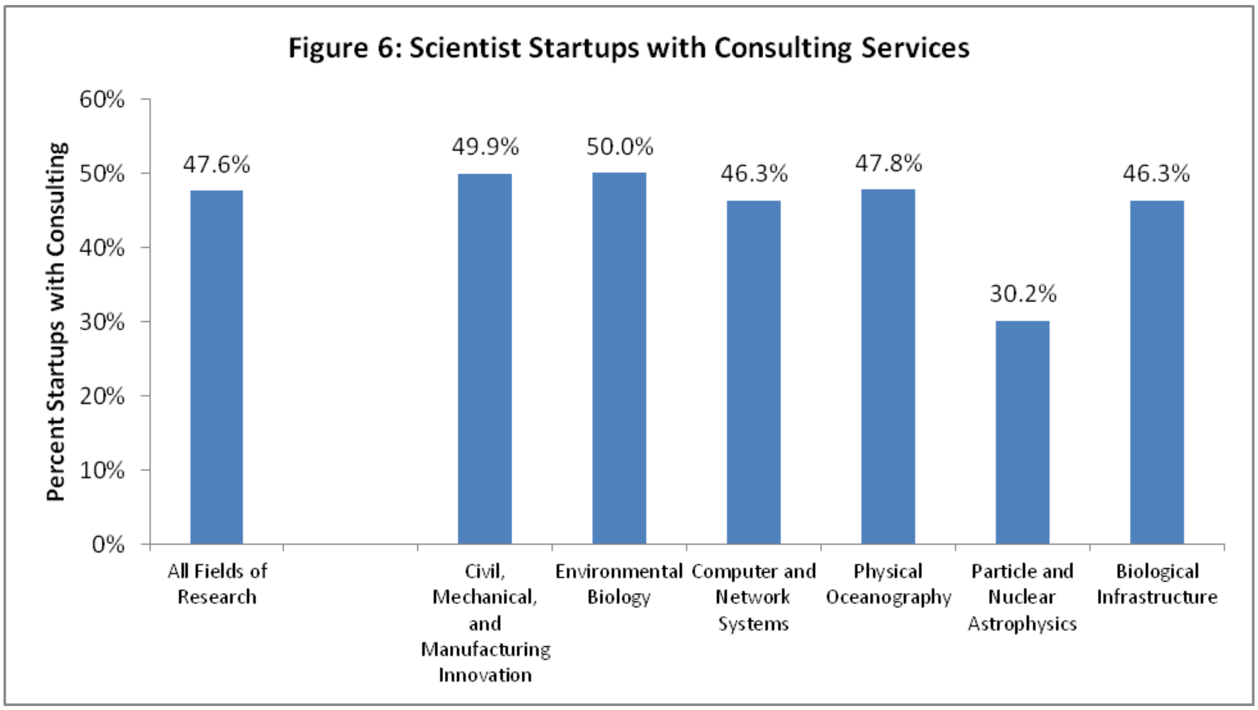
Figure 5 explains the significance of patents in determining the likelihood of scientist startup commercialization through the use of innovative products across the six fields of research. 49 of the 63 scientist startups, an average of 78 percent across six fields of research, have indicated that patents were used in developing innovative products for scientist startup commercialization. This further underscores the significance of patents, in designing innovative products, and facilitating scientist research commercialization through startups.



It is important to note that in most fields of research, except environmental biology and particle and nuclear astrophysics, patents play an important role in determining the use of innovative products in scientist startup commercialization; most likely by increasing the firm's competitiveness and chances of success.

Consulting Services

Figure 6 compares the likelihood of scientist startup commercialization through consulting services across the six fields of research. 63 of the 184 scientist startups, an average of 47.6 percent across six fields of research, have indicated that their startups commercialize research through consulting services. This indicates that one in every two scientist startups offer consulting services, which provides evidence of commercial value of scientist research to the industry on the one end, and the multi-dimensionality of modes of commercialization among scientist startups.



In Summary, these results suggest that one in eight scientists commercialize their research through startups; with one in three startups using scientist patents, one in two startups offering innovative products and consulting services in commercializing their research through startups. These figures provide evidence that scientist startups rely on more than one revenue source in commercializing their research; hence increasing the likelihood of scientist startup success. Table 3 below summarizes scientist startup success rate by their mode of startup commercialization.

Scientist Startups and Firm Success

Table 3 compares the likelihood of scientist startup success between those with innovative products and those with only patents across the six fields of research. 135 of the 185 scientist startups, an average of 73 percent across six fields of research, have indicated that their startups are currently active. This indicates that three out of four scientist startups have been successful in commercializing their research across six fields of research, using various modes of startup commercialization. There is an exceptionally high rate of scientist firm success in the field of physical oceanography (89 percent), and civil, mechanical, and manufacturing

innovation (78 percent). The relatively low rate of success in the field of computer and network systems (though at a significant 68 percent) can be attributed, in part, to the rapid rate of innovation, and competition in scientist research, from industry.

Table 3: Scientist Firm Success, by Innovative Products and Patents

	Number of Firms	% Firm Success	With Innovative Product	With Patent
All Fields of Research	185	73.0%	91.1%	74.2%
Civil, Mechanical, and Manufacturing Innovation	54	77.8%	93.5%	84.2%
Environmental Biology	17	70.6%	100.0%	0.0%
Computer and Network Systems	65	67.7%	91.4%	61.5%
Physical Oceanography	18	88.9%	100.0%	100.0%
Particle and Nuclear Astrophysics	10	70.0%	71.4%	75.0%
Biological Infrastructure	21	71.4%	84.6%	90.0%

It is important to note that across all fields of research, scientist firms' likelihood of success is significantly enhanced when the mode of startup commercialization is through the use of innovative products and patents. The results indicate that nine out of ten scientist startups with an innovative product offering, and three out of four startups with a patent, are likely to succeed across the six different fields of research. Also, there is a wide range of variation in the significance of patents in determining scientist firm success in the fields of Environmental biology and Computer and network systems; possibly due to the competition from large innovative firms in the respective sectors.

3.3.2 Scientist Characteristics

This section compares the characteristics of scientists that commercialized their research through startups with scientists that did not, across the six fields of research.

The scientist life-cycle model suggests that the scientist's decision to commercialize scientific knowledge depends on the scientist's life-cycle and career trajectory (Levin and Stephan, 1991). Scientist's life-cycle explains how scientists make investments in human capital towards production of new economic knowledge in order to build scientific reputation. Scientist career trajectory explains how scientists, under different institutional contexts, establish career-specific priorities in seeking rewards to new scientific knowledge and reputation. Audretsch and Stephan (2000) show that due to differential incentive structures, scientists in the university context primarily seek to advance their careers through publications in scientific journals; whereas scientists working in industry tend to commercialize their research in the market.

The scientist life-cycle and career trajectory are expected to be influenced by the scientist's age, gender, country of origin, and their field of research. Age of the scientist captures how the scientist life-cycle and their career trajectory influence their commercialization decision, by serving as a proxy for the level of scientist human capital and their scientific reputation. The entrepreneurship literature has consistently found gender to be a strong determinant of an individual's decision to become an entrepreneur (Minniti and Nardone, 2007); and as Aldridge and Audretsch (2010 and 2011) suggest, gender also plays a critical role through numerous other mechanisms including scientist's propensity to patent, and their access to financial resources. The scientist's country of origin, measured as the continent in which the scientist completed his/her undergraduate education, is expected to impact the scientist's career trajectory by serving as a proxy for how scientists, from different ethnic backgrounds, prioritize their career-specific decisions and appropriate economic value to new knowledge.

Furthermore, scientist life-cycle and career trajectory, and their decision to commercialize scientific research, is heavily influenced on access to resources, their human and social capital, and importantly the institutional context in which they conduct their research. The significance and influence of these concepts on the scientist's decision to commercialize their research are discussed, and empirically tested, in future sections of this report.

Scientist Startups and Gender

Figure 7 compares the likelihood of scientist startup commercialization by gender, across the six fields of research. Findings indicate that male scientists are two and a half times more likely, across six fields of research, to commercialize their research through startups than female scientists. On average, 13 out of 100 male scientists, and one in five female scientists, reported that they commercialized their research by founding a legally recognized company.

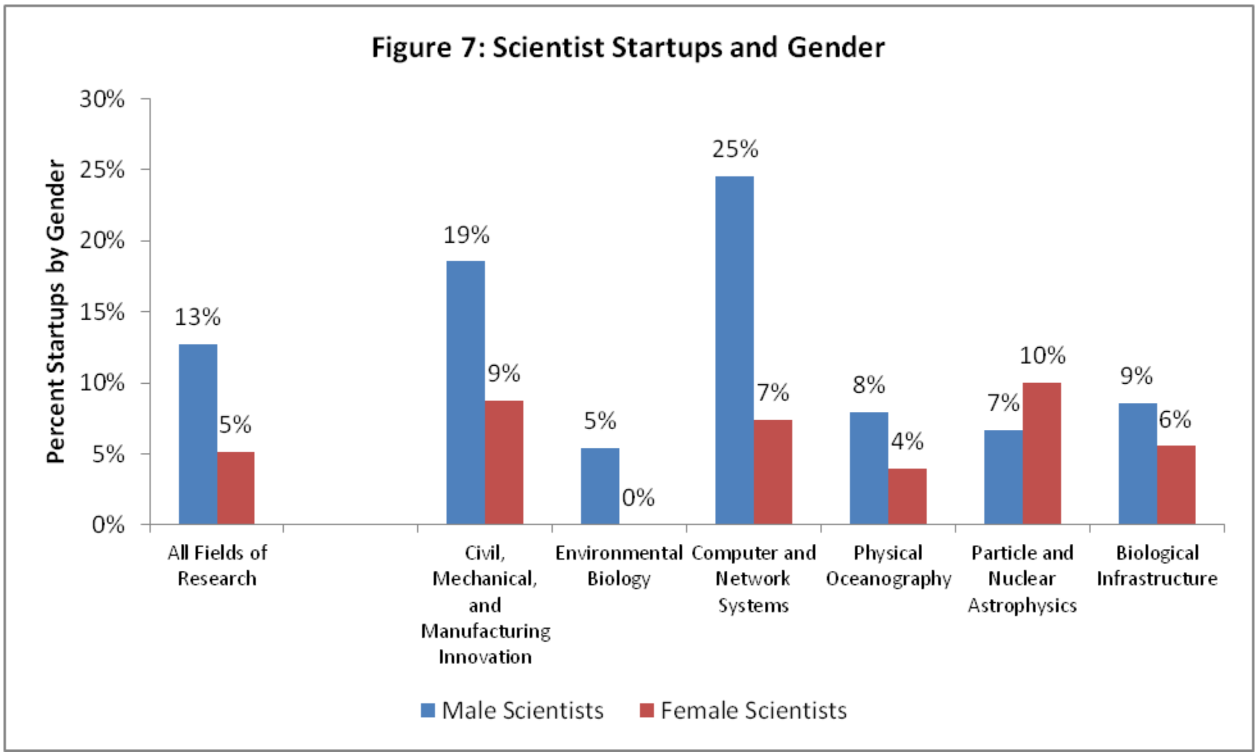
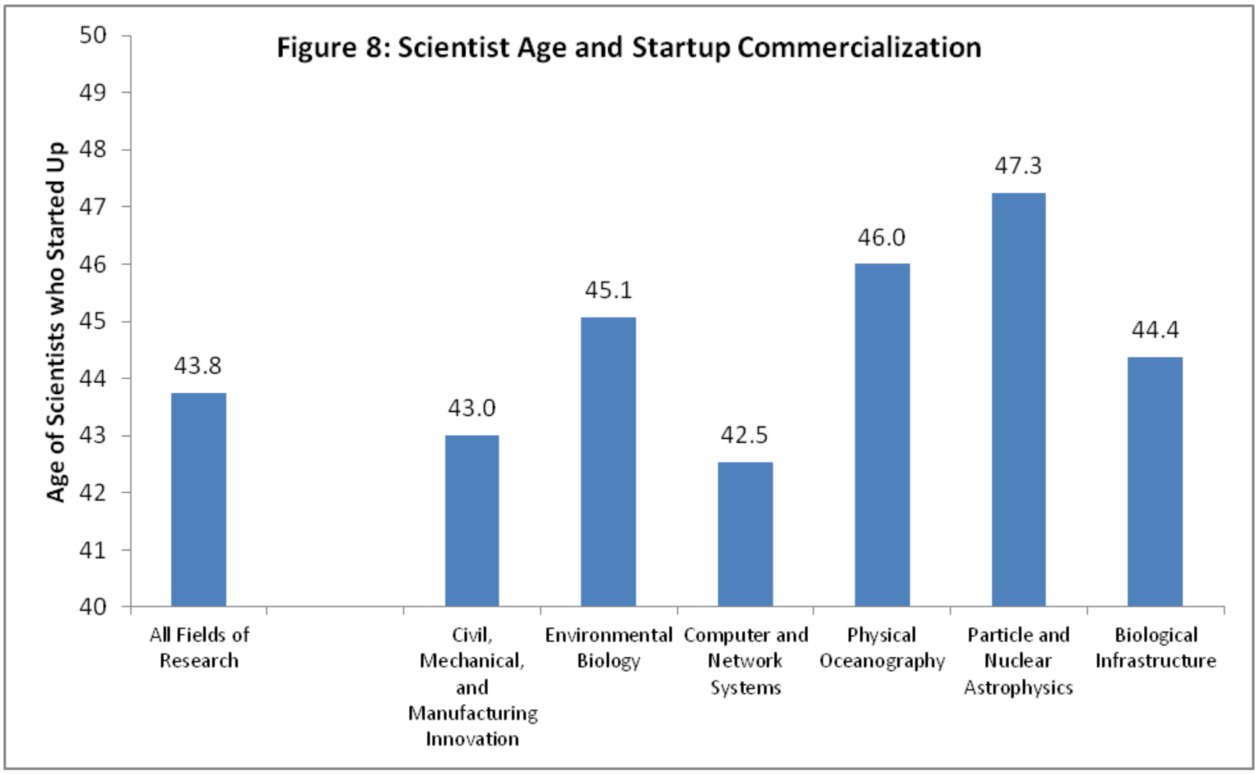


Figure 7: Scientist Startups and Gender

It is interesting to note that in all fields of research, except particle and nuclear astrophysics, male scientists are more likely to commercialize their research through startups than female scientists. Also, in the fields of civil, mechanical, and manufacturing innovation (CMMI), and computer and network systems (CNS), the gender gap appears to be very dominant – approximately one in five, and one in four male scientists reported commercializing their research through startups; whereas only one in ten, and one in fourteen female scientists reported commercializing their research through startups in the fields of CMMI and CNS respectively. This variation can be explained by the predominant gender gap in the fields of engineering and computer science, both in the industry and the academia.

Scientist Startups and Age

Figure 8 compares the average age of scientists that commercialized their research through startups, across the six fields of research. It is observed that average age of a scientist when they commercialized their research through startups was 43.8 years. It is interesting to note that, like the life-cycle model suggests, the scientist entrepreneur's age is significantly higher than what is usually observed among entrepreneurs in the entire population – scientists that commercialize their research through startups do so at significantly later stages of their careers.



There is variation in the average age of scientists across fields of research – on average, scientists in the fields of civil, mechanical, and manufacturing innovation, and computer and network systems are younger than scientists in other fields when they decide to commercialize scientific research through startups. This variation can be explained, in part, by the career trajectory of scientists in the fields of engineering and computer sciences (on average scientists in these fields complete their doctoral education and start their academic careers a few years earlier that other fields), and in part by the greater degree of industry-academia collaboration in these sectors (hence scientists have a better understanding on how to market scientific knowledge to industry).

Country of Origin and Scientist Commercialization

Table 4 compares scientists that commercialized their research through startups by country of origin, across the six fields of research. 1,576 out of 1,899 scientists indicated their continent of origin, measured as the continent in which the scientist completed his/her undergraduate education. 11.46 percent (137 out of 1,195 scientists) from North America, predominantly the United States, 11.42 percent (21 out of 184 scientists) from Europe, 10.14 percent (15 out of 148 scientists) from Asia, and 6.67 percent (2 out of 30 scientists) from South America have commercialized their research through startups.

Table 4: Scientist Startups by Continent of Origin

Continent of Origin	Number of Scientists in the Sample	Number of Scientists who Started Up	Percent Scientist Startups
North America	1,195	137	11.46%
South America	30	2	6.67%
Europe	184	21	11.41%
Africa	15	-	-
Asia	148	15	10.14%
Australia/Oceania	4	-	-
Total	**1,576**	**175**	

It appears that the effect of scientist career trajectory on scientist's decision to commercialize research, across the six fields of research, is very similar for scientists from North America, Europe, and Asia. However, effect of career trajectory for scientists from South America, Africa, and Australia seem to vary considerably based on field of research (See Appendix C) for a comprehensive summary of startups by scientist country of origin across the six fields of research). This provides preliminary evidence of the effect of scientist's ethnicity on his/her decision to commercialize research through startups.

3.3.3 Resources

This section compares the likelihood of scientist commercialization through startups by the amount of financial and human resources available to scientists, across the six fields of research. The basic hypothesis is that the scientist's likelihood to commercialize scientific research through startups increases with greater access to resources.

In the entrepreneurship and innovation literature, resources have often been found to have a strong positive effect on firm's innovative activity and aggregate innovative output. In his model of knowledge production function, Griliches (1979) recommended that investments in knowledge generating inputs have the greatest effect on innovative outputs. Though much of the literature focuses on the innovative activity of firms, as Audretsch and Aldridge (2010 and 2011) suggest the unit of analyses can be extended to the individual scientist, both as an agent utilizing available resources for knowledge creation and as an agent transforming scientific knowledge into innovative outputs. To this end, the scientist entrepreneurship database captures the amount of financial and human resources available to the scientists.

Financial resources are measured as the amount of funding available to the scientist to conduct scientific research from the National Science Foundation (NSF) and the availability of financial resources from other sources of funding such as Non Profits, University, Government, International Governmental Organizations, Industry, and other sources. The amount and availability of financial resources are expected to positively influence the factors in the knowledge production function of the scientist, both in knowledge creation and in transforming scientific knowledge into innovative outputs.

Human resources are measured as the number of student collaborators that worked closely with the scientist during the duration of research (students as factors in the process of knowledge creation), and as the number of student collaborators that were later hired by the scientist's startup subsequent to commercializing research through founding a legally recognized company (students as human capital factors in transforming scientific knowledge into innovative outputs).

Financial Resources

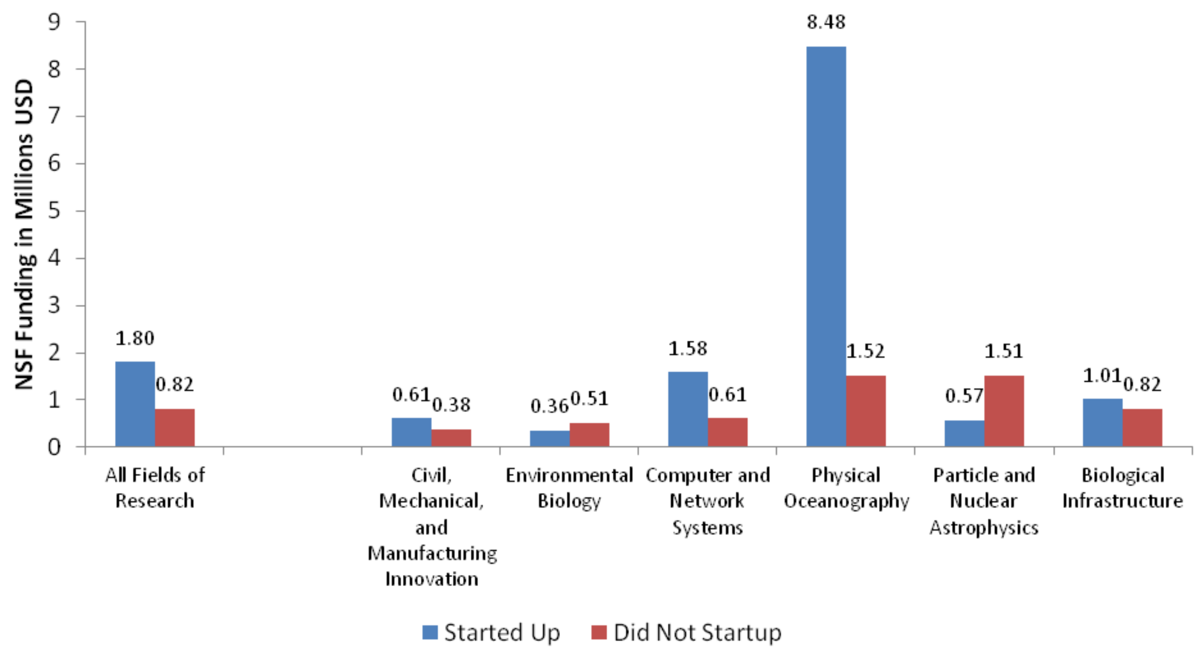
This section describes the likelihood of scientist startup commercialization by their availability and access to funding resources, across the six fields of research. The scientist entrepreneurship database measures financial resources in two different ways – NSF funding amount, and availability of significant sources of funding (>750K) from other sources (Non

Profits, University, Government, International Governmental Orgs., Industry, and other sources).

NSF Funding and Scientist Startups

Figure 9 below compares the average amount of NSF funding received by scientists that commercialized their through startups with scientists that did not, across the six fields of research. On average and across all fields of research, except in the fields of environmental biology and particle and nuclear physics, scientists that commercialized research through startups received greater amounts of funding than scientists that did not.

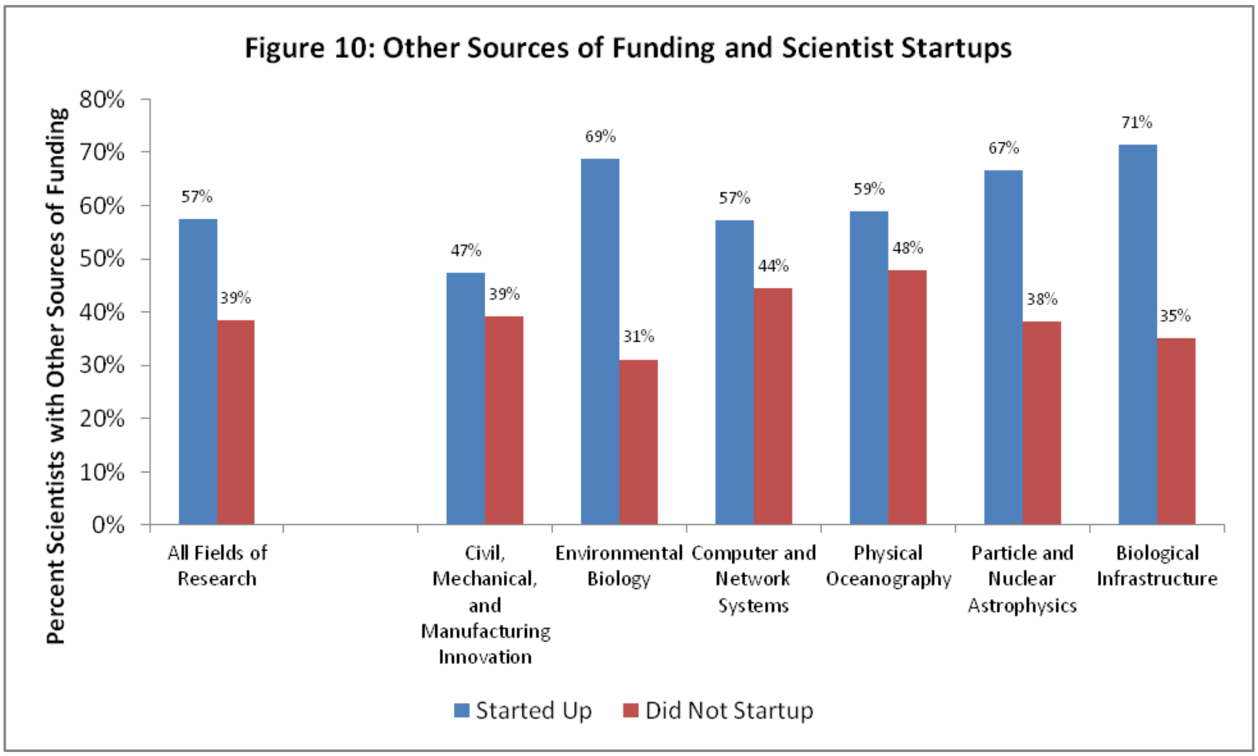
Figure 9: NSF Funding and Scientist Startup Commercialization



The impact of funding appears to be the largest in the field of physical oceanography, possibly due to the high amount of capital required in creating incremental innovations which possess commercial potential in the industry.

Other Sources of Funding

Figure 10 below shows the likelihood of scientist's to commercialize their research through startups by comparing the proportion of scientists that received other significant sources of funding with scientists that did not, across the six fields of research. On average and across all fields of research, scientists that receive funding from other sources are more likely to commercialize their research through startups than scientists that do not.



It is interesting to note that the impact of other sources of funding is the largest in the fields of environmental biology, particle and nuclear physics, and biological infrastructure possibly due to the capital intensive nature in commercializing innovations in these fields. Also, it is possible that these fields probably are in greatest need of funding and collaborations from the industry, non-profits, and the government due to the radical nature of innovations attempted through research. In general, these findings suggest that financial resources have a strong positive impact on the scientist's likelihood to commercialize research through startups.

For a detailed discussion of the impact of funding from various sources by field of research, see Appendix D.

Human Resources

This section describes the likelihood of scientist startup commercialization by their access to human resources, across the six fields of research. The scientist entrepreneurship database measures human resources in two different ways – number of student collaborators that were closely associated with the scientist's research and the number of student collaborators that were subsequently employed the scientist's startup.

Number of Student collaborators

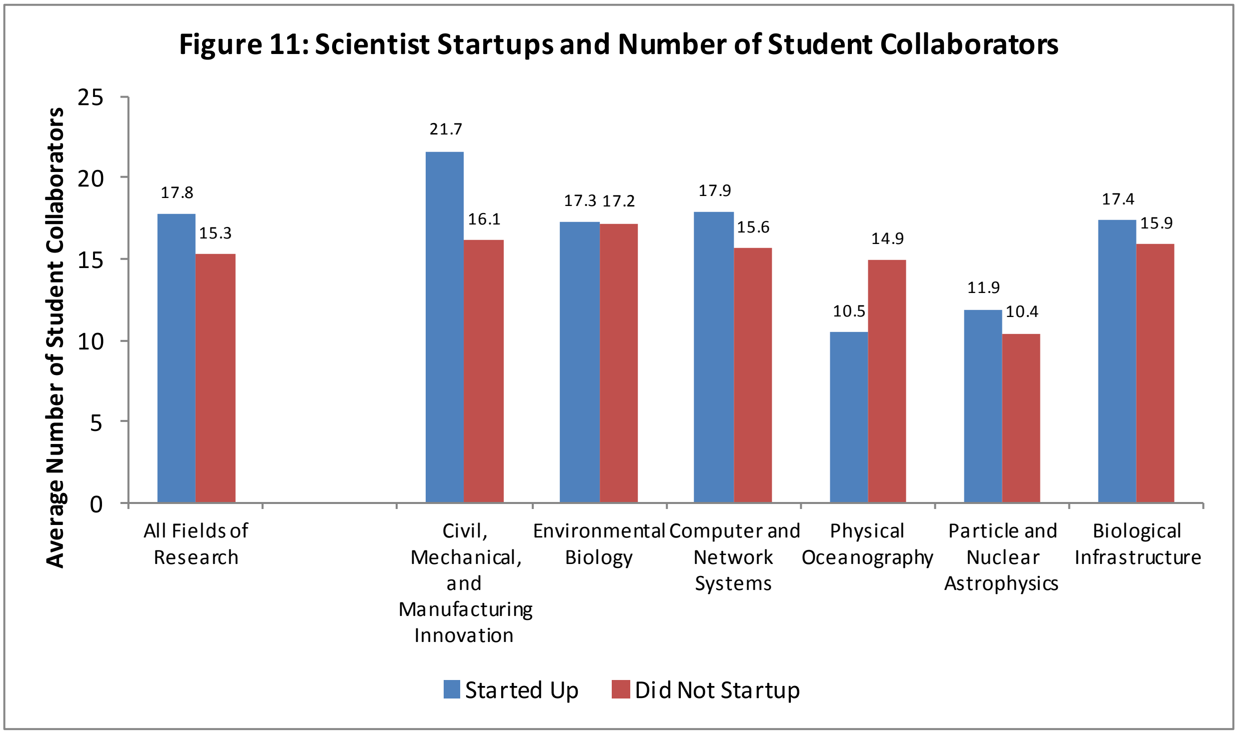


Figure 11 below shows the likelihood of scientist's to commercialize their research through startups by comparing the average number of student collaborators available to the scientists that started up with scientists that did not startup, across the six fields of research. On average and across all fields of research except physical oceanography, scientists with more student collaborators are more likely to commercialize their research through startups. For further discussion of student collaborators' employment decisions subsequent to their collaboration with the scientists see Appendix E.

These results provide preliminary evidence that scientists with greater availability and access to financial and human resources are more likely to commercialize research through startups.

3.3.4 Scientist Human Capital

This section discusses and compares the likelihood of scientist commercialization through startups by the level of scientist human capital, across the six fields of research.

The entrepreneurship literature has extensively examined the link between human capital and entrepreneurship (Bates, 1995; Evans and Leighton, 1989; Gimeno *et al*., 1997; Davidsson and Benson, 2003). The general finding is that, for general population, higher levels of human capital increase the ability of individuals to recognize entrepreneurial opportunities and their propensity to seize those opportunities. There is no reason to believe that the same relationship will hold for the population of scientists, in general. Though higher levels of human capital (measured as scientific reputation) may increase entrepreneurial opportunities, it is important to note that the mechanisms through which human capital affects entrepreneurial decision of scientists may be different from that of the general population, due to the unique institutional contexts in which scientists operate.

As discussed earlier, the knowledge production function, and the scientist life-cycle and career trajectory provide valuable structure in understanding and modeling the commercialization decision of scientists. However, since the scientists represent an exceptionally high achieving section of the general population, it is challenging to find an appropriate measure of their human capital. As the discussion on the effect of scientist life-cycle and career trajectory on entrepreneurship decision (refer to section 3.2) suggests, the most appropriate measure of scientist human capital is a measure of their reputation.

The scientist entrepreneurship database measures the tenure status and the experience (years in tenure) of the scientist. Though the scientist entrepreneurship database has obtained the common measure for scientific reputation as evidenced through citations or number of citations per publication (Audretsch and Stephan, 2000; Aldridge and Audretsch, 2011), it is argued that the tenure status and experience level of the scientist serve as a strong proxy for their relative levels of human capital.

Tenure Status of Scientists

Table 5 compares the tenure status of scientists and their likelihood to commercialize scientific research through startups, across the six fields of research. It is observed that 10.9% of non-tenured scientists and 11 percent of tenured scientists commercialized scientific research through startups. These results are not surprising given that non-tenured scientists may also include scientists with varying degrees of scientific reputation from the industry, along with young non-tenured professors in the academic setting. However, it is important to note that a majority of the scientists that obtained NSF funding are conducting scientific research in a university setting.

Table 5: Scientist Characteristics, Tenure Status

	Total Sample	Number of Startups	Started Up
Non- Tenured Scientists	*156*	*17*	*10.9%*
Tenure Scientists	*1486*	*163*	*11.0%*
Assistant Professor	150	4	2.7%
Associate Professor	442	34	7.7%
Full Professor	716	90	12.6%
Endowed Professor	146	33	22.6%
Emeritus Professor	32	2	6.3%
Total	**1642**	**180**	

The likelihood of commercializing scientific research increases in a linear fashion by the tenure status of the scientist with 2.7 percent of assistant professors, 7.7 percent of associate professors, 12.6 percent of full professors, 22.6 percent of endowed professors and 6.3 percent of emeritus professors commercializing scientific research through startups. These results are not surprising since the tenure status of the scientists also represents their scientific reputation; and as explained by the scientist life-cycle model, scientists with higher levels of human capital (i.e.; scientific reputation) are more likely to commercialize their research.

Another way to measure scientist reputation and human capital is the level of experience i.e.; years in tenured status.

Experience: Years in Tenured Status

Table 6 compares the likelihood of scientists to commercialize scientific research through startups by their level of experience measured as the number of years in tenured status, across the six fields of research. It appears that there is a strong linear relationship between scientist's experience and their likelihood to commercialize scientific research through startups. However, the nature of relationship between scientist experience and their likelihood of startup commercialization appears to be weaker than their tenure status. This anomaly can be explained in one of two ways – First, only 855 of the 1486 tenured scientists revealed their year of tenure-ship; hence it is likely that the nature of missing values are distributed across experience levels in a non-random fashion. Second, experience of scientists in the academic context is influenced by the extent of their linkages with the industry, which may be very specific to the field of research. For example, scientists in computer and network systems are probably more likely to seek tenure status in the academic setting after they have pursued research in the industry for a few years, which may not be the case with scientists in particle and nuclear astrophysics.

Table 6: Scientist Characteristics, Years in Tenured Status

	Total Sample		Started Up
Non- Tenured Scientists	*156*	*17*	*10.9%*
Tenure Scientists			
0-5 Years	67	6	9.0%
6-10 Years	200	31	15.5%
11-15 Years	184	20	10.9%
16-20 Years	170	33	19.4%
21-25 Years	101	13	12.9%
26-30 Years	59	6	10.2%
31-35	42	7	16.7%
More than 35 Years	32	2	6.3%
Total	**1011**	**135**	

Overall, these findings provide evidence of a strong positive relationship between scientist human capital and their likelihood to commercialize scientific research through startups.

3.3.5 Scientist Social Capital

This section compares the likelihood of scientist commercialization through startups by the amount of scientist social capital, across the six different fields of research. Scientist social capital refers to the scientist's potential to derive tangible and intangible benefits from interactions and cooperative activities with other individuals and groups.

The macro-economic growth literature typically lays emphasis on the importance of physical capital and human capital (Solow, 1956), and knowledge capital through the process of knowledge accumulation (Romer 1986, 1994; Lucas 1988). However, the concept of social capital (Putnam, 2000) can be considered as an extension to the usual factors of production in the endogenous growth models as it explains the social dimension in the factors of production.

Numerous recent studies testing the effect of social capital on entrepreneurship have concluded that entrepreneurial activity of general population is enhanced with greater investments in social capital (Mosey and Wright, 2007; Aldrich and Martinez, 2010; Shane and Stuart, 2002; and Davidsson and Benson, 2003).

Furthermore, the entrepreneurship literature proposes numerous causal mechanisms through which social capital enhances the likelihood of entrepreneurial activity. First, interactions and linkages among scientists working in different institutional contexts, such as working with scientists in the industry, function as conduits of knowledge spillovers and flow of information about the process and modes of commercializing scientific research (Thursby and Thursby, 2002; Aldridge and Audretsch, 2011). Second, interactions and linkages with industry, such as being part of the scientific board of firms in the industry facilitate flow of knowledge and information about the latent potential and rate of success in commercializing scientific research. Third, interactions with scientists in the same institutional context such as the entrepreneurial orientation of the head of the department can be posited to facilitate exchange of information and knowledge about the practice of commercializing scientific research among scientists (discussed under regional and institutional contexts).

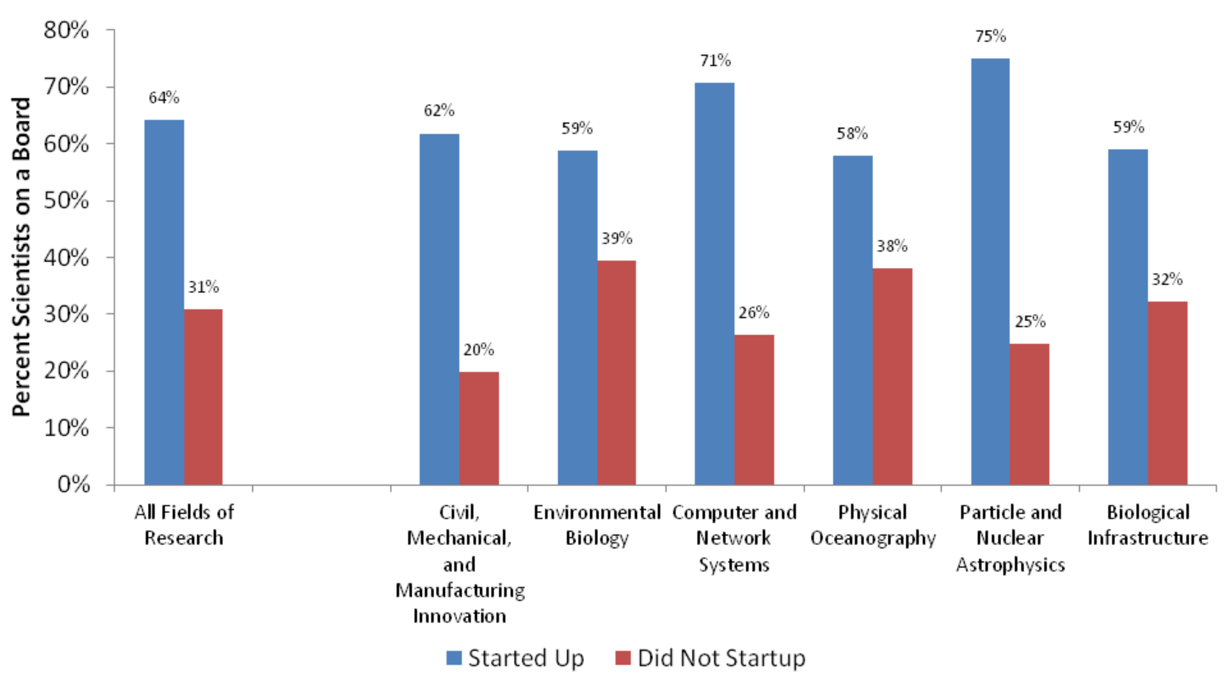
The scientist entrepreneurship database collects information about the board membership of the scientist. It is suggested that the board membership of the scientist serves as a perfect proxy for his/her social capital with regards to the scientist's linkages and interactions with the industry.

Scientist Startups and Board Membership

Figure 12 compares the likelihood of scientists to commercialize research through startups by their membership on the board of directors of firms in the industry, across the six fields of research.

These findings indicate that scientists that are on the board of directors of other firms in the industry are significantly more likely to start a firm of their own, than scientists that do not possess such interactions and linkages with other firms in the industry, across all fields of research. It is most interesting to note that this significance is most striking in the field of particle and nuclear astrophysics, where the nature of research is expected to have the most significant barrier in the knowledge filter.

Figure 12: Scientists on Board of Directors of other firms



On average, scientists with interactions and linkages to the industry through board membership in these six fields of research are two to three times more likely to commercialize their research through startups. These results shed light on the significance of this instrument in influencing the scientist's decision and mode of commercializing scientific research. These results provide evidence of a strong relationship between social capital and the scientist commercialization.

3.3.6 Locational and Institutional Contexts

This section compares and discusses the influence of locational and institutional contexts on the likelihood of scientist commercialization through startups across the six fields of research.

In addition to individual characteristics, access to financial and human resources, and factors of production in the knowledge production function, several locational and institutional factors influence the decision of a scientist to become an entrepreneur. First, knowledge tends to spill over within geographically bounded regions (Jaffe (1989), Audretsch and Feldman (1996), Jaffe, Trajtenberg and Henderson (1993), and Glaeser, Kallal, Sheinkman and Shleifer (1992)). This means that location matters in determining the level of investments in new knowledge, access to technological knowledge in facilitating knowledge spillovers, and in shaping the institutional and scientist behavioral norms and attitudes towards commercialization (Louis *et al*. 1998).

Second, certain institutional features may encourage or act as an impediment to scientist entrepreneurship depending on the institutional contexts in which the entrepreneurial decision is made (Henrekson and Stenkula (2010); Karlsson and Karlsson (2002)). Two distinct features of the institutional context play a role in influencing the scientist's decision to commercialize his/her research through startups– support from the department and characteristics of the technology transfer office. First, the department's conscious efforts in encouraging commercialization of scientific knowledge and the department head's entrepreneurial orientation may act as substitutes in encouraging the scientist to commercialize his/her research. Second, as the characteristics of the technology transfer office (TTO) determine the level of assistance in scientist commercialization depending on their resource availability (Mowery, 2005) and their influence on the scientist's mode of commercialization depending on their organizational priorities (Markman *et. al*. (2005); O'Shea, Wright and Ensley (2005); and Lockett et al. (2005)).

The scientist entrepreneurship database collects information on the locational (region) and institutional (the entrepreneurial orientation of the scientist's department head, TTO characteristics) contexts of the scientist. Though the actual frequency and significance of the scientist's interactions with his/her department head and the TTO's organizational priorities are not measured, it is argued that the department head's entrepreneurial orientation and scientist's perception of the TTO serve as strong proxies for the scientist's institutional context.

Locational Context

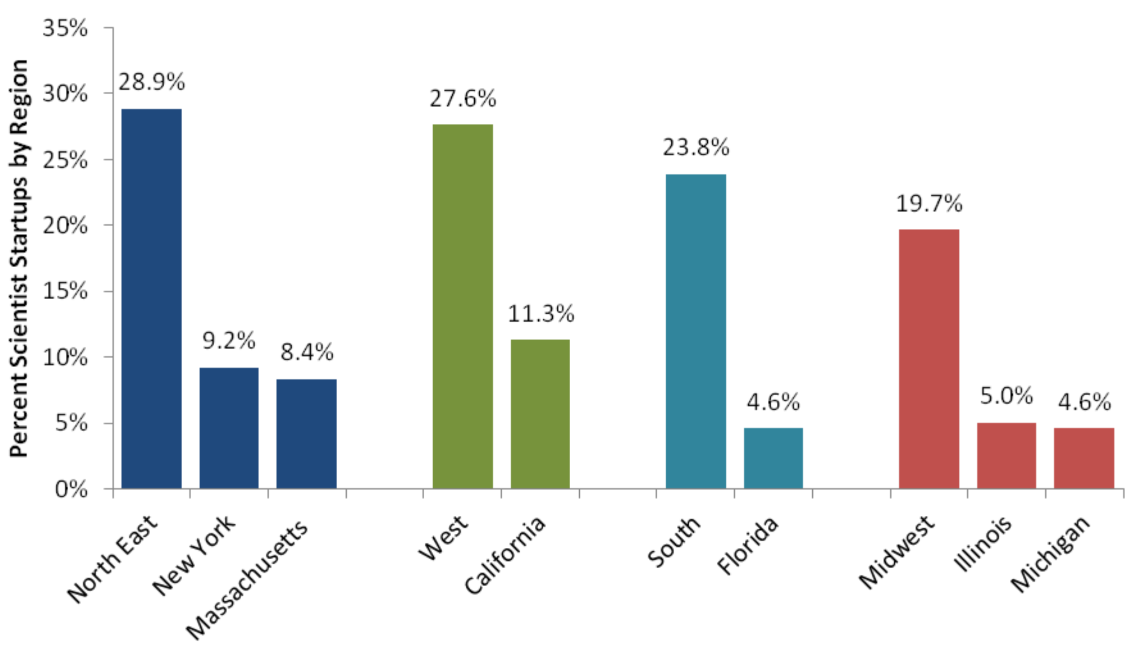
This section compares and discusses the factors through which locational contexts influence the scientist's likelihood to commercialize research through startups, across the six fields of research. Specifically, the influence of regions in the United States – classified as North

East, West, South and Midwest – are discussed. Please refer to Appendix F for a discussion on how the classifications have been made. Though, the analysis does not include an extensive discussion of knowledge spillovers at the university level, the subsequent section on institutional contexts discusses the effect of department and university level factors on the scientist's startup commercialization decision.

Scientist startups and Region

Figure 13 compares the share of scientist startups by location of scientist across all six fields of research.

Figure 13: Share of Scientist Startups by Region



Results indicate that 29 percent of scientist startups across the six fields of research are from the North East region, with 9.2 percent and 8.4 percent of scientist startups are from New York and Massachusetts respectively. Furthermore, 27.6 percent of scientist startups are from the Western Region United States, with 11.3 percent from the state of California – the highest from any one state in the United States. The South and Midwest regions contribute 23.8 percent and 19.7 percent of the startups respectively. These results provide evidence for the influence of two distinct locational factors. First, there is significant amount of variation in the number of scientist startups by region – this can be attributed in part to the variation in the level of investment in new knowledge creation, and in part to the access to technological knowledge in facilitating knowledge spillovers. Second, with a dominant proportion of startups from one or two states – this can be attributed to the institutional and scientist behavioral norms and attitudes towards commercialization in those states, and to the state-specific investments, especially in public universities, in different fields of research.

Scientist startups by fields of research

Table 7 below compares the proportion of scientists that commercialize their research through startups, by their location and fields of research. Findings indicate that roughly 15 percent, one in seven, scientists in the North-East region; 13.17 percent of scientists in West region; 12.21 percent in Midwest region; and 10.69 percent in the South region commercialize their research through startups. These findings are not surprising since we know that the technological knowledge in facilitating knowledge spillovers is greater in the North East and West Regions, especially in California, New York, and Massachusetts.

Table 7: Scientist Startups by Region, across Fields of Research

	North East	Midwest	South	West
All Fields of Research	14.97%	12.21%	10.69%	13.17%
Civil, mechanical, and manufacturing innovation	19.48%	27.47%	19.49%	12.82%
Environmental biology	5.38%	0.00%	3.31%	9.43%
Computer and network systems	30.21%	23.08%	15.00%	27.00%
Physical oceanography	12.66%	0.00%	5.88%	10.68%
Particle and nuclear astrophysics	5.08%	5.66%	10.00%	2.70%
Biological infrastructure	11.94%	5.41%	6.98%	8.89%

Furthermore, results also indicate the location specific effects on fields of research. We find that the proportion of scientists that are in the field of civil, mechanical, and manufacturing innovation based in the Midwest region are most likely to commercialize their research through startups. These findings are not surprising given the competitiveness of the manufacturing sector in the Midwest states. In the field of environmental biology, scientists from the West region are most likely to commercialize their research through startups – this maybe largely due to the vibrant biotechnology sector and heavy investments in research and development from the industry in California and Washington. In the fields of physical oceanography and biological infrastructure, scientists from the North East region are most likely to commercialize their research through startups – this is possibly due to large industry research and development investments in environment and biological sciences in New York, Massachusetts, and Pennsylvania.

The fields of computer and network systems and particle and nuclear astrophysics are the most peculiar with regards to the effect of locational factors on the scientist's likelihood of commercializing research through startups due to the nature of innovative activity in these fields.

First, scientists in the field of computer and network systems seek incremental innovations, in that they tend to accumulate knowledge by building upon existing knowledge and resources and hence are faced with lesser barriers in facilitating knowledge spillovers between and from the industry; whereas scientists in the field of particle and nuclear astrophysics seek radical innovations, in that they tend to produce innovations that require completely new knowledge and/or resources in commercializing their research and hence are faced with greater barriers in facilitating knowledge spillovers between and from the industry.

Second, scientists in the field of computer and network systems tend to have more industry interactions and linkages and more favorable institutional factors in commercializing their research than scientists in the field of particle and nuclear astrophysics due to the applied and incremental nature of their research and more favorable scientist-community norms towards commercialization and firm failure. Hence, we observe that a larger proportion of scientists in the field of computer and network systems are able to commercialize their research through startups than scientist in the field of particle and nuclear astrophysics.

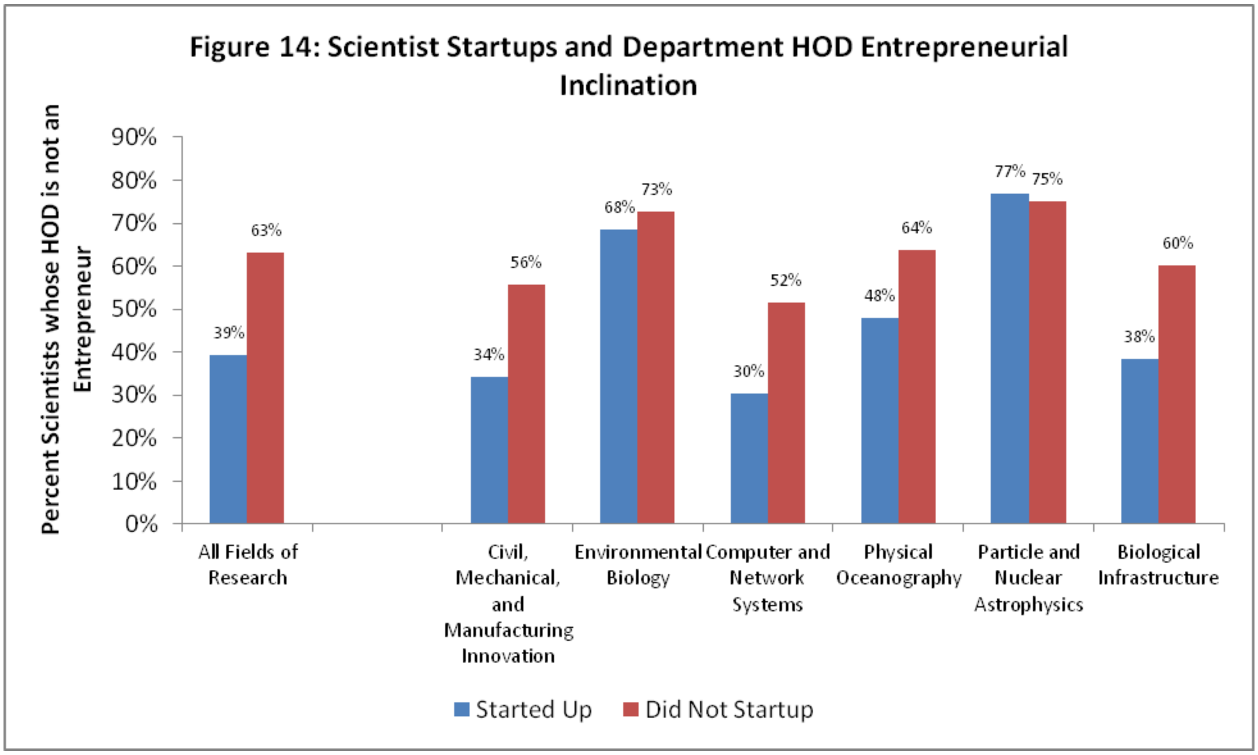
Overall, we observe that locational factors strongly influence scientist startup commercialization decision depending on the nature of technological knowledge in facilitating knowledge spillovers and the field of research.

Institutional Context

This section compares and discusses the factors through which institutional contexts influence the scientist's likelihood to commercialize research through startups, across the six fields of research. Specifically, we discuss the effect of department and university/industry level institutional factors on the scientist's startup commercialization decision.

Department Head's Entrepreneurial Inclination

Figure 14 compares the likelihood of scientist commercialization through startups depending on the head of department's entrepreneurial orientation, across the six fields of research. Though the actual frequency of scientist's interactions with his/her department head are not measured, it is argued that the department head's entrepreneurial orientation serves as strong proxies for the scientist's departmental context.



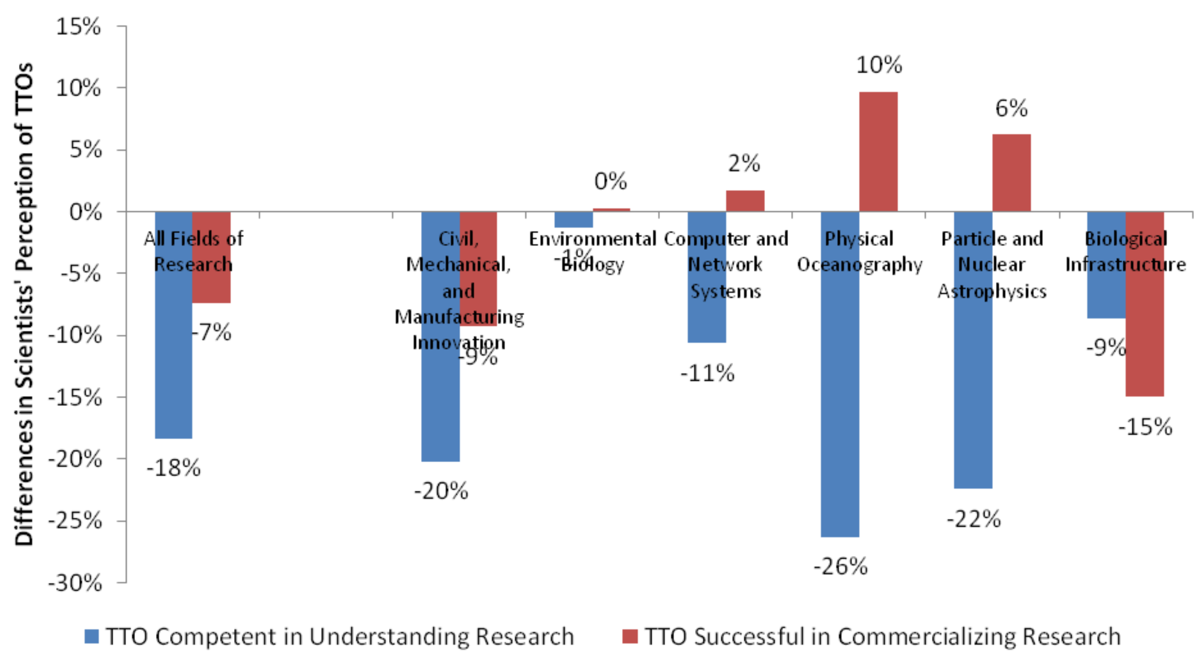
Findings suggest that in all fields of research, except particle and nuclear astrophysics, the head of department's entrepreneurial orientation, i.e.; if the department head commercialized scientific research through starting up a legally founded company, is positively related to the scientist's likelihood of commercializing research through startups. As discussed earlier, the insignificance of department head's entrepreneurial orientation in the field of particle and nuclear astrophysics is possibly due to the radical nature of innovations typical to the field.

Technology Transfer Office (TTO) Characteristics and Scientist Startups

This section discusses the effect of the Technology Transfer Office (TTO) characteristics on the likelihood of scientist to commercialize research through startups. Roughly, 25 percent of the scientists described the TTOs as incompetent in understanding their area of research, and 15 percent of the scientists described TTOs as unsuccessful in commercializing research. However, the majority of the scientist responses indicated that the TTOs are of significant help in assisting scientists in overcoming the knowledge filter. Practical significance and hypothesis for future empirical research are discussed.

Figure 15 below shows the difference in scientist's perception of the Technology Transfer Office (TTO) characteristics between scientists' that commercialized their research through startups and scientists that did not.

Figure 15: Difference in Scientist's Perception of TTO Institutional Factors



The Scientist Entrepreneurship database captures scientist's perception of TTO characteristics in two ways – competence of the TTO in understanding the scientist's area of research and success of the TTO in commercializing scientist's research. Results indicate that, on average, scientists that started up have found the TTO to be relatively less competent in understanding the scientist's area of research and unsuccessful in commercializing scientist's research. These results are not surprising given that scientist's that are either unsuccessful in seeking help from the TTO or that choose not to use the services offered by the TTO tend to commercialize their research through startups (Aldridge and Audretsch, 2011).

Furthermore, it appears that scientists in the fields of computer and network systems, physical oceanography, and particle and nuclear astrophysics that started up felt that their TTO was successful in commercializing their research. However, on average, it can be said that scientist's that started up seem to be less appreciative of the TTO than scientist's that did not. These results are not surprising given that most scientist's that did not startup found the TTO to be more helpful either since they did not seek a very specific area of expertise from the TTO or because they found the TTO to be more knowledgeable about the mechanisms of knowledge spillovers in their field of research than themselves (due to their own limited interactions and linkages with the industry).

4. Determinants of Scientist Entrepreneurship

4.1 Introduction

While very little literature has been devoted to understanding and analyzing scientist entrepreneurship, a much broader research has generated a plethora of studies focusing on entrepreneurship in a more general context (Acs & Audretsch, Handbook of Entrepreneurship, 2010). At the heart of this literature is the question of what exactly distinguishes those people who choose to become an entrepreneur from those who choose not to become an entrepreneur. The entrepreneurship literature has been developed at both a theoretical and empirical level (Acs & Audretsch, Handbook of Entrepreneurship, 2010).

In his exhaustive survey of the entrepreneurship, Parker (2010) finds that the basic theoretical building block is the conceptual framework or model of entrepreneurial choice. The following section explains the model of entrepreneurial choice. The subsequent sections apply the model of entrepreneurial choice to the context of the university scientist. The scientist context of entrepreneurial choice involves five distinct types of factors or influences that shape the decision of a scientist to become an entrepreneur. These five factors involve first characteristics specific to the individual. The second factor involves human capital. The third factor involves social capital. The fourth factor involves the institutional context. Finally, the fifth factor involves access to resources in general and financial capital in particular.

4.2 The Model of Entrepreneurial Choice

According to the model of entrepreneurial choice, an individual weighs the benefits of becoming an entrepreneur against those benefits that could be obtained through employment in an existing firm. The greater is the gap between the benefits accruing from entrepreneurship and those earned from being an employee the more likely that person is to become an entrepreneur (Parker, 2010).

The model of entrepreneurial choice has been empirically tested in a number of contexts, but almost never for the context of university scientists. In fact, a large body of literature has been developed that relates individual characteristics to the decision to become or not to become an entrepreneur (McClelland, 1961; Roberts, 1991; Brandstetter, 1997; Gartner, 1990 and Blanchflower and Oswald, 1998)). One of the pioneering studies was by McClelland (1961). More recently, Zhao and Seibert (2006) link the personality characteristics of entrepreneurs to the decision to start a new business. Similarly, Reynolds, Carter, Gartner, and Greene, (2004) use a large database, the Panel Study of Income Dynamics (PSID), to identify the role that personality characteristics play in the decision that an individual makes to start a new business.

The role of intentions to become an entrepreneur has played a particularly important role in the entrepreneurship (Wright, Westhead and Ucbasaran (2006), Shapero and Sokol (1982) and Ajzen (1991); Gaglio and Katz, 2001). While these studies find that entrepreneurial intentions are important in the entrepreneurial process, none of these studies focus on the context of university scientists. Thus, Aldridge and Audretsch (2011) suggest that it is not clear whether the consistent findings concerning entrepreneurship and entrepreneurial intentions for the more general population would also be expected to be valid for the context of university scientists.

4.3 Career Experience

Aldridge and Audretsch (2011) posit there are important reasons that the main influences underlying entrepreneurial intentions for university scientists may in fact not simply mirror that found for the more general population. The Levin and Stephan (1991) and Stephan and Levin (1992) both provided a compelling theoretical argument along with supportive empirical evidence suggesting the existence of a life cycle model of scientist commercialization. According to the Levin and Stephan (1991) and Stephan and Levin (1992) scientist life cycle model, the age of a scientist may impact the decision to become an entrepreneur differently than has been found for the more general population. A well-known finding in the overall literature of entrepreneurship is that younger people have a greater propensity to become an entrepreneur, while older people are less likely to become an entrepreneur. However, Levin and Stephan (1991) and Stephan and Levin (1992) found that a positive relationship between the age of a scientist and the likelihood that they start a business. Levin and Stephan (1991) and Stephan and Levin (1992) interpret their results using the lens of a life-cycle framework. According to their life-cycle model, when a scientist is in the early career stages, scientist productivity and output tends to be the greatest. During the early life cycle stages, the scientist therefore has the greatest incentives to invest in creating knowledge which is public in nature, through publication of their scientific findings in scholarly journals, which has the impact of enhancing the scientist's scientific reputation. As the scientist matures and has carved out a reputation of scientific prominence, diminishing returns set in to both scientific productivity as well as the reputation of the scientist. The incentive to the scientist shifts towards investing not so much in public knowledge, but rather scientific research which can be commercialized. Thus, as the scientist matures over the life cycle, the incentives to become an entrepreneur also increase.

The predictions of Levin and Stephan (1991) and the Stephan and Levin (1992) model of scientist commercialization over the life cycle of the scientist is consistent with the few studies that have focused on the commercialization and entrepreneurial activities of scientists. For example, Wright, Westhead and Ucbasaran (2006), Shapero and Sokol (1982), Gaglio and Katz (2001) and Ajzen (1991) all have found that entrepreneurial intentions and the propensity to be sensitive to entrepreneurial opportunities may increase as a scientist matures and garners more career experience.

However, while there are compelling reasons to predict that age is positively related to the decision of a scientist to enter into entrepreneurship, Aldridge and Audretsch (2011) did not find any empirical evidence suggesting that age or experience influences the propensity of a scientist to become an entrepreneur. Still, their findings highlight that the role of age in the entrepreneurial decision of university scientists does not simply mirror that of the more general population.

4.4 Gender

A second important individual specific characteristic that has consistently been found to be important in shaping the decision to become an entrepreneur is gender (Minniti and Nardone, 2007). Gender, of course, is independent of the life cycle of a scientist, and thus is not applicable to the life-cycle models of Levin and Stephan (1991) and Stephan and Levin (1992). Most of the literature has generated empirical evidence suggesting that females are less likely to become an entrepreneur (Allen, Langowitz, and Minitti, 2007). For example, the female self-employment rate in the United States of females is around half as great as the self-employment rate for males (Allen, Langowitz, and Minitti, 2007). While nearly seven percent of females participating in the labor force are classified as being self-employed, the self-employment rate of males is considerably greater, well over twelve percent. The Global Entrepreneurship Monitor (GEM) finds that well over one in ten females in the United States owns' a business (Allen, Langowitz, and Minitti, 2007). By contrast, just under, one in five males owns' a business in the United States (Allen, Langowitz, and Minitti, 2007).

While not many studies have been undertaken examining the impact of gender on the decision to become an entrepreneur in high technology and knowledge based industries, several studies have presented evidence suggesting that it is considerably lower for females than for males. For example, Elston and Audretsch (2010) find that females have a lower likelihood to be an entrepreneur in a study based on Small Business Innovation Research (SBIR) grants to start a firm, and that, in particular, Elston and Audretsch (2010) provide evidence showing that the reliance on grants from the SBIR program as a primary source of start-up capital is considerably lower for females than for males. Elston and Audretsch (2010) find that the negative effect of being female on probability of receiving SBIR funding was robust and persistent even after controlling for personal characteristics such as age, race, education, and wealth.

In a different study analyzing firms receiving funding from the SBIR, Link and Scott (2009) find that, just under, one in five of the SBIR firms in their sample from the National Institutes of Health (NIH) SBIR program were owned by females. The remaining four-fifths of the SBIR firms receiving funding were owned by males. Thus, the empirical evidence from several studies implies that gender plays an even larger role in the decision to become an entrepreneur in knowledge based and high technology fields. While Aldridge and Audretsch (2011) used these studies as a basis for hypothesizing that the likelihood of becoming an entrepreneur is lower for female university scientists than for their male counterparts, their results in fact suggested that gender plays no role in influencing the entrepreneurial activities of scientists. This would suggest a sharp contrast to the findings for the overall population, where gender is one of the greatest determinants of who becomes an entrepreneur and who does not.

4.5 Human Capital

In the more general entrepreneurship literature, human capital plays a central role in the decision of individuals to become an entrepreneur (Acs & Audretsch, Handbook of Entrepreneurship, 2010). A number of studies have explicitly focused on the relationship between the human capital of individuals and their propensity to become an entrepreneur or start a new business (Evans and Leighton, 1989; Bates, 1995; Gimeno, *et al.*, 1997; Davidsson and Honig, 2003 and Wright, M. *et al.,* 2007). The ability of an individual to recognize the existence of an entrepreneurial opportunity has been found by studies to be positively related to the level of human capital. Similarly, the willingness of and ability to actually implement and pursue those entrepreneurial opportunities has been found to be positively related to the level of human capital.

In terms of measurement, human capital is most frequently measured by the number of years in education, or else, alternatively, the highest degree attained. The empirical literature has found, with very few exceptions, that human capital is positively related to the propensity to become an entrepreneur.

Aldridge and Audretsch (2011) suggest that the positive relationship between human capital and the likelihood of becoming an entrepreneur found for the general population would also be expected to hold for university scientists. In fact, their findings do not support the hypothesis that the human capital of the scientist is positively related to the propensity to become an entrepreneur. Rather, their study suggests that the level of human capital seems to have no statistically significant impact on the entrepreneurial decision of a university scientist. Aldridge and Audretsch (2011) interpret this non-significance of the human capital variable as reflecting a sample of university scientists with extremely high levels of human capital, so that the variance in human capital is not found to make any significant difference in the scientist decision to become an entrepreneur.

4.6 Social Capital

While human capital refers to the knowledge capabilities of the individual, the extent of social capital reflects the extent to which an individual can take advantage of linkages and connections to other people. Just as *physical capital* refers to the importance of factories and machines to generate economic value (Solow, 1956), the endogenous growth theory (Romer 1986; Lucas 1988) shifted the emphasis to knowledge accumulation, so that *knowledge capital* takes on a key role in generating economic value.

By contrast, Putnam (1993) and Coleman (1988) introduced the concept of *social capital* to reflect the relationships, connections and linkages to other people. Coleman (1988) explains that social capital involves "a variety of entities with two elements in common: they all consist of some aspect of social structure, and they facilitate certain actions of actors…within the structure." According to Putnam (2000, p.19) social capital has a positive impact on innovation and growth, "Whereas physical capital refers to physical objects and human capital refers to the properties of individuals, social capital refers to connections among individuals – social networks. By analogy with notions of physical capital and human capital – tools and training that enhance individual productivity – social capital refers to features of social organization, such as networks that facilitate coordination and cooperation for mutual benefits."

The scholarly literature in entrepreneurship has found a positive and significant relationship between various measures of social capital and the propensity for an individual to become an entrepreneur (Mosey and Wright, 2007; Aldrich and Martinez, 2010, Shane and Stuart, 2002, and Davidsson and Benson, 2003). Aldridge and Audretsch (2011) argue that social capital should play a key role in the decision of a university scientist to become an entrepreneur. In particular, they suggest that linkages, connections to and relationships with other scientists employed by industry, as well as connections to industrial firms, will facilitate the ability of the scientist to recognize entrepreneurial opportunities and to act on those opportunities through entrepreneurial activity. Aldridge and Audretsch (2011) do provide empirical evidence suggesting that those university scientists with a greater extent of social capital have a greater propensity to become an entrepreneur.

4.7 Institutional Influences

The general literature on entrepreneurship (Acs & Audretsch, Handbook of Entrepreneurship, 2010) has also identified the institutional context within which an individual confronts the decision to become an entrepreneur as influencing the outcome of that entrepreneurial decision (O'Shea, *et al.*, 2005 and Mowery, D., 2005). They suggest that certain aspects of the institutional context have been found to encourage individuals to become an entrepreneur, while other aspects have been found to deter or impede entrepreneurship, (Saxenien, A., 1994, Karlsson and Karlsson, 2002 and Henrekson and Stenkula, 2010).

Aldridge and Audretsch (2011) argue that, just as the literature has found for entrepreneurship within the general population, the institutional context may also play an important role in shaping the entrepreneurial decision for university scientists (Thursby and Thursby, 2002). For example, the technology transfer office (TTO) can play an important role in either encouraging or alternatively impeding entrepreneurial activity among university scientists (Mustar *et al.*, 2006; Chapple *et al.*, 2005). In fact, meticulously undertaken studies have found indications that TTOs do not have the same impact on entrepreneurial and other scientist commercialization activities among different universities (Roberts and Malone, 1996; Vohora, A., Wright, M. and Lockett, A., 2004; Siegel and Wright, 2007; Wright, M. *et al.,* 2007, and Breznitz, O'Shea and Allen, 2008). The studies suggest that there is considerable heterogeneity in the organization and strategies of technology transfer offices across different universities. For example, offices of technology transfer differ considerably in terms of size, access to human resources, and access to financial resources (Mowery, Nelson, Sampat and Ziedonis, 2005). As Aldridge and Audretsch (2010) suggest, those offices of technology transfer office which have better access to more resources may be better situated to assist university scientists commercialize their research in the form of entrepreneurial activity.

Markman *et al.* (2005) explain that considerable heterogeneity exists across offices of technology transfer with respect to their strategies and orientation. In particular, Markman *et al.* (2005) show that some OTTs place a greater priority on licensing of intellectual property rather than on generating the startup of new firms by scientists. Markman *et al.* (2005) examine the mission statements from the office of technology from 128 universities. They find that most university TTOs prioritizes licensing intellectual property over encouraging the scientist to start a new business. Similar findings have been found by O'Shea, Allen, Chevalier and Roche (2005), and Lockett *et al.* (2005). These studies find that while some offices of technology transfer encourage university scientists to license their technology to existing companies, others are more encouraging to enabling university scientists to start a new business. In their 2010 and 2011 studies, Aldridge and Audretsch find considerable evidence that the TTO has an impact on the commercialization and entrepreneurial activities of university scientists.

4.8 Financial and Other Resources

An important finding in the general entrepreneurship literature is that access to financial resources, as well as other types of related resources, can have a significant influence on the propensity for people to become an entrepreneur (Acs & Audretsch, Handbook of Entrepreneurship, 2010 and Parker, 2010). For example, Kerr and Nanda (2009, p. 1) suggest that the availability of financial resources is one of the biggest issues confronting nascent entrepreneurs and influences their decision as to whether to actually start a new business, "Financing constraints are one of the biggest concerns impacting potential entrepreneurs around the world." In a different study, Gompers and Lerner (2010) suggest that the importance of overcoming financing constraints may be even more important for scientists, because the ideas upon which the entrepreneurial startup is based are characterized by an even greater degree of uncertainty, asymmetries and transactions costs. In fact, Aldridge and Audretsch (2010 and 2011) find support for the hypothesis that financial resources facilitate the propensity for a university scientist to become an entrepreneur.

5. Regression Results

5.1 Introduction

The purpose of this section is to identify factors that are conducive, and those that are an impediment, to scientist commercialization through startups across the six fields of research. This section outlines the descriptive statistics, means and standard deviations, and simple correlation matrix of key determinants of scientist entrepreneurship discussed in section 3.3.

Section 5.1 outlines the descriptive statistics, means and standard deviations, and simple correlation matrix of key determinants of scientist entrepreneurship discussed in section 3.3.

Section 5.2 discusses the estimation model and the measures of key determinants of scientist entrepreneurship that are used to calculate the likelihood of scientist commercialization through startups.

Section 5.3 discusses the probit regression results for estimating the likelihood of scientist entrepreneurship across all fields of research.

Section 5.4 discusses the probit regression results for estimating the likelihood of scientist entrepreneurship in Civil, Mechanical, and Manufacturing Innovation.

Section 5.5 discusses the probit regression results for estimating the likelihood of scientist entrepreneurship in Environmental Biology.

Section 5.6 discusses the probit regression results for estimating the likelihood of scientist entrepreneurship in Computer and Network Systems.

Section 5.7 discusses the probit regression results for estimating the likelihood of scientist entrepreneurship in Physical Oceanography.

Section 5.8 discusses the probit regression results for estimating the likelihood of scientist entrepreneurship in Particle and Nuclear Astrophysics.

Section 5.9 discusses the probit regression results for estimating the likelihood of scientist entrepreneurship in Biological Infrastructure.

Section 5.10 summarizes the relationships between key determinants of scientist entrepreneurship discussed in sections 5.3 through 5.9 by the field of research.

The means and standard deviations presented in the Appendix G indicate that, on average, 12.75 percent of scientists have commercialized their research through startups. The average funding amount to the sample of scientists is 950,000 USD, which is higher than the average of the scientist population discussed in section 3.1. About 41 percent of scientists, across the six fields of research received funding from other external sources.

The scientist sample is observed to have 16 years of tenured experience, with a mean age of 50.3 years. Furthermore, about 44 percent of scientists have reported that they are full professors. This indicates that the scientist sample, on average, has a high degree of scientist reputation. Please refer to the Appendix H for a complete summary of the means and standard deviations of key variables used in the estimation model.

The simple correlation matrix of all variables used in the probit model estimations presented in the Appendix H suggests that there is little correlation between most variables, except age and scientist tenure experience signifying the relative exogenous nature of the sample. Though the scientists self-selected to participate in the survey, it appears that the scientist entrepreneurship database is pretty robust in its representativeness of the scientist population.

5.2 Estimation Model

Dependent Variable

The dependent variable in our analyses is scientist commercialization through firm creation; the dependent variable assumes a value of 1 if scientist who responded to the survey, answered yes to our question – "Have you started a legally recognized company?", and 0 if the scientist answered no.

The scientist entrepreneurship database measures numerous key determinants of scientist entrepreneurship that are expected to affect the scientist's likelihood to commercialize scientific research through numerous mechanisms (as discussed in section 3.3). The probit regression models presented in Tables 8 through 14 analyze the effect of scientist social capital, human capital, access and availability to financial and human resources, locational and institutional factors, and other demographic control variables on the scientist's likelihood to commercialize research through startups, across the six fields of research.

Independent Variables – Financial Resources

The scientist entrepreneurship database includes two measures of financial resources – NSF grant award amount and availability of funding from other sources. The grant award amounts are secondary information obtained from the Web of Knowledge database, which were then matched to the survey responses of scientists in the scientist entrepreneurship database. We aggregated the grant award amounts by scientist research, during 2005-2012-Q2, in millions of dollars. The database gathered information about funding from other sources using the survey instrument – "Did you have any other major sources of funding directly relating to your research from 2005 to 2010 (totaling over $750,000)?" This variable was coded 1 if the scientist responded that their research was funded by other major sources of funding and 0 if the scientist answered no.

Independent Variables – Human Resources

The scientist entrepreneurship database includes two measures of human resources – total number of human resources, and the number of student collaborators. The total number of human resources available to the scientist was measured using the survey instrument – "Roughly what total number of undergraduate and graduate students have you worked with in your specific field of research from 2005 to 2010?" and the number of student collaborators was measured using the survey instrument – "Roughly what number of undergraduate and graduate students have you worked closely with in your specific field of research from 2005 to

2010?”. The estimation results include the number of student collaborators both as a measure of dedicated human resources as well as a measure for the source of ideas. This variable is an ordinal variable indicating the number of students closely associated with the research sponsored by the award.

Independent Variables – Human Capital

The scientist entrepreneurship database includes two measures of scientist human capital – scientist experience and scientist reputation. Scientist experience is measured as the number of years since they first obtained tenure; this ordinal variable was constructed using the year of tenure information provided by the scientists. Scientist reputation is measured as a dummy variable for full professorship. Hence, scientists who indicated their tenure status as full professorship are coded as 1 and all other scientists, including those scientists who indicated non-tenured status, are coded as 0.

Independent Variables – Social Capital

The scientist entrepreneurship database includes a measure of scientist social capital, which was gathered using the survey instrument – “Do you sit (or have you sat) on a board of directors or scientific advisory board?” This variable is coded as 1 if the scientist responded that he/she is on the board of directors or a scientific advisory board of other firms and 0 if scientist responded no.

Independent Variables – Locational Context

The scientist entrepreneurship database includes secondary information of scientist’s location of research obtained from the Web of Knowledge database. The secondary information on scientist’s location includes their primary university affiliation and the state in which they are conducting their research. The probit estimation models include a control for scientist’s location in one of four regions in the United States – North East, Midwest, South, and West.

Independent Variables – Institutional Context

The scientist entrepreneurship database includes two factors of the scientist’s institutional context– departmental context and characteristics of the university technology transfer office.

The scientist’s departmental context is measured by the level of encouragement from department to commercialize their research, and the entrepreneurial orientation of the department head. The level of encouragement from department to commercialize scientist research is measured using the survey instrument – “Please indicate on a scale from 1 to 7 to what extent you agree or disagree with the following statement…. My department encourages me to commercialize my research.” This ordinal variable is coded with the value 7 being ""strongly agree"" with the statement and the value 1 being ""strongly disagree with the statement.

The entrepreneurial orientation of the department head is measured using the survey instrument – "The head/chair of your department at the time of your first NSF funding between 2005 and 2010, to the best of your knowledge, had which of the following. – i) do not know, ii) never, iii) before funding, and iv) after funding" This variable was coded as 0 if the chair of the department never started up and 1 if otherwise.

The characteristics of the university technology transfer office are measured using the following survey instrument – "Please indicate on a scale from 1to 7 to what extent you agree or disagree with the following statement…. My Technology Transfer Office is successful at commercializing my field of research." This ordinal variable is coded with the value 7 being ""strongly agree"" with the statement and the value 1 being ""strongly disagree with the statement. Though the TTO's organizational priorities and the actual frequency and significance of the scientist's interactions with the TTO are not measured, it is argued that the scientist's perception of the success of TTO in his/her field of research serves as a strong proxy for the degree of influence the university TTO has on the scientist's decision to commercialize.

Independent Variables – Scientist Demographic Controls

The scientist entrepreneurship database includes information about scientist's demographic characteristics. We control for scientist demographics like age, gender and national origin in the probit estimation model.

5.3 Scientist Startups– All fields of Research

This section discusses the effect of, and the nature of relationship between, several key determinants of scientist entrepreneurship on the likelihood of scientist commercialization through startups across all the six fields of research – civil, mechanical, and manufacturing innovation, environmental biology, computer and network systems, physical oceanography, particle and nuclear astrophysics, and biological infrastructure – among scientists who received funding from the National Science Foundation (NSF) between 2005 and 2012-Q1.

Table 8 below presents the probit regression results for estimating the likelihood of scientist startup commercialization. In Model 1, we observe that measures for financial resources and social capital of the scientist are positively associated with the probability of scientist entrepreneurship through startups; whereas the measures for human resource and institutional factors are negatively associated with the probability of scientist entrepreneurship through startups. Furthermore, we observe that, on average, male scientists are more likely to commercialize research through startups and that scientist's age and experience/reputation are not statistically significant at the 10% level.

These results identify relationships between several important factors that are expected to affect scientist commercialization through startups and in determining the likelihood of scientist entrepreneurship. First, the amount of NSF funding and the scientist's likelihood of receiving significant amount of funding other sources towards their research are strong determinants of, and conducive to, the scientist's decision and their potential in commercializing their research through startups.

Second, scientist's social capital measured as their membership on the board of directors/scientific advisory board of other firms increases the scientist's likelihood of commercializing their research through startups.

Third, the amount of human resources available to the scientist in conducting their research is negatively related to the scientist's likelihood to commercialize research through startups. However, the effect of this measure is practically insignificant (-0.001), compared to the effect of NSF funding amount (0.01) and availability of funding from other sources (0.343). The negative relationship can be interpreted as the excess allocation (redundancy) of human resources in scientific research, across the six fields of research.

Fourth, the institutional factors, department head's entrepreneurial orientation and department's encouragement to commercialize scientific research seem to function as substitutes in the scientist's decision to commercialize research through startups. However, it is crucial to note that the head of department's entrepreneurial orientation has a larger positive effect (0.525) than the effect of department's encouragement in commercializing their research (-0.132). Overall, the effect of institutional factors on the scientist's likelihood to commercialize their research through startups is positive.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Also, in Models 2-4, we do not control for scientist age since the correlation factor between scientist age and their tenure experience is high (0.8)

Results from model 2 indicate that there is negative relationship between full-professor's tenured status and their likelihood to commercialize research through startups, after controlling for their tenure experience. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results from model 3 indicate that there is a negative relationship between scientist's nativity (if the scientist is from Asia) and their likelihood to commercialize research through startups. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results from model 4 indicate that there is a positive relationship between the success of university TTO office in commercializing the scientist's field of research and their likelihood to commercialize research through startups. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results in Tables 8 through 14 present probit regression estimates (using models 1 through 4 discussed for table 1) of scientist entrepreneurship, by their field of research.

Table 8: Probit regression results estimating likelihood of scientist startups, all fields of research

Independent variables	(1)	(2)	(3)	(4)

Grant Amount (in millions) - *Fin Res.*	0.01	0.011	0.011	0.011
	(1.85)*	(2.07)**	(2.04)**	(2.13)**
Other Funding (>750K) - *Fin Res.*	0.343	0.282	0.297	0.316
	(2.69)***	(2.27)**	(2.36)**	(2.46)**
# of Students - *Human Res.*	-0.001	-0.001	-0.001	-0.001
	(-1.95)*	(-1.88)*	(-1.89)*	(-2.03)**
Years in Tenure - *Human Capital*	-0.017	-0.011	-0.01	-0.009
	(-1.46)	(-1.45)	(-1.32)	(-1.27)
Full Professor - *Human Capital*		-0.209	-0.196	-0.201
		(-1.33)	(-1.23)	(-1.26)
Board Membership - *Social Capital*	0.702	0.66	0.636	0.662
	(5.30)***	(5.26)***	(5.06)***	(5.19)***
Dept. Encourages Commercialization	-0.167	-0.161	-0.17	-0.191
	(-4.14)***	(-4.07)***	(-4.24)***	(-4.47)***
Dept. Head Entrepreneurial Orientation	0.525	0.512	0.521	0.523
	(4.02)***	(4.04)***	(4.04)***	(3.97)***
Univ. TTO Success				0.048
				(1.15)
Male	0.445	0.469	0.458	0.466
	(2.33)**	(2.51)**	(2.43)**	(2.46)**
Age of Scientist	0.015			
	(1.2)			
Asia - *Country of Origin*			-0.122	-0.115
			(-0.59)	(-0.54)
Midwest *Region*	-0.194	-0.034	-0.037	-0.026
	(-1.03)	(-0.19)	(-0.20)	(-0.14)
South *Region*	0.048	0.054	0.05	0.057
	(0.28)	(0.32)	(0.3)	(0.33)
West *Region*	-0.064	-0.019	-0.043	-0.027
	(-0.37)	(-0.11)	(-0.25)	(-0.16)
Constant	-1.476	-0.613	-0.57	-0.753
	(-2.38)**	(-1.66)*	(-1.53)	(-1.84)*
Number of Observations	758	786	777	758
Wald Chi-sq.	76.32	76.1	74.86	78.2

Notes: Absolute z values in parenthesis

* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

5.4 Scientist Startups– Civil Mechanical and Manufacturing Innovation

This section discusses the effect, and nature of relationship between, several key determinants of scientist entrepreneurship on the likelihood of scientist commercialization through startups in the field of civil, mechanical, and manufacturing innovation (CMMI).

Table 9 below presents the probit regression results for estimating the likelihood of scientist startup commercialization in the field of Civil, Mechanical, and Manufacturing Innovation. In Model 1, we observe that measure for scientist social capital is positively associated with the likelihood of scientist entrepreneurship; whereas the measures of scientist human capital (scientist experience) is negatively associated with the probability of scientist entrepreneurship. Furthermore, we observe that, on average, scientist gender (male), age, and locational and institutional factors are significant determinants of scientist entrepreneurship; and are not statistically significant at the 10% level.

These results identify several important differences in the effect of scientist entrepreneurship determinants between CMMI scientists and scientists from other fields of research. First, it is observed that the amount of NSF funding and the scientist's likelihood of receiving significant amount of funding other sources towards their research have a positive effect on the scientist's likelihood of commercializing their research through startups. However, the effect of financial resources is not statistically significant at the 10% level indicating that the CMMI scientist's decision to commercialize their research is not determined by the availability and access to financial resources.

Second, scientist's human capital (tenure experience) decreases the scientist's likelihood of commercializing their research through startups. Though, the same effect was observed for the population of scientists across the six fields of research, this effect was not statistically significant in table 1. This means that younger, less experienced, CMMI scientists are more likely to commercialize their scientific research through startups.

Third, the CMMI scientist's institutional factors and gender are not strong determinants of their likelihood to commercialize research through startups. Though the direction of effect from these factors is consistent with that of the aggregate scientist population, it is observed that the scientist's institutional factors and gender are not statistically significant.

Fourth, consistent with the findings for general population, CMMI scientist's social capital is found to be a strong determinant of their likelihood to commercialize research through startups.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Also, in Models 2-4, we do not control for scientist age since the correlation factor between scientist age and their tenure experience is high (0.79)

Results from model 2 indicate that there is a negative relationship between full-professor's tenured status and their likelihood to commercialize research through startups, after controlling for their tenure experience. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results from model 3 indicate that there is a negative relationship between the scientist's nativity (if the scientist is from Asia) and their likelihood to commercialize research through startups. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results from model 4 indicate that there is a negative relationship between the success of university TTO office in commercializing the scientist's field of research and their likelihood to commercialize research through startups. This relationship is not statistically significant effect at the 10% level. However, we observe a negative effect of CMMI scientist's nativity and their likelihood to commercialize research through startups.

In summary, these results indicate that younger, CMMI scientists, with less tenure experience and high social capital, are more likely to commercialize their research through startups. This likelihood is significantly enhanced among CMMI scientists who obtained their undergraduate education from Non-Asian countries, predominantly the United States.

Table 9: Probit regression results estimating likelihood of scientist startups, Civil, Mech, Manu, Innovation

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	0.196	0.111	0.116	0.116
	(0.75)	(0.72)	(0.67)	(0.63)
Other Funding (>750K) - *Fin Res.*	0.064	0.038	-0.022	-0.018
	(0.2)	(0.14)	(-0.08)	(-0.06)
# of Students - *Human Res.*	0	0	-0.001	-0.001
	(-0.33)	(-0.42)	(-0.76)	(-0.89)
Years in Tenure - *Human Capital*	-0.051	-0.035	-0.04	-0.042
	(-1.88)*	(-2.07)**	(-2.31)**	(-2.37)**
Full Professor - *Human Capital*		-0.051	-0.088	-0.125
		(-0.16)	(-0.28)	(-0.38)
Board Membership - *Social Capital*	1.238	1.082	1.057	1.053
	(4.17)***	(4.08)***	(3.92)***	(3.92)***
Dept. Encourages Commercialization	-0.12	-0.116	-0.104	-0.059
	(-1.30)	(-1.44)	(-1.31)	(-0.65)
Dept. Head Entrepreneurial Orientation	0.415	0.45	0.431	0.427
	(1.50)	(1.71)*	(1.60)	(1.57)
Univ. TTO Success				-0.094
				(-0.88)
Male	0.493	0.549	0.52	0.468
	(1.32)	(1.6)	(1.49)	(1.32)
Age of Scientist	0.029			
	(0.97)			
Asia - *Country of Origin*			-0.587	-0.633
			(-1.56)	(-1.75)*
Midwest *Region*	0.693	0.815	0.941	0.93
	(1.47)	(1.83)*	(2.13)**	(2.09)**
South *Region*	0.763	0.72	0.812	0.782
	(1.55)	(1.57)	(1.78)*	(1.70)*
West *Region*	-0.332	-0.026	0.014	0.008
	(-0.59)	(-0.05)	(0.03)	(0.01)
Constant	-2.577	-1.151	-1.005	-0.612
	(-1.72)*	(-1.43)	(-1.26)	(-0.65)
Number of Observations	147	158	156	155
Wald Chi-sq.	33.15	35.73	37.57	37.69

Notes: Absolute z values in parenthesis
* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

5.5 Scientist Startups– Environmental Biology

This section discusses the effect, and nature of relationship between, several key determinants of scientist entrepreneurship on the likelihood of scientist commercialization through startups in the field of environmental biology (DEB).

Table 10 below presents the probit regression results for estimating the likelihood of scientist startup commercialization in the field of Environmental Biology. In Model 1, we observe that none of the important determinants of scientist entrepreneurship are statistically significant (at the 10% level). However, the nature of relationships between these factors and the likelihood of DEB scientist commercialization through startups are generally consistent with those observed for the aggregate scientist population.

These results identify some key differences between DEB scientists and scientists from other fields of research. First, it is observed that the amount of NSF funding and the scientist's likelihood of receiving significant amount of funding from other sources are not strong determinants of the scientist's likelihood of commercializing their research through startups. Furthermore, it is observed that the amount of NSF funding has as negative effect on DEB scientists' likelihood to commercialize research through startups.

Second, scientist's social capital has a negative relationship with the scientist's likelihood of commercializing their research through startups. This finding is very different from the statistically significant positive relationship observed among the aggregate scientist population.

Third, both institutional factors were found to hold an inverse relationship to the DEB scientist's likelihood of commercializing research through startups. This means that departments that encourage DEB scientists to commercialize their research, with department heads who are entrepreneurs, are less conducive to scientist entrepreneurship among DEB scientists. However, these relationships are not statistically significant at the 10% level.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Also, in Models 2-4, we do not control for scientist age since the correlation factor between scientist age and their tenure experience is high (0.81)

Results from model 2 indicate that there is positive relationship between full-professor's tenured status and their likelihood to commercialize research through startups, after controlling for their tenure experience. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results from models 3 and 4 indicate that there is a statistically significant positive relationship between the availability of significant amount of funding from other sources and the scientist's likelihood of commercializing their research through startups. This implies that

DEB scientists whose research is supported by funding from other sources are more likely to commercialize their research through startups.

Results from model 4 indicate that there is a positive relationship between the success of TTO in commercializing scientist research and their likelihood to commercialize research through startups. However, this relationship is not statistically significant effect at the 10% level.

In summary, these results indicate that DEB scientists whose research is supported by funding from other sources are more likely to commercialize their research through startups, than DEB scientists that do not receive external funding.

Table 10: Probit regression results estimating likelihood of scientist startups, Environmental Biology

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	-0.26	-0.508	-0.549	-0.538
	(-0.81)	(-1.32)	(-1.30)	(-1.32)
Other Funding (>750K) - *Fin Res.*	0.419	0.539	0.611	0.613
	(1.14)	(1.51)	(1.70)*	(1.69)*
# of Students - *Human Res.*	0	0	-0.001	-0.001
	(-0.62)	(-0.86)	(-1.04)	(-1.04)
Years in Tenure - *Human Capital*	-0.016	0.016	0.02	0.02
	(-0.53)	(0.83)	(1.05)	(1.05)
Full Professor - *Human Capital*		0.539	0.554	0.526
		(0.93)	(0.97)	(0.91)
Board Membership - *Social Capital*	-0.076	0.115	0.18	0.178
	(-0.19)	(0.33)	(0.52)	(0.52)
Dept. Encourages Commercialization	0.014	0.03	0.038	0.02
	(0.13)	(0.3)	(0.38)	(0.18)
Dept. Head Entrepreneurial Orientation	-0.511	-0.446	-0.425	-0.411
	(-1.1)	(-0.89)	(-0.85)	(-0.81)
Univ. TTO Success				0.04
				(0.26)
Male	.	.	.	.
	.	.	.	.
Age of Scientist	0.039			
	(1.05)			
Asia - *Country of Origin*			.	.
			.	.
Midwest *Region*	.	.	.	.
	.	.	.	.
South *Region*	-0.173	0.136	0.148	0.134
	(-0.34)	(0.3)	(0.32)	(0.29)
West *Region*	0.715	0.674	0.748	0.744
	(1.62)	(1.53)	(1.64)	(1.59)
Constant	-4.12	-2.98	-3.141	-3.236
	(-2.46)**	(-3.29)***	(-3.44)***	(-2.91)***
Number of Observations	115	116	113	110
Wald Chi-sq.	12.58	16.7	18.79	18.31

Notes: Absolute z values in parenthesis

* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

5.6 Scientist Startups– Computer and Network Systems

This section discusses the effect, and nature of relationship between, several key determinants of scientist entrepreneurship on the likelihood of scientist commercialization through startups in the field of computer and network systems (CNS).

Table 11 below presents the probit regression results for estimating the likelihood of scientist startup commercialization in the field of Computer and Network Systems. In Model 1, we observe that measure for social capital of the scientist and the institutional factors are positively associated with the probability of scientist entrepreneurship through startups.

These results identify a few key differences in the effect of scientist entrepreneurship determinants between CNS scientists and scientists in other fields of research. First, it is observed that the financial resources have a positive effect. However, these results do not have a statistically significant effect on the CNS scientists' likelihood of commercializing their research through startups.

Second, the scientist's institutional factors are strong determinants of CNS scientist entrepreneurship. The nature and magnitude of the relationship between institutional factors and the CNS scientists' likelihood to commercialize their research was found to be consistent with that of the aggregate scientist population.

Third, consistent with the findings for general population, the CNS scientist's social capital is found to be a strong determinant of their likelihood to commercialize research through startups.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Also, in Models 2-4, we do not control for scientist age since the correlation factor between scientist age and their tenure experience is high (0.66)

Results from model 2 indicate that there is negative relationship between full-professor's tenured status and their likelihood to commercialize research through startups, after controlling for their tenure experience. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results from model 3 indicate that there is a negative relationship between the scientist's nativity (if the scientist is from Asia) and their likelihood to commercialize research through startups. However, this relationship is not statistically significant effect at the 10% level.

Results from model 4 indicate that there is a positive relationship between the success of TTO in commercializing scientist research and their likelihood to commercialize research through startups. However, this relationship is not statistically significant effect at the 10% level.

In models 2 through 4, we observe that, on average, male CNS scientists are more likely to commercialize research than female CNS scientists.

In summary, these results indicate that CNS scientists with high social capital, and more conducive departmental conditions, are more likely to commercialize their research through startups. This likelihood is found to be significantly higher among male scientists CNS scientists than female CNS scientists.

Table 11: Probit regression results estimating likelihood of scientist startups, Computer Network Systems

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	0.133	0.155	0.201	0.261
	(1.08)	(1.05)	(1.29)	(1.50)
Other Funding (>750K) - *Fin Res.*	-0.049	-0.257	-0.189	-0.128
	(-0.18)	(-0.95)	(-0.69)	(-0.44)
# of Students - *Human Res.*	-0.001	-0.001	-0.001	-0.001
	(-1.34)	(-0.98)	(-1.15)	(-1.26)
Years in Tenure - *Human Capital*	0.001	0.017	0.018	0.013
	(0.06)	(1.05)	(1.12)	(0.85)
Full Professor - *Human Capital*		-0.181	-0.197	-0.205
		(-0.41)	(-0.44)	(-0.45)
Board Membership - *Social Capital*	0.894	1.017	0.927	0.972
	(3.23)***	(3.71)***	(3.27)***	(3.34)***
Dept. Encourages Commercialization	-0.222	-0.238	-0.295	-0.311
	(-2.38)**	(-2.54)**	(-2.98)***	(-2.94)***
Dept. Head Entrepreneurial Orientation	0.531	0.481	0.575	0.534
	(1.99)**	(1.85)*	(2.15)**	(1.96)*
Univ. TTO Success				0.039
				(0.45)
Male	0.781	0.808	0.828	0.81
	(1.61)	(1.81)*	(1.83)*	(1.75)*
Age of Scientist	0.032			
	(1.4)			
Asia - *Country of Origin*			-0.397	-0.405
			(-1.19)	(-1.18)
Midwest *Region*	-0.216	-0.168	-0.222	-0.212
	(-0.54)	(-0.40)	(-0.49)	(-0.46)
South *Region*	-0.308	-0.255	-0.286	-0.214
	(-0.84)	(-0.70)	(-0.76)	(-0.56)
West *Region*	-0.207	-0.086	-0.188	-0.074
	(-0.68)	(-0.29)	(-0.62)	(-0.24)
Constant	-2.337	-0.734	-0.433	-0.622
	(-1.87)*	(-0.73)	(-0.44)	(-0.61)
Number of Observations	135	143	140	135
Wald Chi-sq.	28.68	36.58	36.16	38.53

Notes: Absolute z values in parenthesis

* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

5.7 Scientist Startups– Physical Oceanography

This section discusses the effect, and nature of relationship between, several key determinants of scientist entrepreneurship on the likelihood of scientist commercialization through startups in the field of physical oceanography (OCE).

Table12 below presents the probit regression results for estimating the likelihood of scientist startup commercialization in the field of Physical Oceanography. In Model 1, we observe that scientist social capital and institutional factors are negatively related to determinants of scientist entrepreneurship, which is contrary to the strong positive relationship observed in the aggregate scientist population across the six fields of research.

These results identify a few key differences in the effect of scientist entrepreneurship determinants between OCE scientists and scientists in other fields of research. First, it is observed that scientist social capital is negatively associated to OCE scientist entrepreneurship. However, this relationship is not statistically significant at the 10% level. These results indicate that social capital does not play a significant role in determining the OCE scientist's likelihood in commercializing research through startups.

Second, departmental institutional factors have a statistically significant negative association with OCE scientist entrepreneurship. These results indicate that departments that encourage OCE scientists to commercialize their research are significantly less conducive to OCE scientist entrepreneurship.

Third, locational factors (negative coefficient for west region) have a statistically significant association with OCE scientist entrepreneurship. This means that OCE scientists in the North East region, predominantly Massachusetts and New York are more likely to commercialize their research than OCE scientists in California (West region). This relationship can be explained by more efficient knowledge spillovers between academia and industry in the North-East region compared to the West region.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Also, in Models 2-4, we do not control for scientist age since the correlation factor between scientist age and their tenure experience is high (0.82)

Results from model 2 indicate that there is positive relationship between full-professor's tenured status and their likelihood to commercialize research through startups, after controlling for their tenure experience. However, this relationship is not statistically significant effect at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

Results from model 3 and 4 indicate several important relationships for OCE scientist entrepreneurship. First, there is a statistically significant positive relationship between the success of TTO in commercializing scientist research and their likelihood to commercialize research through startups. Furthermore, the magnitude of effect from university TTO office offsets the negative effect from non-conducive departmental contexts. This means that overall, institutional factors have a strong positive relationship, and are hence more conducive, to OCE scientist entrepreneurship.

Second, there is a statistically significant positive relationship between financial resources and OCE scientist's likelihood of commercializing research through startups.

Third, OCE scientist human capital (scientist experience) is a strong determinant of the scientist's commercialization decision.

In summary, these results indicate that experienced OCE scientists with funding from external sources, in a university setting with an effective TTO, are more likely to commercialize their research through startups. This likelihood is found to be significantly higher among OCE scientists in the North-East region compared to scientists in the West region.

Table 12: Probit regression results estimating likelihood of scientist startups, Physical Oceanography

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	0.009	0.009	0.009	0.009
	(1.18)	(1.32)	(1.32)	(1.63)
Other Funding (>750K) - *Fin Res.*	0.466	0.495	0.479	0.85
	(1.21)	(1.21)	(1.16)	(2.03)**
# of Students - *Human Res.*	-0.001	-0.001	-0.001	-0.002
	(-0.69)	(-0.62)	(-0.61)	(-1.10)
Years in Tenure - *Human Capital*	0.02	0.028	0.028	0.041
	(0.56)	(1.42)	(1.39)	(1.76)*
Full Professor - *Human Capital*		0.325	0.321	0.222
		(0.5)	(0.49)	(0.34)
Board Membership - *Social Capital*	-0.374	-0.364	-0.36	-0.591
	(-0.83)	(-0.82)	(-0.81)	(-1.21)
Dept. Encourages Commercialization	-0.416	-0.424	-0.416	-0.492
	(-2.16)**	(-2.21)**	(-2.13)**	(-2.54)**
Dept. Head Entrepreneurial Orientation	-0.095	0	-0.012	-0.251
	(-0.2)	0	(-0.03)	(-0.43)
Univ. TTO Success				0.556
				(2.99)***
Male	.	.	.	.
	.	.	.	.
Age of Scientist	0.008			
	(0.16)			
Asia - *Country of Origin*			.	.
			.	.
Midwest *Region*	.	.	.	.
	.	.	.	.
South *Region*	-0.445	-0.445	-0.44	-0.792
	(-0.78)	(-0.77)	(-0.78)	(-1.21)
West *Region*	-0.888	-0.87	-0.87	-1.175
	(-1.99)**	(-2.00)**	(-2.02)**	(-2.31)**
Constant	-0.205	-0.127	-0.13	-3.03
	(-0.08)	(-0.09)	(-0.09)	(-2.09)**
Number of Observations	90	90	87	87
Wald Chi-sq.	16.55	16.26	15.81	30.66

Notes: Absolute z values in parenthesis
* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

5.8 Scientist Startups– Particle and Nuclear Astrophysics

This section discusses the effect, and nature of relationship between, several key determinants of scientist entrepreneurship on the likelihood of scientist commercialization through startups in the field of particle and nuclear astrophysics (PHY).

Table 13 below presents the probit regression results for estimating the likelihood of scientist startup commercialization in the field of particle and nuclear astrophysics. In Model 1, we observe that NSF funding amount, scientist human capital (scientist experience) and departmental institutional contexts are negatively associated with the likelihood of PHY scientist entrepreneurship. Furthermore, scientist gender (male) and locational context (Mid-West region has a statistically significant positive difference to the North-East region).

These results identify a few key differences in the effect of scientist entrepreneurship determinants between PHY scientists and scientists in other fields of research. First, the NSF grant funding is negatively associated with (-2.9), whereas funding from other sources is positively associated with (4.4) the likelihood of PHY scientist entrepreneurship. This relationship can be explained by the heterogeneity in scientist research aimed at theoretical and application based advancements. Overall, the effect of financial resources is positively associated with PHY scientist entrepreneurship.

Second, scientist human capital is negatively related to the likelihood of PHY scientist entrepreneurship. This indicates that there is a generational effect in PHY scientists, which young scientists more likely to commercialize their research through startups than more experienced scientists.

Third, we observe that male PHY scientists are more likely to commercialize their research than female PHY scientists.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Also, in Models 2-4, we do not control for scientist age since the correlation factor between scientist age and their tenure experience is high (0.85)

Results from model 2 indicate that there is statistically significant negative relationship between full-professor's tenured status and their likelihood to commercialize research through startups, after controlling for their tenure experience. This provides further evidence to the conjecture that there is a generational effect in PHY scientists' likelihood to commercialize research through startups.

It is also interesting to note that the overall effect of financial resources in model 2 is negative, and hence is an impediment, to PHY scientist entrepreneurship. Furthermore, scientist social capital is found to be statistically significant at the 1% level, indicating that PHY scientists with greater linkages and interactions with the industry are more likely to commercialize their research through startups than PHY scientists without those linkages.

Models 3 and 4 indicate that there is a negative relationship between the success of TTO in commercializing scientist research and PHY scientist entrepreneurship. However, these results are not statistically significant at the 10% level.

In Summary, we observe that younger PHY scientists, with high social capital are more likely to commercialize their research through startups. Furthermore, the likelihood of PHY scientist entrepreneurship is greater among male scientists from the Midwest region.

Table 13: Probit regression results estimating likelihood of scientist startups, Particle and Nuclear Physics

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	-2.906	-1.144	-1.29	-1.276
	(-2.33)**	(-2.53)**	(-2.76)***	(-2.84)***
Other Funding (>750K) - *Fin Res.*	4.433	0.826	0.773	0.676
	(2.97)***	(1.49)	(1.34)	(1.3)
# of Students - *Human Res.*	0.005	0.006	0.005	0.006
	(0.97)	(1.05)	(0.99)	(1.08)
Years in Tenure - *Human Capital*	-0.354	-0.099	-0.117	-0.126
	(-1.84)*	(-2.46)**	(-2.31)**	(-2.30)**
Full Professor - *Human Capital*		-2.18	-2.265	-2.024
		(-3.03)***	(-3.34)***	(-3.22)***
Board Membership - *Social Capital*	.	3.366	3.869	3.683
	.	(3.40)***	(3.14)***	(3.10)***
Dept. Encourages Commercialization	-1.644	-0.165	-0.151	-0.053
	(-2.55)**	(-1.15)	(-0.97)	(-0.36)
Dept. Head Entrepreneurial Orientation	-0.612	0.078	0.564	0.752
	(-0.59)	(0.11)	(0.79)	(1.14)
Univ. TTO Success				-0.209
				(-1.13)
Male	5.372	1.192	1.68	1.525
	(2.17)**	(1.84)*	(2.36)**	(1.65)*
Age of Scientist	-0.103			
	(-1.06)			
Asia - *Country of Origin*			.	.
			.	.
Midwest *Region*	3.868	1.785	2.209	2.533
	(2.04)**	(2.24)**	(2.43)**	(2.62)***
South *Region*	0.985	-0.199	0.177	0.31
	(0.96)	(-0.32)	(0.25)	(0.48)
West *Region*	-1.726	-0.863	-0.893	-0.67
	(-1.32)	(-0.77)	(-0.77)	(-0.62)
Constant	10.166	-1.316	-1.528	-0.679
	(1.87)*	(-1.38)	(-1.57)	(-0.55)
Number of Observations	35	103	98	95
Wald Chi-sq.	14.63	19.13	22.5	24.5

Notes: Absolute z values in parenthesis

* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

5.9 Scientist Startup Commercialization – Biological Infrastructure

This section discusses the effect, and nature of relationship between, several key determinants of scientist entrepreneurship on the likelihood of scientist commercialization through startups in the field of biological infrastructure (DBI).

Table 14 below presents the probit regression results for estimating the likelihood of scientist startup commercialization in the field of biological infrastructure. In Model 1, we observe that financial resources from external sources and social are positively associated with the likelihood of DBI scientist entrepreneurship. Furthermore, availability of human resources has a statistically significant negative association with DBI scientist entrepreneurship; however the magnitude (-0.003) of this effect is practically insignificant.

These results identify a few key differences in the effect of scientist entrepreneurship determinants between DBI scientists and scientists in other fields of research. First, funding from other sources is positively associated with (0.8) the likelihood of DBI scientist entrepreneurship.

Second, we observe that availability of human resources is negatively associated with DBI scientist entrepreneurship. Third, we observe that scientist social capital is a strong determinant of DBI scientist entrepreneurship. Fourth, scientist human capital and gender are found to be insignificant determinants of PHY scientist entrepreneurship.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Also, in Models 2-4, we do not control for scientist age since the correlation factor between scientist age and their tenure experience is high (0.85)

Results from model 2 indicate that there is negative relationship between full-professor's tenured status and their likelihood to commercialize research through startups, after controlling for their tenure experience. However, this relationship is not significant at the 10% level.

It is also interesting to note that the overall effect of financial resources in model 2 is positive, and hence is conducive, to DBI scientist entrepreneurship.

Results from model 3 indicate that there is negative relationship between DBI scientist's continent of origin and their likelihood to commercialize research through startups. However, this relationship is not significant at the 10% level.

Results from model 4 indicate that there is a positive relationship between the success of TTO in commercializing scientist research and DBI scientist entrepreneurship. However, these results are not statistically significant at the 10% level. The effects of other scientist entrepreneurship determinants are unchanged.

In Summary, we observe that DBI scientists, with high social capital are greater access to financial resources more likely to commercialize their research through startups.

Table 14: Probit regression results estimating likelihood of scientist startups, Biological Infrastructure

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	0.082	0.144	0.149	0.147
	(1.04)	(1.74)*	(1.83)*	(1.71)*
Other Funding (>750K) - *Fin Res.*	0.828	0.855	0.886	0.88
	(1.90)*	(2.20)**	(2.13)**	(2.07)**
# of Students - *Human Res.*	-0.003	-0.003	-0.004	-0.004
	(-2.22)**	(-2.20)**	(-2.26)**	(-2.12)**
Years in Tenure - *Human Capital*	0.004	-0.012	-0.013	-0.008
	(0.12)	(-0.66)	(-0.70)	(-0.44)
Full Professor - *Human Capital*		0.21	0.234	0.319
		(0.45)	(0.5)	(0.76)
Board Membership - *Social Capital*	1.079	0.917	0.934	1.022
	(3.05)***	(2.82)***	(2.89)***	(3.06)***
Dept. Encourages Commercialization	-0.132	-0.075	-0.069	-0.14
	(-1.18)	(-0.72)	(-0.63)	(-1.21)
Dept. Head Entrepreneurial Orientation	0.407	0.573	0.58	0.597
	(0.92)	(1.33)	(1.33)	(1.36)
Univ. TTO Success				0.157
				(1.21)
Male	-0.004	-0.141	-0.132	-0.074
	(-0.01)	(-0.32)	(-0.30)	(-0.17)
Age of Scientist	-0.011			
	(-0.29)			
Asia - *Country of Origin*			-0.288	-0.391
			(-0.38)	(-0.52)
Midwest *Region*	-0.84	-0.531	-0.546	-0.594
	(-1.24)	(-0.92)	(-0.93)	(-1.04)
South *Region*	0.069	-0.083	-0.076	-0.164
	(0.13)	(-0.18)	(-0.16)	(-0.36)
West *Region*	0.501	0.19	0.203	0.125
	(1.19)	(0.48)	(0.5)	(0.3)
Constant	-0.651	-1.046	-1.097	-1.809
	(-0.32)	(-1.16)	(-1.19)	(-1.63)
Number of Observations	102	107	106	103
Wald Chi-sq.	25.27	24.95	25.9	25.2

Notes: Absolute z values in parenthesis
* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

5.10 Summary of Scientist Entrepreneurship Determinants by fields of research

This section summarizes the relationships between key determinants of scientist entrepreneurship discussed in sections 5.3 through 5.9 by the field of research.

Table 15 below provides a comprehensive summary of all statistically significant effects among key determinants of scientist entrepreneurship by the direction and nature of their propensities to include scientist commercialization through startups. These results are a synthesis of model 4 in tables 8 through 14. A positive relationship indicates that the factor is conducive to scientist entrepreneurship and a negative relationship indicates that the factor is an impediment to scientist entrepreneurship.

Table 15 highlights several important findings of this research. First, the availability and access to financial resources are found to have a positive effect on scientist entrepreneurship across all fields of research, except in the field of particle and nuclear astrophysics where there is heterogeneity in nature of theoretical and applied research. Also, financial resources do not have a significant effect in civil, mechanical, and manufacturing innovation.

Second, availability of human resources is generally found to have a negative effect on scientist entrepreneurship across all fields of research – however, this relationship is particularly significant in the fields of civil, mechanical, and manufacturing innovation and Biological Infrastructure. The magnitude of the effect of human resources was found to be practically insignificant, ranging from -0.001 to -0.003.

Third, scientist human capital is found to have a positive effect on scientist entrepreneurship in the field of physical oceanography and a negative effect on scientist entrepreneurship in the field of particle and nuclear astrophysics. However, we did not observe a strong relationship between human capital and likelihood of scientist entrepreneurship across other fields of research.

Fourth, scientist social capital is found to have a positive effect on scientist entrepreneurship across all fields of research, except environmental biology. This explains the significance of linkages and interactions in enhancing scientist entrepreneurship.

Fifth, institutional factors are found to have overall positive effect on scientist entrepreneurship, especially in the fields of computer and network systems and physical oceanography. However, it is important to note that the departmental institutional factors are found to be driving the nature of this relationship; especially the department head's entrepreneurial orientation. Furthermore, the effect of university TTO was found to be positive only in the field of physical oceanography.

Sixth, on average, male scientists were found to be more entrepreneurial than female scientists. However, this relationship did not hold universally. In fact, the relationship was only statistically significant in the field of particle and nuclear astrophysics. This finding is contrary to findings in entrepreneurship literature for the entire population.

Finally, locational factors were found to have a significant effect in the fields of civil, mechanical, and manufacturing innovation and physical oceanography. Further research needs to be conducted to elaborate on the exact mechanisms of knowledge spillovers in these fields of research to draw general inferences.

Table 15: Summary of Key Determinants of Scientist Entrepreneurship by Field of Research

	All Fields	CMMI	DEB	CNS	OCE	PHY	DBI
Financial Resources	**+**		**+**		**+**	**-**	**+**
Grant Amount	+					-	+
Other Funding (>750K)	+		+		+		+
Human Resources	**-**	**-**					**-**
# of Students	-	-					-
Human Capital					**+**	**-**	
Years in Tenure					+	-	
Full Professor						-	
Social Capital	**+**	**+**		**+**		**+**	**+**
Board Membership	+	+		+		+	+
Institutional Factors	**+**			**+**	**+**		
Dept. Encourages Commercialization	-			-	-		
Dept. Head Entrepreneurial Orientation	+			+			
Univ. TTO Success					+		
Scientist Demographics							
Male	**+**					**+**	
Asia - *Country of Origin*		-					
Midwest *Region*		+				+	
South Region		+					
West Region					-		

Notes: CMMI is Civil, Mechanical, and Manufacturing Innovation; DEB is Environmental Biology; CNS is Computer and Network Systems; OCE is Physical Oceanography; PHY is Particle and Nuclear Astrophysics; and DBI is Biological Infrastructure

6. Incremental and Radical Innovation by Scientist Entrepreneurs

6.1 Introduction

This section discusses the effect of key determinants of scientist entrepreneurship on the likelihood of scientist startups by the nature of innovative activity (startups with patents, innovative products, and consulting services across the six fields of research). This section also includes a discussion of firm success comparing startups with patents, innovative products, and consulting services.

The central argument is that, by comparing scientist startups that use either patents or innovative products or both with scientist startups that don't use both patents and innovative products, we will be able to elaborate on the nature of mechanisms and success of scientist entrepreneurs in commercializing radical and incremental innovations. We abstract those scientist startups with patents as a scientist commercialization of radical innovations and those with innovative products as incremental innovation. There are exceptions to this construct of radical innovation, especially since we do not record the nature and extent of radicalness (popularly measured as the number of patent citations) of patents used in scientist startups. However, we argue that these estimates, particularly those of startups with both patent and innovative products, provide preliminary estimates for, and insights into, the nature of mechanisms through which radical and incremental innovations are realized through the scientist startup route.

The purpose of this section is to a) identify factors that are conducive, and those that are an impediment, to scientist startups by the nature of innovative activity – i.e.; use of patents, innovative products, and consulting services, and b) identify the factors which increase the likelihood of firm success with the nature of innovative activity.

In section 5 we were primarily interested in the question on why do some scientists commercialize their research through startups and why others don't. Hence, we explored the nature and significance of the effect of key determinants of scientist entrepreneurship on the likelihood of scientist's research commercialization through startups.

In this section, we are interested in the effect of those key determinants of scientist entrepreneurship on the likelihood that scientist startups use either one or more of the following – patents, innovative products, and consulting services. Essentially, we are exploring the nature and significance of the variation in key determinants of scientist entrepreneurship based on innovative activity of scientist entrepreneur. We argue that scientist startups providing consulting services are neither operationalizing incremental or radical innovation.

Also, as discussed in Figure 5 section 3.3.1, the scientist firm's success is significantly enhanced when the mode of startup commercialization is through the use of innovative products and patents. In order to explore the possible mechanisms through which the significant positive relationship between firm success and use of innovative products in scientist startups is obtained, we compare the success of scientist firms that use patents and innovative products with firms that do not operationalize either innovation.

6.2 Scientist Startups with Patents

In this section we discuss the effect of key determinants of scientist entrepreneurship on the likelihood of scientist startups with patents across the six fields of research. We examine the nature of relationship between several key determinants of scientist entrepreneurship on the likelihood of scientist startups using patents. To this end, we compare scientist startups with a patent and scientist startups without the use of a patent using the probit estimation model discussed in section 5.

Table 16 below presents the probit regression results for estimating the likelihood of scientist startups with patents. In Model 1, we observe that scientist social capital and institutional factors are positively related to the probability of scientist startups using patents; whereas the measures for human resource is negatively associated with the probability of scientist startups using patents. However, we observe that the statistically significant effect of departmental institutional measures is negative on the measure which records the level of encouragement (towards commercialization) from the department.

It is interesting to note that the measure of social capital and departmental institutional variables enhance the likelihood of scientist startups with patents. This implies that scientist's linkages and interactions with the industry and conducive institutional contexts significantly enhance the likelihood of scientist startups using patents.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. In these models we observe that the effects of social capital are unchanged. However, we notice that the departmental institutional measure which records the level of encouragement (towards commercialization) from the department is no longer significantly negative. Furthermore, the availability of human resources reduces the likelihood of scientist startups using patents; however these results are practically insignificant (-0.003). Hence, we conclude that scientist social capital is the most influential determinant of the use of patents in scientist startups.

Table 16: Probit regression results estimating likelihood of scientist startups using patents

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	0.068	0.091	0.089	0.088
	(1.03)	(1.41)	(1.37)	(1.35)
Other Funding (>750K) - *Fin Res.*	0.448	0.309	0.292	0.288
	(1.43)	(1.06)	(0.98)	(0.96)
# of Students - *Human Res.*	-0.003	-0.003	-0.003	-0.003
	(-1.72)*	(-1.93)*	(-1.90)*	(-1.81)*
Years in Tenure - *Human Capital*	-0.015	-0.015	-0.016	-0.016
	(-0.54)	(-0.77)	(-0.80)	(-0.79)
Full Professor - *Human Capital*		0.334	0.29	0.293
		(0.95)	(0.82)	(0.82)
Board Membership - *Social Capital*	0.736	0.949	0.961	0.954
	(2.20)**	(2.79)***	(2.80)***	(2.78)***
Dept. Encourages Commercialization	-0.136	-0.155	-0.139	-0.138
	(-1.84)*	(-2.10)**	(-1.83)*	(-1.63)
Dept. Head Entrepreneurial Orientation	0.18	0.175	0.18	0.181
	(0.64)	(0.64)	(0.65)	(0.65)
Univ. TTO Success				-0.003
				(-0.03)
Male	-0.478	-0.535	-0.501	-0.5
	(-0.92)	(-1.14)	(-1.06)	(-1.06)
Age of Scientist	-0.003			
	(-0.11)			
Asia - *Country of Origin*			0.133	0.133
			(0.33)	(0.33)
Midwest *Region*	-0.349	-0.554	-0.553	-0.557
	(-0.78)	(-1.28)	(-1.28)	(-1.29)
South *Region*	-0.089	-0.094	-0.068	-0.071
	(-0.23)	(-0.24)	(-0.18)	(-0.19)
West *Region*	-0.361	-0.4	-0.365	-0.368
	(-0.95)	(-1.13)	(-1.03)	(-1.03)
Constant	0.641	0.275	0.23	0.24
	(0.45)	(0.34)	(0.28)	(0.28)
Number of Observations	102	109	107	106
Wald Chi-sq.	24.67	29.03	28.46	27.28

Notes: Absolute z values in parenthesis

* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

6.3 Scientist Startups with Innovative Products

In this section we discuss the effect of key determinants of scientist entrepreneurship on the likelihood of scientist startups with innovative products across the six fields of research. We examine the nature of relationship between several key determinants of scientist entrepreneurship on the likelihood of scientist startups using innovative products. To this end, we compare scientist startups with an innovative product and scientist startups without an innovative product using the probit estimation model discussed in section 5.

Table 17 below presents the probit regression results for estimating the likelihood of scientist startups with innovative products. Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively.

In Model 2, we observe that scientist social capital and human capital are positively related to the probability of scientist startups using innovative products; whereas the measures for institutional factors is negatively associated with the probability of scientist startups using innovative products. Furthermore, we observe that the grant amount has a statistically significant negative effect on the likelihood of scientist startups with innovative products. This implies that scientists who commercialize their research through startups using an innovative product have significantly higher amounts of social and human capital, even in comparison to other scientist's that started up.

Models 3 and 4 demonstrate two key differences between scientist startups with innovative products and those without innovative products. First, the locational factors play an important role in determining the likelihood of scientist startups with an innovative product. Scientist startups in Northeast region are more likely to have innovative products than scientist startups in West region. Second, the university and departmental institutional factors have a statistically significant negative relationship with the likelihood of scientist startups with innovative products. Hence, we conclude that scientist social capital, human capital, and institutional factors are highly influential in determining the likelihood of scientist startups with innovative products.

Table 17: Probit regression results estimating likelihood of scientist startups with Innovative Products

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	-0.009	-0.009	-0.009	-0.009
	(-1.64)	(-1.99)**	(-1.94)*	(-1.94)*
Other Funding (>750K) - *Fin Res.*	0.325	0.359	0.324	0.298
	(1.06)	(1.18)	(1.05)	(0.95)
# of Students - *Human Res.*	-0.001	-0.001	-0.001	-0.001
	(-1.01)	(-1.21)	(-1.11)	(-0.72)
Years in Tenure - *Human Capital*	0.02	-0.022	-0.02	-0.017
	(0.71)	(-1.13)	(-1.03)	(-0.89)
Full Professor - *Human Capital*		0.985	0.982	1.031
		(2.69)***	(2.65)***	(2.79)***
Board Membership - *Social Capital*	0.263	0.775	0.811	0.867
	(0.81)	(2.50)**	(2.57)**	(2.72)***
Dept. Encourages Commercialization	-0.111	-0.13	-0.113	-0.045
	(-1.50)	(-1.74)*	(-1.47)	(-0.50)
Dept. Head Entrepreneurial Orientation	-0.166	-0.301	-0.346	-0.376
	(-0.59)	(-1.08)	(-1.21)	(-1.31)
Univ. TTO Success				-0.165
				(-1.84)*
Male	0.666	0.661	0.676	0.628
	(1.37)	(1.5)	(1.55)	(1.29)
Age of Scientist	-0.078			
	(-2.38)**			
Asia - *Country of Origin*			0.692	0.642
			(1.45)	(1.37)
Midwest *Region*	-0.137	-0.321	-0.336	-0.487
	(-0.31)	(-0.79)	(-0.82)	(-1.17)
South *Region*	-0.347	-0.353	-0.326	-0.412
	(-0.90)	(-0.84)	(-0.77)	(-0.96)
West *Region*	-0.431	-0.88	-0.828	-0.858
	(-1.17)	(-2.30)**	(-2.13)**	(-2.17)**
Constant	3.824	-0.803	-0.994	-0.443
	(2.58)***	(-1.04)	(-1.27)	(-0.53)
Number of Observations	104	111	109	108
Wald Chi-sq.	30.24	28.68	33.54	42.91

Notes: Absolute z values in parenthesis

* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

6.4 Scientist Startups with Consulting Services

In this section we discuss the effect of key determinants of scientist entrepreneurship on the likelihood of scientist startups with Consulting Services, across the six fields of research. We examine the nature of relationship between several key determinants of scientist entrepreneurship on the likelihood of scientist startups providing Consulting Services to the industry or the government. To this end, we compare scientist startups offering Consulting Services and scientist startups without that do not offer consulting services using the probit estimation model discussed in section 5.

Table 18 below presents the probit regression results for estimating the likelihood of scientist startups offering Consulting Services to the industry or to the government. In model 1 we observe a statistically significant positive effect from departmental-institutional factors. Furthermore, we observe a statistically significant negative effect with grant amount and a statistically significant positive effect with human resources.

Models 2 through 4 compare the effect of scientist's full professorship tenure status, country of origin (if the scientist is from Asia), and the success of TTO in commercializing scientist research respectively. Models 3 and 4 demonstrate three key differences between scientist startups providing consulting services and those that do not provide consulting services. First, the locational factors play an important role in determining the likelihood of scientist startups with providing consulting services. Scientist startups in South region are more likely to have innovative products than scientist startups in Northeast region. Second, the departmental institutional factors have a statistically significant positive relationship with the likelihood of scientist startups with consulting services. Third, scientists' continent of origin is important in determining the likelihood of scientist startups providing consulting services; scientist entrepreneurs from Asia are less likely to provide consulting services than scientist entrepreneurs from North America, predominantly the United States.

Hence, we conclude that scientists' locational factors, departmental-institutional factors, and country of origin are highly influential in determining the likelihood of scientist startups with innovative products.

Table 18: Probit regression results estimating likelihood of scientist startups with Consulting Services

Independent variables	(1)	(2)	(3)	(4)
Grant Amount (in millions) - *Fin Res.*	-0.012	-0.01	-0.011	-0.01
	(-2.15)**	(-1.86)*	(-1.93)*	(-1.99)**
Other Funding (>750K) - *Fin Res.*	0.264	0.175	0.282	0.289
	(0.82)	(0.61)	(0.96)	(0.93)
# of Students - *Human Res.*	0.003	0.003	0.002	0.003
	(1.99)**	(2.09)**	(1.99)**	(1.90)*
Years in Tenure - *Human Capital*	-0.063	-0.006	-0.01	-0.01
	(-2.55)**	(-0.27)	(-0.49)	(-0.51)
Full Professor - *Human Capital*		0.51	0.41	0.406
		(1.29)	(1.02)	(1.01)
Board Membership - *Social Capital*	-0.223	-0.245	-0.271	-0.365
	(-0.71)	(-0.82)	(-0.88)	(-1.14)
Dept. Encourages Commercialization	0.198	0.232	0.228	0.162
	(2.53)**	(3.02)***	(2.87)***	(1.75)*
Dept. Head Entrepreneurial Orientation	0.106	0.249	0.4	0.499
	(0.38)	(0.93)	(1.41)	(1.76)*
Univ. TTO Success				0.149
				(1.53)
Male	0.036	-0.144	-0.066	0.014
	(0.07)	(-0.31)	(-0.14)	(0.03)
Age of Scientist	0.074			
	(2.32)**			
Asia - *Country of Origin*			-1.108	-1.106
			(-2.10)**	(-2.04)**
Midwest *Region*	0.184	0.137	0.154	0.186
	(0.39)	(0.31)	(0.35)	(0.42)
South *Region*	0.697	0.809	0.843	0.844
	(1.81)*	(1.87)*	(1.94)*	(1.92)*
West *Region*	0.225	0.323	0.281	0.192
	(0.56)	(0.85)	(0.73)	(0.49)
Constant	-4.756	-1.96	-1.897	-2.425
	(2.58)***	(-1.04)	(-1.27)	(-0.53)
Number of Observations	102	109	107	106
Wald Chi-sq.	23.97	21.08	28.91	30.69

Notes: Absolute z values in parenthesis

* Denotes significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

6.5 Summary of Key Determinants of Scientist Startups using Patents, Innovative Products, and Consulting

This section summarizes the key determinants of scientist startups by nature of innovative activity – radical innovations (patents), incremental innovations (innovative product), and consulting services (knowledge spillover).

Table 19 highlights several important findings regarding the determinants of scientist startups by nature of innovative activity. First, both scientist startups with radical innovations (patents) and incremental innovations (innovative product) have a statistically significant positive relationship with scientist social capital. This means that scientist entrepreneurs who commercialized their research through radical and incremental innovations had a greater amount of social capital, on average, than scientist entrepreneurs that did not.

Second, both scientist startups with radical innovations (patents) and incremental innovations (innovative product) have a statistically significant negative relationship with departmental-institutional contexts. This means that scientist entrepreneurs who commercialized their research through radical and incremental innovations received little or no help from their department/TTO, on average, than scientist entrepreneurs that did not. Interestingly, scientist startups that provided consulting services had more encouraging departmental-institutional contexts compared to scientist startups that did not. These results suggest that departmental/university characteristics are powerful determinants of innovation activity of scientist startups.

Third, financial resources did not have a statistically significant impact on the nature of innovative activity in scientist startups.

In summary, these results provide preliminary evidence that the nature of radical and incremental innovations realized through the scientist startup route are strongly determined by the scientist social capital and departmental/university institutional contexts, even among scientists with very high likelihood to commercialize their research.

Table 19: Summary of Key Determinants of Scientist Startups using Patents, Innovative Products, and Consulting

	Scientist Startups	With Patents	With Innovative Product	With Consulting Services
Financial Resources	**+**			
Grant Amount	+		-	-
Other Funding (>750K)	*+*			
Human Resources	**-**	**-**	**-**	**+**
# of Students	-	-	-	+
Human Capital			**+**	
Years in Tenure			+	
Full Professor				
Social Capital	**+**	**+**	**+**	
Board Membership	+	+	+	
Institutional Factors	**+**	**-**	**-**	**+**
Dept. Encourages Commercialization	-	-		+
Dept. Head Entrepreneurial Orientation	+			+
Univ. TTO Success			-	
Scientist Demographics				
Male	**+**			
Asia - *Country of Origin*				-
Midwest *Region*				
South Region				+
West Region			-	

Notes: CMMI is Civil, Mechanical, and Manufacturing Innovation; DEB is Environmental Biology; CNS is Computer and Network Systems; OCE is Physical Oceanography; PHY is Particle and Nuclear Astrophysics; and DBI is Biological Infrastructure

6.6 Scientist Firm Success with Patents and Innovative Products

This section describes the likelihood of firm success based on key determinants of scientist entrepreneurship and innovation activity of scientist startups. The main dependent variable, firm success, is defined as 1 if the firm is active and 0 if the firm is inactive as of 2012-Q2.

Models 1 through 4, in Table 20, presents the results for probit model estimates for the likelihood of scientist firm success based on the type of innovation activity. In Models 1 through 4, we observe a statistically significant positive effect from other sources of funding and a statistically significant negative effect with scientist human capital. This indicates that scientist firms founded by young scientists with a greater likelihood of funding from external sources are more likely to succeed than firms founded by highly experienced scientists without significant sources of funding from external sources, across all innovation activities.

Models 2 through 4 compare the effect of innovative activity on the likelihood of scientist firm's success across the following innovation activities (incremental innovation), patent (radical innovation), innovative products and patents (higher radical innovation) respectively. In Models 2 through 4, we observe similar effect of scientist human capital and other sources of funding. Furthermore, Models 2 and 3 indicate that incremental innovation activities have a strong positive effect on the likelihood of scientist firm success; whereas radical innovation activities have a statistically insignificant negative effect on the likelihood of scientist firm success. These results suggest that scientist firms attempting radical innovations, on average, are less successful than those attempting incremental innovations.

Results in model 4 provide preliminary evidence that scientist firms attempting higher-radical innovations – i.e. using both patents and innovative products are more likely than scientist firm's attempting incremental innovations. In summary, these results suggest that scientist firms founded by young scientists, who are more likely to receive funding from external sources and attempting to commercialize incremental innovations, are more likely to succeed.

The extent to which radical innovations decrease the likelihood of scientist firm success – i.e.; the effect of radical significance/potential of patents measured as the number of patent citations – needs to be addressed by future research to provide insights into the mechanisms through which radical and incremental innovations affect scientist entrepreneurship.

Table 20: Firm Success of Scientist Startups with Patents and Innovative Products

Independent variables	Base Model	Innovative Product	Patents	Both Patents and Innovative Product
Innovative Product Startups		1.558		1.676
		(5.05)***		(3.57)***
Patent Startups			-0.212	-1.233
			(-0.68)	(-1.92)*
Innovative Product and Patent Startups				0.559
				(0.66)
Grant Amount (in millions) - *Fin Res.*	-0.028	-0.068	-0.019	-0.054
	(-0.35)	(-0.91)	(-0.24)	(-0.71)
Other Funding (>750K) - *Fin Res.*	0.713	0.757	0.677	0.726
	(2.27)**	(2.27)**	(2.12)**	(2.10)**
# of Students - *Human Res.*	0	0.001	0	0
	(0.19)	(0.57)	(-0.08)	(-0.18)
Years in Tenure - *Human Capital*	-0.047	-0.044	-0.049	-0.048
	(-2.21)**	(-2.10)**	(-2.31)**	(-2.26)**
Full Professor - *Human Capital*	0.532	0.105	0.546	0.164
	(1.55)	(0.3)	(1.53)	(0.45)
Board Membership - *Social Capital*	0.301	-0.171	0.366	0.016
	(0.9)	(-0.51)	(1.04)	(0.04)
Dept. Encourages Commercialization	0.035	0.058	0.021	-0.023
	(0.41)	(0.62)	(0.23)	(-0.22)
Dept. Head Entrepreneurial Orientation	0.222	0.449	0.219	0.486
	(0.77)	(1.53)	(0.76)	(1.58)
Univ. TTO Success	-0.048	0.034	-0.044	0.068
	(-0.57)	-0.37	(-0.52)	-0.7
Male	0.747	0.627	0.698	0.527
	(1.68)*	-1.44	-1.54	-1.18
Asia - *Country of Origin*	-0.052	-0.481	-0.031	-0.48
	(-0.10)	(-0.83)	(-0.06)	(-0.91)
Constant	-0.308	-0.893	-0.149	-0.526
	(-0.42)	(-1.14)	(-0.19)	(-0.59)
Number of Observations	106	106	103	103
Wald Chi-sq.	18.61	38.52	18.92	45

Notes: Absolute z values in parenthesis. * Denotes significant at the 10% level; ** at 5% level; *** at 1% level

7. Conclusions

Universities have evolved over time from being institutions that were largely peripheral to contributing to economic growth, employment creation and global competitiveness to being at the heart of creating the types of resources and capabilities that have emerged as the driving engine or economic prosperity. Even as knowledge created by university research and science has emerged as a crucial input driving economic performance, investments in such knowledge do not at all guarantee that they will result in the desired growth, job creation and global competitiveness.

Rather, mechanisms are needed to facilitate the spillover of university research and science for commercialization and innovative activity. The Bayh Dole Act along with the advent of the Offices of Technology Transfer were designed to facilitate knowledge spillovers from universities. An enormous scholarly literature has analyzed the impact of university technology transfer. These studies have invariably and almost exclusively relied upon data collected by the Offices of Technology Transfer and compiled by the AUTM to assess the impact of universities on innovation. While a number of important and invaluable insights have been gleamed from such studies, an important oversight is the entrepreneurial activities of individual university scientists that do not work explicitly or directly with the OTTs.

This paper has analyzed scientist entrepreneurship not by asking the university technology transfer offices what they do in terms of entrepreneurial activities but rather university scientists directly what they do in terms of entrepreneurial activities. The results from this study are as startling and novel as they are revealing. While the Offices of Technology Transfer databases suggest that new firm startups by university scientists are an infrequent activity, this study finds exactly the opposite. Most strikingly, using a large database of scientists funded by grants from the United States National Foundation this study finds that around 13 percent of the scientists have started a new firm. These findings would suggest that university scientist entrepreneurship is considerably more prevalent that would be indicated by the data collected by the Offices of Technology Transfer and compiled by AUTM.

In addition, the propensity for a university scientist to be engaged in entrepreneurial activity apparently varies considerably across scientific fields. In certain fields, such as computer and network systems, the prevalence of entrepreneurship is remarkably high, 23.8 percent. Similarly, in civil, mechanical, and manufacturing innovation, over one in five of the university scientists report starting a new business.

By contrast, in other scientific fields, the prevalence of entrepreneurship is considerably more subdued. For example, in environmental biology, only 4.6 percent of the university scientists report having started a new business. Similarly, in particle and nuclear astrophysics 6.2 percent of the scientists have started a new firm, and in biological infrastructure 8.2 percent of the scientists have started a new firm.

There is also considerable evidence that university scientist entrepreneurship mirrors that for the more general population in certain important ways, while at the same time, in other ways scientist entrepreneurship clearly differs from more general entrepreneurial activity. In sharp contrast to what has been found in the entrepreneurship literature for the general population, certain personal characteristics of university scientists, such as age and experience, do not seem to influence the likelihood of a scientist becoming an entrepreneur. However, gender influences the entrepreneurial decision of university scientists in much the same way it does for the general population. Males have a greater likelihood of starting a new business, both for university scientists as well as for the more general population. Similarly, access to resources and high social capital, in the form of linkages to private companies, encourages entrepreneurial activity among university scientists, just as it does for the overall population.

However, the determinants of university scientist entrepreneurship apparently are not constant across scientific fields. Rather, what is important in influencing scientific entrepreneurship in some scientific fields is less important in other scientific fields. For example, the extent of social capital has no statistically significant impact on the entrepreneurial activity of university scientists in scientific fields such as environmental biology, while it has a positive and statistically significant impact on entrepreneurial activity in civil, mechanical, and manufacturing innovation, as well as in computer and network systems.

While the age of the university scientist generally does not play an important role, the empirical evidence does point to a negative relationship between age and entrepreneurial activity that is more radical and less innovative in nature. In particular, those university scientists starting a new business for products that are highly innovative tend to be younger.

Thus, the findings of this paper based on asking scientists about their entrepreneurial activities suggest that entrepreneurship is considerably more prevalent among a broad spectrum of university scientists than had been identified using databases reporting what offices of technology transfer are doing in terms of entrepreneurship. These results would suggest that the spillover of knowledge from universities for commercialization, innovation and ultimately economic growth, employment creation and global competitiveness is substantially more robust than had been previously thought.

At the same time, the findings from this study caution against generalizations across heterogeneous fields of science. Just as the prevalence of entrepreneurship is found to vary substantially across scientific fields, so too do the determinants of entrepreneurial activity.

Future research needs to build upon and extend the findings of this paper by widening the spectrum of scientific and academic contexts analyzed for the commercialization of university science and research. Subsequent research would be well advised to consider not just the data reported by the Technology Transfer Offices to measure and analyze what universities contribute directly to commercialization and entrepreneurship, but also to continue to uncover the actual commercialization and entrepreneurial activities of the scientists themselves.

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APPENDICES

Appendix A: Survey Response Rates of Key Determinants of Scientist Entrepreneurship

Survey Response Rates of Key Determinants of Scientist Entrepreneurship

	Number of Responses	Response Rate
Overall Survey Response Rate	1899	20.8%
Key Dependent Variable		
Scientist Startups	1889	99.5%
Other Scientist Startup Characteristics		
Startups using Patents	221	91.7%
Startups using Innovative Products	187	77.6%
Startups providing Consulting Services	184	76.3%
Determinants of Scientist Entrepreneurship		
Financial Resources		
Award Amount	1892	99.6%
Other Sources of Funding	1678	88.4%
Human Resources		
Number of Student Collaborators	1756	92.5%
Human Capital		
Tenure Status	1627	85.7%
Years of Tenure	855	45.0%
Social Capital		
Board of Directors/Scientific Board Membership	1818	95.7%
Institutional Characteristics		
Dept. Head Entrepreneurial Orientation	1899	100.0%
Dept. Encourages Research Commercialization	1617	85.2%
Univ. TTO Competent in Understanding Research	1573	82.8%
Univ. TTO Successful in Commercialization	1558	82.0%
Scientist Characteristics		
Age of Scientist	1503	79.1%
Gender of Scientist	1563	82.3%
Race of Scientist	1549	81.6%
Continent of Origin of Scientist	1576	83.0%

APPENDIX B: SURVEY QUESTIONAIRE (ONLINE ADAPTIVE SURVEY)

1. Have you started a legally recognized company?
   a. YES
   b. NO

(If response to Q1 is YES, Continue to Section 1; if response to Q2 is NO, jump to Section 2)

SECTION 1: Administered to scientists that started up (Q2-Q8)

2. What sort of startup have you founded? (choose all that apply)

   a. Founded a company that <u>does NOT (nor did not) own patents</u> where you or other founding firm members are listed as the <u>legal patent inventor</u>.
   b. Founded a company that <u>does (or did) own patents</u> where you are listed as the <u>legal patent inventor</u>.

3. Approximately, what percentage of equity does the Technology Transfer Office (TTO) own?

Answer: <TEXT BOX>

4. If the Technology Transfer Office (TTO) no longer has equity in your firm, what year did they no longer have equity?

Answer: <TEXT BOX>

5. What year was your company legally founded?

Answer: <TEXT BOX>

6. Is your firm still active?
   a. YES
   b. NO

7. Does your business currently or intend to sell an innovative product?
   a. YES
   b. NO

8. Does your business do a majority of consulting service with Industry or Government?
   a. YES
   b. NO

SECTION 2: Administered to all scientists (Q9-Q25)

9. Do you sit (or have you sat) on a board of directors or scientific advisory board?
    a. YES
    b. NO

10. *(If response to Q9 is YES)* What year did you first sit on a board?

Answer: <TEXT BOX>

11. Roughly what total number of undergraduate AND graduate students have you worked with in your specific field of research from 2005 to 2010?

Answer: <TEXT BOX>

12. Roughly what number of undergraduate AND graduate students have you worked **closely** with in your specific field of research from 2005 to 2010?

Answer: <TEXT BOX>

13. Of those students with whom you have worked closely, roughly how many have:
    a. Started their own firm <TEXT BOX>
    b. You employed in your firm after graduating from their degree <TEXT BOX>
    c. Went to work for large firms in the area of your research <TEXT BOX>
    d. Went to work for small firms in the area of your research <TEXT BOX>
    e. Pursuing another advanced degree in the area of your research <TEXT BOX>

14. Did you have any other major sources of funding directly relating to your research from 2005 to 2010 (totaling over $750,000)?
    a. YES
    b. NO

15. (If answer to Q14 is YES) Of those students with whom you have worked closely, roughly how many have:
    a. Nonprofit (e.g. Foundations)
    b. University (e.g. University sponsored)
    c. Governmental (e.g. NSF, NIH, SBA etc.)
    d. International Governments (e.g. World Bank, The European Union or the Chinese Academy of Sciences)

e. Industry (e.g. For-profit firms)
f. Other <TEXT BOX>

16. What is the cumulative amount of International Governments (e.g. World Bank, The European Union or the Chinese Academy of Sciences) funding received?

Answer: <TEXT BOX>

17. What is your current level of professorship?
    a. Not tenured professorship
    b. Assistant professor
    c. Associate professor
    d. Full professor
    e. Endowed professor
    f. Emeritus professor

18. (If answer to Q17 is b through f) In what year did you attain "tenure" status?

Answer: <TEXT BOX>

19. Please select all that apply;

The head/chair of your department at the time of your first NSF funding, between 2005 and 2010, to the best of your knowledge, had which of the following:

a. Do not know
b. Never started a company
c. Started a company before your first NSF funding between 2005-2010
d. Started a company after your first NSF funding between 2005-2010

20. Please indicate on a scale from 1 to 7 to what extent you agree or disagree with the following statements.

The value 7 being "strongly agree" with the statement and the value 1 being "strongly disagree".

The head/chair of your department at the time of your first NSF funding, between 2005 and 2010, to the best of your knowledge, had which of the following:

a. My department encourages me to commercialize my research. *(1 through 7)*
b. My Technology Transfer Office competently understands my specific area of research. *(1 through 7)*
c. My Technology Transfer Office is successful at commercializing my field of research. *(1 through 7)*

21. What is your year of birth?

Answer: <TEXT BOX>

22. What is your gender?
    a. Male
    b. Female

23. What is your race?
    a. American Indian / Alaska Native
    b. Asian / Pacific Islander
    c. Black / African American
    d. White / Caucasian
    e. Other

24. On which continent did you receive your undergraduate degree?
    a. North America
    b. South America
    c. Europe
    d. Africa
    e. Asia
    f. Australia / Oceania

25. Are you interested in reading the final results of our study?
    a. YES
    b. NO

APPENDIX C: Scientist Startup Rates by Country of Origin, across Fields of Research

Summary of Scientist Startup Rates by Country of Origin, across Fields of Research

	All Fields	CMMI	DEB	CNS	OCE	PHY	DBI
North America	11.5%	19.3%	4.9%	23.8%	7.9%	7.6%	8.2%
South America	6.7%	28.6%	0%	0%	0%	0%	0%
Europe	11.4%	15.7%	0%	23.5%	3.8%	7.5%	5.9%
Africa	0%	0%	0%	0%	0%	0%	0%
Asia	10.2%	10.6%	0%	12.7%	0%	0%	10.0%
Australia/Oceania	0%	0%	0%	-	-	-	0%

APPENDIX D: Summary of all Financial Resources

Summary of all Financial Resources by Field of Research

	All Fields	CMMI	DEB	CNS	OCE	PHY	DBI
Grant Amount	941,230	427,047	501,299	841,000	2,164,245	1,452,961	831,687
Other Sources of Funding >750K	40.6%	40.6%	32.7%	47.1%	48.6%	40.1%	37.9%
OtherFunding Sources- Total							
Non Profits	9.2%	5.3%	9.5%	6.5%	13.8%	7.5%	12.9%
University	9.1%	9.7%	9.8%	6.5%	9.7%	9.6%	8.9%
Government	37.6%	38.7%	30.1%	42.5%	44.5%	37.4%	35.4%
International Governmental Orgs.	2.5%	3.5%	2.1%	4.5%	2.0%	0.5%	2.1%
Industry	9.7%	17.9%	2.9%	19.2%	5.7%	3.2%	6.1%
Other	1.3%	1.6%	1.8%	1.0%	1.2%	1.1%	0.7%
OtherFunding Sources- Started Up							
Non Profits	16.9%	12.7%	25.0%	9.5%	23.5%	16.7%	38.1%
University	15.8%	18.2%	18.8%	12.7%	11.8%	16.7%	19.0%
Government	53.6%	45.5%	62.5%	50.8%	52.9%	66.7%	71.4%
International Governmental Orgs.	7.7%	7.3%	6.3%	12.7%	5.9%	0.0%	0.0%
Industry	21.9%	25.5%	18.8%	25.4%	11.8%	8.3%	23.8%
Other	2.7%	0.0%	6.3%	4.8%	0.0%	8.3%	0.0%
OtherFunding Sources- Did not Start Up							
Non Profits	8.2%	3.8%	8.8%	5.7%	13.0%	6.9%	10.8%
University	8.2%	8.0%	9.4%	4.9%	9.6%	9.1%	8.1%
Government	35.6%	37.3%	28.7%	40.4%	43.9%	35.4%	32.4%
International Governmental Orgs.	1.9%	2.7%	1.9%	2.4%	1.7%	0.6%	2.3%
Industry	8.2%	16.3%	2.2%	17.6%	5.2%	2.9%	4.6%
Other	1.1%	1.9%	1.7%	0.0%	1.3%	0.6%	0.8%

APPENDIX E: Summary of all Student Collaborations by Field of Research

Summary of Student Collaborations by Field of Research

	All Fields	CMMI	DEB	CNS	OCE	PHY	DBI
Total Number of Student Collaborators	17.76	21.65	17.27	17.89	10.47	11.92	17.36
Student Collaborators- Total							
Hired by the Firm	2.0%	1.7%	2.5%	2.3%	2.6%	0.9%	1.5%
Started up on their own	1.6%	1.5%	0.6%	3.7%	1.0%	1.7%	1.1%
Hired by a Large Firm	20.5%	32.2%	7.3%	42.0%	14.4%	13.0%	9.8%
Hired by a Small Firm	10.3%	15.5%	5.7%	15.9%	9.8%	5.1%	8.2%
Pursued Higher Education	29.7%	21.1%	38.6%	16.8%	33.2%	34.4%	37.1%
Student Collaborators - Started Up							
Hired by the Firm	5.5%	5.6%	5.7%	5.4%	7.2%	6.7%	4.4%
Started up on their own	4.0%	3.8%	0.8%	4.8%	3.3%	4.5%	3.1%
Hired by a Large Firm	31.2%	30.7%	12.5%	43.1%	25.1%	22.9%	20.6%
Hired by a Small Firm	14.6%	18.5%	11.0%	12.9%	25.8%	7.9%	7.8%
Pursued Higher Education	27.2%	26.5%	37.5%	16.3%	44.0%	44.3%	30.3%
Student Collaborators - Did not Start Up							
Hired by the Firm	1.6%	1.0%	2.4%	1.6%	2.2%	0.5%	1.2%
Started up on their own	1.3%	1.0%	0.5%	3.4%	0.8%	1.5%	1.0%
Hired by a Large Firm	19.2%	32.5%	7.1%	41.8%	13.7%	12.3%	9.0%
Hired by a Small Firm	9.8%	14.9%	5.5%	16.6%	8.7%	4.9%	8.3%
Pursued Higher Education	30.0%	20.0%	38.6%	17.0%	32.5%	33.7%	37.6%

APPENDIX F: Technology Transfer Office(TTO) Characteristics and Scientist Startups

Technology Transfer Office(TTO) Characteristics and Scientist Startups

	Started Up	Did Not Startup
TTO Competent in Understanding Area of Research		
All Fields of Research	4.09	4.79
Civil, Mechanical, and Manufacturing Innovation	3.83	4.30
Environmental Biology	5.56	5.37
Computer and Network Systems	3.98	4.46
Physical Oceanography	3.93	4.95
Particle and Nuclear Astrophysics	3.64	4.62
Biological Infrastructure	4.38	4.92
TTO Successful in Commercializing Research		
All Fields of Research	4.80	5.17
Civil, Mechanical, and Manufacturing Innovation	4.52	4.78
Environmental Biology	5.81	5.62
Computer and Network Systems	5.56	4.93
Physical Oceanography	5.27	5.28
Particle and Nuclear Astrophysics	4.64	5.01
Biological Infrastructure	5.05	5.32

APPENDIX G

Means and Standard Deviations of Variables used in the Estimation Model

	Mean	Std. Dev.	Min	Max
Scientist Startups	0.13	0.33	0	1
Startups using Patents	0.32	0.47	0	1
Startups using Innovative Products	0.55	0.50	0	1
Startups providing Consulting Services	0.34	0.48	0	1
Award Amount (in Millions USD)	0.95	5.58	0	166.27
Other Sources of Funding (>750K)	0.41	0.49	0	1
Number of Student Collaborators	15.54	16.13	0	250
Non-Tenured	0.10	0.29	0	1
Assistant Professor	0.09	0.29	0	1
Associate Professor	0.27	0.45	0	1
Full Professor	0.44	0.50	0	1
Endowed Professor	0.09	0.29	0	1
Emeritus Professor	0.02	0.14	0	1
Years of Tenure	16.08	9.00	0	52
Board of Directors	0.34	0.47	0	1
Dept. Head Entrepreneurial Orientation	0.40	0.49	0	1
Dept. Encourages Research Commercialization	4.47	1.77	1	7
Univ. TTO Competent in Understanding Research	4.71	1.74	1	7
Univ. TTO Successful in Commercialization	5.13	1.64	1	7
Age of Scientist	50.32	9.76	29	82
Male Scientist	0.79	0.41	0	1
Asia - Continent of Origin	0.09	0.29	0	1
North East Region	0.24	0.43	0	1
Midwest Region	0.20	0.40	0	1
South Region	0.28	0.45	0	1
West Region	0.26	0.44	0	1

APPENDIX H: Simple Correlation Matrix of Key Variables used in the Estimation Model

	Startups	Board Membership	Award Amount	Other Funding (>750K)	# Student Collaborators
Startups	1				
Board Membership	0.2291	1			
Award Amount	0.0714	-0.0215	1		
Other Funding (>750K)	0.158	0.134	0.0599	1	
# Student Collaborators	-0.0411	0.0101	0.0213	0.0335	1
Tenure Experience	-0.0233	0.0566	0.013	-0.0695	-0.0087
Full Professor	-0.0574	-0.1069	0.0205	-0.0589	-0.0194
Dept. Commercialize	-0.225	-0.0547	-0.0278	-0.1514	0.05
Dept Head E.O.	0.1824	0.0497	-0.0424	0.1091	-0.0316
Univ TTO Success	-0.0965	-0.0289	-0.0256	-0.1431	0.0488
Male	0.0729	-0.0208	0.0305	-0.0126	-0.0074
Age	-0.0111	0.0839	0.064	-0.1501	-0.0116
Asia Descent	0.0269	-0.0282	-0.0205	0.0676	-0.0598
Midwest	-0.0278	-0.0119	-0.0211	0.0355	0.0282
South	0.0179	-0.0202	-0.0338	-0.0714	0.0121
West	-0.0111	-0.0576	0.0206	0.0604	-0.0213

	Tenure Experience	Full Professor	Dept. Commercialize	Dept Head E.O.	Univ TTO Success
Tenure Experience	1				
Full Professor	-0.282	1			
Dept. Commercialize	-0.0382	-0.0414	1		
Dept Head E.O.	-0.0025	-0.0289	-0.2022	1	
Univ TTO Success	-0.0782	-0.0455	0.5144	-0.1886	1
Male	0.1377	-0.0105	-0.0887	-0.0431	-0.0788
Age	0.797	-0.2516	0.0045	-0.039	-0.0148
Asia Descent	-0.0724	-0.0069	-0.052	0.1525	-0.0511
Midwest	-0.0074	0.0422	0.018	-0.0001	0.0383
South	-0.0452	0.02	-0.0345	-0.0571	-0.0155
West	-0.0372	0.0522	0.0009	0.0671	-0.0193

	Male	Age	Asia Descent	Midwest	South
Male	1				
Age	0.1017	1			
Asia Descent	0.083	-0.1139	1		
Midwest	-0.0032	-0.0329	0.0146	1	
South	0.038	-0.0351	0.0023	-0.2964	1
West	-0.0775	-0.0069	0.0153	-0.3212	-0.3713