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There is a small but growing body of literature that examines the role of principal investigators in publicly funded R&D projects. In this dissertation I discuss the literature on principal investigators and R&D project failure and found there is limited intersection between the two. I provide a theoretical model in this dissertation which explains how firm characteristics, including those of the principal investigator, impact the probability of failure. The theoretical model serves as a structural form model to motivate the empirical analysis which assesses the probability of failure in small technology-based firms that received a Phase II award from the Department of Energy's Small Business Innovation Research program. Using a Probit model, I estimate a reduced form specification of the structural model to estimate the probability a firm will experience failure conditional on characteristics of the principal investigator and the firm. I found that prior experience of the firm with a similar technology, university faculty involvement, and the age of the principal investigator are negatively associated with project failure. I also found a positive relationship between failure and firms where the principal investigator was the sole founder and CEO of the firm.

WHEN INNOVATIVE RESEARCH FAILS: EXPLORING THE ROLE OF PRINCIPAL INVESTIGATORS

by

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DEDICATION

To my wife.

APPROVAL PAGE

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CHAPTER I: INTRODUCTION

Innovation is fundamental to long-term economic growth, and investments in research and development (R&D) are key to the perpetuation of innovation. Public support of innovation has occurred in the United States for over a century, but public support of innovation has gained more attention in recent decades. In fact, there has been a notable shift towards an expectation of commercialization of the output from publicly supported (i.e., publicly financed) R&D activities especially in universities. Boehm and Hogan (2014, p. 134) discuss this point, stating, "The commercialisation of scientific knowledge has become a primary objective for universities worldwide."

Innovation is defined in this dissertation as a new technology put into use or more specifically technology that enters the market as a product, process, or services. Although commercialization of technology is becoming a traditional measure of R&D success, especially when the R&D is publicly supported, there is a limited research related to the characteristics of individuals associated with commercialization success or failure. This dissertation contributes to that body of research in at least five ways:

1. It presents a complete literature review on R&D project failure that spans both the economics and management disciplines literature.
2. A theoretical model for research project failure is provided; there are no theoretical models to explain this concept to-date. It analyzes U.S. Department of Energy (DOE) data using the National Research Council's (NRC's) second round survey data; these data have not been described in the literature to-date.
3. It replicates the empirical probability of failure using the NRC second round survey data which provides support for previous studies findings.
4. It provides principal investigators (PIs) as a new-to-the-literature covariate with R&D project failure.

The remainder of the dissertation is organized as follows. Chapter II discusses the history of DOE in an effort to provide context for the data used from that Department in the empirical analysis that follows. The DOE data used in this dissertation is related to its Small Business Innovation Research (SBIR) program.

Chapter III overviews the legislative history of the SBIR program along with DOE's historical involvement in the program. Also, in Chapter III is a review of the relevant economics literature related to the SBIR program. One conclusion from the literature review is that there is a body of research that identifies covariates with the programmatic success of an SBIR project when measured in terms of the likelihood of project commercialization. Absent from that literature is a detailed theoretical analysis of SBIR project failure; project failure being the focus of this dissertation.

Chapter IV reviews the relevant literature related to R&D project failure. This multi-disciplinary literature is limited and there is a very limited set of literature that spans the literature discussed in both Chapters III and IV. Perhaps an explanation for the limited set of literature on R&D project failure is the lack of data to support empirical research on research failure.

Chapter V reviews the literature on PIs. A conclusion of this review is that there is a conspicuous absence of studies that focused on research success or failure.

Chapter VI presents a microeconomic theoretical model that describes whether a research project succeeds or fails. The model is cast in terms of the success or failure of the search process for a commercializable technology.

A discussion of the data used to examine the testable hypotheses from the theoretical model are presented in Chapter VII as well as descriptive statistics on the dependent variables from the DOE SBIR data.

The findings from the initial empirical analysis are presented in Chapter VIII.

Chapter IX concludes the dissertation with a summary of the empirical findings and a suggested roadmap for future research.

CHAPTER II: U.S. DEPARTMENT OF ENERGY

The U.S. Department of Energy (DOE) is a cabinet-level department with a stated mission "…to ensure America's security and prosperity by addressing its energy, environmental and nuclear challenges through transformative science and technology solutions" (DOE - About Us, n.d). It was officially created through the Department of Energy Organization Act of 1977 (Public Law 95-91), which was signed into law by President Jimmy Carter on August 4, 1977.

Since inception, the DOE has had 14 Secretaries that served under seven Presidents (see Table 2.1), yet the objectives of the agency have remained largely unchanged. With just over 40 years as a cabinet-level department, the DOE is still relatively new compared with other departments, though it has a rich history that can be traced back for several additional decades.

The Early History of DOE

Less than one year before Germany's invasion of Poland on September 1, 1939 (which marked the start of World War II), two German radiochemists discovered uranium.[1] Not long after the discovery, Germany stopped selling uranium and began researching its potential uses. Concerned with the possibility Germany was researching fission chain reactions using uranium with the goal of building an extremely powerful bomb, Albert

[1]This chapter draws largely from the DOE Office of History and Heritage (OHH) online resources as they provide the most complete and detailed history (https://www.osti.gov/). As such, I have referenced where direct quotes and/or text have been paraphrased but would like to emphasize that this history follows that described by the DOE OHH closely.

Einstein drafted a letter to President Franklin D. Roosevelt alerting him of his concerns. President Roosevelt received the letter on August 2, 1939 and wrote back to Einstein several days later explaining that in response to the letter he had assembled a committee of civilian and military personnel to advise on the research of uranium. On October 21, 1939, the Advisory Committee on Uranium, headed by Lyman J. Briggs, met for the first time.

Table 2.1: Department of Energy Secretaries

No.	Name	State of Residence	Took office	Left office	Party	President(s)
1	James Schlesinger	Virginia	6-Aug-77	23-Aug-79	Republican	Jimmy Carter
2	Charles Duncan	Texas	24-Aug-79	20-Jan-81	Democratic	
3	James Edwards	South Carolina	23-Jan-81	5-Nov-82	Republican	Ronald Reagan
4	Donald Hodel	Oregon	5-Nov-82	7-Feb-85	Republican	
5	John Herrington	California	7-Feb-85	20-Jan-89	Republican	
6	James Watkins	California	1-Mar-89	20-Jan-93	Republican	George H. W. Bush
7	Hazel O'Leary	Virginia	22-Jan-93	20-Jan-97	Democratic	William Clinton
8	Federico Peña	Colorado	12-Mar-97	30-Jun-98	Democratic	
9	Bill Richardson	New Mexico	18-Aug-98	20-Jan-01	Democratic	
10	Spencer Abraham	Michigan	20-Jan-01	1-Feb-05	Republican	George W. Bush
11	Samuel Bodman	Illinois	1-Feb-05	20-Jan-09	Republican	
12	Steven Chu	California	20-Jan-09	22-Apr-13	Democratic	Barack Obama
13	Ernest Moniz	Massachusetts	21-May-13	20-Jan-17	Democratic	
14	James Richard Perry	Texas	2-Mar-17	Incumbent	Republican	Donald Trump

Source: https://www.energy.gov/management/history/secretaries-energy

In June 1940, President Roosevelt aligned the newly constituted Committee on Uranium to be under the recently created National Defense Research Committee (NDRC). Vannevar Bush was appointed to head of the NDRC, and he reorganized the Committee on Uranium into a scientific community thus ending military membership. By eliminating the dependence on the military for funding, the NDRC was able to gain more direct access to funding for uranium research. The Committee on Uranium still held responsibility for uranium research under the NDRC and recommended that funding continue for the remainder of 1940. Bush approved the funding for the uranium research but also banned the publication of any research on uranium and barred foreign-born scientists from the committee for the sake of national security.

During 1940, German forces experienced wartime success in Europe. This success led many to believe it was only a matter of time before the United States became involved in the war. While the U.S. Government funded uranium research in 1940, the scientific community worried about the pace of research was proceeding too leisurely. Ernest O. Lawrence, director of the Radiation Laboratory at the University of California, Berkeley was one of the most outspoken scientists concerned with the pace of uranium research. Lawrence was enthusiastic about uranium's potential and hypothesized a method to separate larger and purer amounts of uranium-235 for study. Eager to speed up this research, Lawrence contacted Karl T. Compton and Alfred L. Loomis, both of Harvard University, who were also doing work for the NDRC. Lawrence shared his views and hypotheses with Compton and Loomis. Sympathetic to Lawrence's urgency to speed up uranium research, Compton and Alfred Loomis shared Ernest Lawrence's agreement with Bush that the Committee on Uranium were moving too slowly, especially, in the face of Germany's progress.

After a meeting between Vannevar Bush and Ernest Lawrence, Bush believed Lawrence was on the right track and appointed him to be an advisor to Lyman Briggs. Bush also requested that the National Academy of Sciences, headed by Arthur Compton, review the uranium research program. In May 1941, Lawrence in conjunction with Karl Compton, released the first report from the National Academy of Sciences (Academy) on the uranium program. The report stated that it was possible uranium could be used for creating a radioactive weapon as early as 1943, in the event of war. However, the expected time of when a large bomb would be needed was undetermined, and it was thought that it would certainly not be needed before 1945. Bush was not appeased by the findings in the report and requested the Academy conduct a review of the first report from an engineering standpoint. The second report, dated July 11, 1941, confirmed the results of the first report, and this was a disappointment according to Bush.

At the time Bush received the second Academy report, he had become the director for the Office of Scientific Research and Development (OSRD). The Committee on Uranium, code-named the S-1 committee, then became the OSRD Section on Uranium. While the U.S. efforts weaponizing uranium were moving slowly, in July 1941 a draft of the so-called MAUD report, codenamed for a British group of researchers, founded in 1940 to study uranium, was provided to Bush. The MAUD report was one of the most influential reports of the time as it provided details on how to build a nuclear bomb. Recognizing the importance of the MAUD report, Bush decided to strengthen the S-1 committee and requested Compton to address technical questions related to the MAUD report.

In October 1941, before Bush had received Compton's latest report, he met with President Roosevelt and Vice President Henry Wallace to discuss the positive outlook of uranium research as a result of the MAUD report. Bush received permission from the President to engage the U.S. Army to explore construction of a bomb. The President instructed Bush to move quickly but to only conduct R&D; he also required Bush to seek additional approval to move forward with production if the situation permitted.

Just over a month before Japan bombed Pearl Harbor (December 7, 1941), Compton's committee submitted a report to Bush that confirmed the basic conclusions of the MAUD report. Bush shared this information with President Roosevelt who responded through a written note stating, "V. B. OK – returned – I think you had best keep this in your own safe FDR" (DOE - OHH, n.d.).

The United States entered World War II following the attack on Pearl Harbor. This event, coupled with the concern Germany was progressing towards creation of an atomic weapon, sparked urgency in the federal government to support the U.S. avenues of developing its own bomb. Through the first half of 1942, Bush reorganized the overall organizational structure of the effort to build an atomic bomb. This was in parallel with troves of new scientific information pouring in that needed to be analyzed and prioritized for the upcoming production phase. Throughout the year, progress was made towards entering the production phase of an atomic bomb. On December 9, 1942, the S-1 committee met to discuss a report prepared by Warren K. Lewis of the Massachusetts Institute of Technology (MIT), and a draft was prepared for Bush to send to President Roosevelt with recommendations for next steps. On December 28, 1942, the President approved $2 billion in spending to be used to build an atomic bomb. His also gave the Manhattan Project approval to construct the plants and facilities needed to build the bomb.

With the full support of President Roosevelt, the Manhattan Project moved forward in the efforts to build an atomic bomb. Across the country, multiple sites were working towards producing plutonium and enriched uranium. With plutonium production increasing significantly late in 1944, the facility in Los Alamos that focused on the actual design of a nuclear weapon was also making substantial progress.

On August 6, 1945, with President Harry Truman's approval, a 9,700-pound uranium bomb, nicknamed "Little-Boy" was dropped on Hiroshima, Japan with devastating effects. Just three days later a plutonium bomb nicknamed "Fat-Boy" was dropped on the city of Nagasaki, again with devastating effects. On August 10, 1945, the emperor of Japan forced military leaders to offer a surrender. After some reluctance by the Japanese military leaders, Japan officially surrendered on September 2, 1945.

Following the end of World War II, the United States had to deal with the issue of how to proceed now that the world knew the forcefulness of nuclear power. Perhaps the most contentious point was whether the infrastructure developed through the Manhattan Project should be controlled by the military or by civilians. The debate was settled on August 1, 1946, when President Truman signed the Atomic Energy Act (Public Law 79-

585) which went into effect January 1, 1947. The Act established the civilian lead, Atomic Energy Commission (AEC) intended to promote the "utilization of atomic energy for peaceful purposes to the maximum extent consistent with the common defense and security and with the health and safety of the public" (EPA, 2018, para. 1).

For the next few years, the AEC expanded its weapon making sites as the so-called Cold War between the Soviet Union and the United States intensified. In August 1949, the Soviet Union detonated its first atomic weapon, which sparked President Truman to request the AEC to expedite the development of a thermonuclear weapon.

On June 25, 1950, North Korea invaded South Korea which ignited the Korean War. The global turmoil lead President Truman to approve a $1.4 billion spending bill to expand AEC facilities to produce more uranium and plutonium for nuclear weapons. On November 1, 1952, the United States detonated its first thermonuclear weapon; it created an explosion approximately 700 times greater than the uranium bomb dropped on Hiroshima.

On January 20, 1953, Dwight D. Eisenhower was inaugurated. Eight months into Eisenhower's presidency the Soviet Union tested a bomb that was a precursor to a thermonuclear bomb. At the same time the United States had made progress on harnessing nuclear energy for naval propulsion; the U.S. Navy launched its first nuclear powered submarine in January 1954.

On August 30, 1954 President Eisenhower signed the Atomic Energy Act of 1954 (Public Law 83-703), which is now one of the fundamental laws of the Nuclear Regulatory Commission (NRC). The law, as it pertained to the development of civilian nuclear power programs, stated: "the development, use, and control of atomic energy shall be directed so as to promote world peace, improve the general welfare, increase the standard of living, and strengthen free competition in private enterprise" (OGC, 2013, p. 15).

Although the Soviet Union continued to make advances in its nuclear program, including the detonation of a thermonuclear weapon in 1955, a third world war was feared but never occurred. In August 1958, President Eisenhower declared a moratorium on all nuclear weapon testing effective October 31. The moratorium was in conjunction with the British and Soviets, the only other nations with nuclear programs at the time. After three years, the Soviet Union began extensive nuclear weapon testing again, breaking the 1958 moratorium agreement. Just days later the United States resumed nuclear weapon testing. Negotiations for an international agreement among the United States, the United Kingdom (U.K.), and the Soviet Union nuclear weapon programs continued for a couple years. On August 5, 1963, the three nations signed the Limited Test Ban Treaty which prohibited underwater, atmospheric, and outer space nuclear test, but did not ban underground testing.

In December 1963, plans were announced for the first nuclear power plant to be built without government aid and able to compete with conventional plants. The Jersey Central Power and Light Company was the entrepreneurial effort behind the plans. With the need for energy ever increasing the, AEC focused on development of the Liquid Metal Fast Breeder. In a report explaining the Breeder Reactors, AEC commissioner Glen Seaborg stated: "The development and use of the breeder reactor will give us an even greater amount of power-perhaps enough for thousands of years" (Mitchel and Turner, 1971, p. 1). The concern over producing enough reliable energy became a reality on November 9, 1965, when the northeastern United States experienced a major power blackout. Following the blackout in 1965, the United States and AEC continued to work towards developing a Liquid Metal Fast Breeder Reactor. By 1972, the AEC was actively working on plans with industry partners to build a Breeder Reactor.

In June 1973, President Richard Nixon recognized that nuclear research and development activities had propagated since the Manhattan Project. The energy crisis of the 1970's was also underway and beginning to hit U.S. consumers. As such, the President requested

Dixy Lee Ray, Chairman of the AEC at the time, to conduct a review of all energy related research and development activities and to recommend a unified national program. Later that month, President Nixon established the Energy Policy Office. Within six months President Nixon replaced the Energy Policy Office with the Federal Energy Office (FEO). The new office was given responsibility for controlling the price of oil and gasoline and rationing petroleum supplies to refiners. Only a few month later the President replaced the FEO with the Federal Energy Administration through the Federal Administration Act of 1974 (Public Law 93-275).

Shortly after President Gerald R. Ford took office, with the energy crisis in full swing, he signed the Energy Reorganization Act of 1974 (Public 93-438) which replaced the AEC with the NRC and the Energy Research and Development Administration (ERDA). The NRC was tasked with regulating civilian use of nuclear materials and the ERDA administered research and development programs related to the use of various energy sources. Also, during President Ford's administration, construction began on the Trans-Alaska Pipeline; this was largest private construction project in American history at the time. Along with the construction of the pipeline came debate over potential negative environmental impacts of the 800-mile pipeline. These concerns plus the desire to create an oil reserve prompted the enactment of the Energy Policy and Conservation Act (Public Law 94-163), signed into law by President Ford on December 22, 1975.

Four months into President Carter's presidency, in April 1977, he delivered his first major speech on energy. Through his speech, he unveiled a plan to establish an energy department. In President Carter's address to the nation he stated: "The energy crisis has not yet overwhelmed us, but it will if we do not act quickly. It's a problem that we will not be able to solve in the next few years, and it's likely to get progressively worse through the rest of this century" (Carter, 1977). Following the President's address, in August 1977, President Carter signed the Department of Energy Organization Act (Public Law 95-91) thus abolishing the Federal Energy Administration and the ERDA. The

Department of Energy was officially formed on October 1, 1977, consolidating many entities from several departments and agencies. In accordance with President Carter's plan, the Act was intended, as stated in Public Law 95-91: "To establish a Department of Energy in the executive branch by the reorganization of energy functions within the Federal Government in order to secure effective management to assure a coordinated national energy policy, and for other purposes." The DOE was also given responsibility over the U.S. nuclear weapons program, whose lineage can be traced back directly to the Manhattan Project.

DOE is Formalized

James R. Schlesinger was appointed to be the first Secretary of Energy. Since the DOE brought together several, largely independent agencies and offices, Schlesinger's first task was to meld all of them into a unified department. The new department consisted of approximately 20,000 employees with an annual budget of $10.4 billion. The newly created department: "despite its diverse origins, was structured to allow for the continuity of programs and functions from predecessor organizations while blending their expertise into new management teams" (Fehner and Holl, 1994, p. 23). The Department also inherited, mostly from the AEC through the ERDA, many regional and field offices, laboratories, research centers, and university programs from predecessor agencies. Thus, the Department of Energy was not intended to reduce resources through consolidation but was formed to build on previous efforts with a more strategic structure.

Through the end of 1977, President Carter focused on creating legislation that would bring his administration's energy policies together to form a National Energy Plan. However, public opinion was not favorable to President Carter's plan, and special interest groups opposed to the plan were successful in preventing any legislation to be enacted. Not creating an official National Energy plan was a big disappointment for the Carter Administration, so they continued to push a policy forward in the first half of 1978. On

November 9, 1978, President Carter was finally successful in creating a National Energy Plan when he signed into law the National Energy Act of 1978. The legislation was substantial; it consisted of five major Public Laws:

- The National Energy Conservation Policy Act (Public Law 95-619)
- The Powerplant and Industrial Fuel Use Act (Public Law 95-620)
- The Public Utilities Regulatory Policy Act (Public Law 95-617)
- The Energy Tax Act (Public Law 95-618)
- The Natural Gas Policy Act (Public Law 95-621)

The National Energy Act was considered a success for President Carter and the DOE. With an official National Energy Plan in place, Secretary Schlesinger and the DOE had a new-found charter and the funding to work towards their new goals.

Successfully passing the National Energy Act was only a small step towards effective energy policies. The DOE submitted its first comprehensive budget request for the year 1980, as opposed to an aggregation of legacy agency budget requests. With an $8.4 billion budget and thousands of employees, the DOE was not a simple organization to manage. Well over a year after the agency was established, the organization was still trying to find its rhythm which thus created many critics of the DOE.

As the DOE was trying to get its footing and iron out its initial start-up issues, the ongoing energy crisis took an unfortunate turn for the worse. In 1979, the world began to experience an oil shortage driven by turmoil in Iran leading to the cessation of oil exports from the country. As energy prices spiked, Secretary Schlesinger realized there would be no easy solution to the crisis. Considerations were given to voluntary conservation measures, however the situation continued to deteriorate. As if the energy crisis was not straining the relatively new DOE enough, another challenge arose with an accident at a nuclear power plant in Harrisburg, Pennsylvania. Failures in the system resulted in the release of radioactive material that cost about $1 billion to cleanup (New York Times, 1993). Though the world was facing oil shortages, President Carter made it clear that the use of nuclear power should be a last resort.

The Energy Crisis intensified during the first half of 1979, and in some cases, violence broke out due to the need for rationed gasoline. President Carter addressed the nation explaining that not one single factor caused the crisis and that the American people must speak out to combat the oil companies' special interests in high prices. The DOE created teams of auditors to check up on refiners and individual service stations to try and enforce gasoline ceiling price regulations. Congress was not behind the President's methods in resolving the energy the crisis; however, President Carter persisted that renewable energy would help alleviate the dependence on foreign oil. Nonetheless, a majority of Americans at the time believed the energy crisis was artificially contrived by the government, oil companies, and oil-producing nations. The skepticism did not bode well for the DOE's reputation.

Secretary Schlesinger resigned his office on July 16, 1979. President Carter then selected Charles W Duncan, Jr. to be the second Secretary of Energy. Secretary Duncan believed that the business of energy belonged in the private sector and that the proper role of government was the effective allocation of public resources. He also suggested that the government should provide proper incentives to private enterprise to help transition to an energy-diversified economy from one dependent on oil. The DOE was still in its infancy when Secretary Duncan took the reins; thus, part of his task was to improve the management structure of the department. The original structure of the department was based on the evolution of technologies from research and development through commercialization. Secretary Duncan reorganized the department according to respective fuel or technology types, a more traditional structure.

During the summer of 1979, the energy crisis began to subside. Americans were consuming less oil driven by an economic downturn and high gas prices. The following year a presidential election took place. President Carter and republican presidential candidate Ronald Reagan largely avoided making the nation's energy issues a major issue in their campaigns. Reagan, the victor, criticized the past administrations energy policy and advocated for the abolishment of the DOE. Following Reagan's election, he nominated James B. Edwards as the third Secretary of Energy. Edwards and the Reagan Administration quickly refocused the DOE's mission. As opposed to President Carter's policies, they did not want the government involved in activities that the private sector and markets could manage, such as price controls and regulations that slowed domestic production. On February 25, 1981, Secretary Edwards announced an organizational structure change that would permit the DOE to focus more on research, development, and production.

Only four years after the DOE was established, the agency had become to many a symbol of the ineffectiveness of government overreach. Secretary Edwards was in favor of dismantling the DOE and reorganizing a more research focused administration under the Department of Commerce. When the Department of Energy Organization Act was created, it included a clause that required the President to submit a review of the Department to Congress before the Department could be dismantled. Unfortunately for President Reagan, Congress gave the DOE sound marks in achieving its goals and would not permit the complete abolishment of the department. By 1982, the nation's energy situation had improved, and Secretary Edward touted that free markets and little government intervention were behind the change. Secretary Edwards had basically declared the end of the energy crisis and shortly thereafter gave his resignation to President Reagan.

On October 5, 1982, Donald P. Hodel was named the fourth Secretary of Energy. Secretary Hodel held similar a sentiment as his immediate predecessor and tried to reorganize the DOE under the Department of Commerce (DoC). One main sticking point with his plan was that Congress did not believe the nuclear weapons program, maintained by the DOE, should be a program under the DoC. With the DOE remaining intact, Secretary Hodel largely carried out President Reagan's objectives deregulating energy markets and reducing the department's personnel. During Secretary Hodel's tenure as secretary, one of the most hotly debated issues revolved around the government's role in energy research and development. Secretary Hodel believed that research and development should lie in the private sector but that government should intervene when research was too expensive for the private sector to undertake but had potential for large benefits.

Ten days before President Reagan was inaugurated for his second term, he appointed John S. Herrington as the fifth secretary of energy. Secretary Herrington's priorities were roughly in line with those of his predecessor. Secretary Herrington suggested energy policy should consist of three objectives: energy stability, energy security, and energy strength. Energy stability and energy security had been the focus of the DOE since the energy crisis in 1973, so Secretary Herrington wanted to focus on energy strength to make progress towards his view of an effective energy policy. By the mid1980's, the United States had become much more efficient in how it consumed energy. Energy conservation was no longer just a slogan, it had become an energy resource. Conservation, coupled with nuclear and coal energy, were the three components Secretary Herrington believed would help the United States achieve energy strength.

Secretary Herrington was also a strong proponent of government funded basic research. In 1986 and 1987, his views were appeased when major breakthroughs in electric technology efficiency provided the means to achieve superconductivity (zero electrical resistance) at lower costs. President Reagan had become impressed with the potential for basic scientific research to provide life-changing innovations. Secretary Herrington believed this new breakthrough showcased how the president's energy policy and the DOE worked at its best. The key formula was the exchange of information and ideas among universities, private industry, scientific laboratories and government. In fact, in a press conference President Reagan suggested the Superconductivity initiative demonstrated the administration's policy for, "the swift transfer of technology and technical information from the government to the private sector" (White House, 1987, p. 1).

As President Reagan's presidency concluded, the DOE was much different from when it was created. President Reagan was not successful at eliminating the department but Secretary Herrington believed the current state was much more appealing to the president. The DOE was no longer focused on regulatory functions, instead was supporting R&D and weapons facilities. After a decade since the DOE's inception, arguments over energy policy had largely subsided.

Over the next decade two more presidents would hold the office; George H. W. Bush from January 20, 1989, to January 20, 1993, and William J. Clinton from January 20, 1993, to January 20, 2001. Under President Bush, Admiral James Watkins was named the Secretary of Energy. Early in his tenure as secretary of energy, Secretary Watkins's biggest challenge was handling environmental problems caused by nuclear waste from the nuclear weapons complexes. This problem was essentially solved through enactment of the Waste Isolation Pilot Plant Land Withdrawal Act (Public Law 102-579). The Act was signed into law in 1992 and designated a single location to store defense related waste. Apart from the issues of nuclear waste, the DOE under the Bush administration largely echoed the energy policy of the Reagan administration. The Bush administration stressed that a diversified energy portfolio, consisting of coal, nuclear power, oil and natural gas, renewables, alternative fuels, and conservation was needed for the nation's energy security. Along these lines, President Bush presented the National Energy Strategy to the nation, including Congress, which was touted as a pro-production strategy. Secretary Watkins suggested the strategy was a first of its kind to provide energy security and environmental quality through de-regulation, free markets, and investment in research and development. Although the strategy had mixed opinion it did not cause any major political waves and was largely implemented through the passage of the Energy Policy Act of 1992 (Public Law 102-486).

When President Clinton took office, the Cold War had ended, thus the DOE's defense related activities were giving way to environmental restoration and waste management activities. Energy itself had largely fallen off the radar of most Americans but how energy interacted with the environment had become a major concern. Early in his presidency, President Clinton made it clear that the secretaries of energy and commerce were crucial to his economic policy and the DOE would be central to the administration's policy goals. According to the Clinton Administration and echoed by Hazel Rollins O'Leary, President Clinton's first appointed Secretary of Energy, the DOE would be focused on energy policy that relied more heavily on American natural gas, conservation through efficiency gains, alternative fuels, and more consideration for the environment. Over the course of President Clinton's first term as President, he and the DOE continued to push their environmental policy forward. By the start of President Clinton's second term a debate on whether the DOE should focus on applied or basic research was underway. Secretary O'Leary pushed the department towards applied research and thought technology transfer from public laboratories to the private sector would be key to maintaining the public laboratories following the end of the Cold War. Although the Bush Administration also pushed for technology transfer, under Secretary O'Leary, and in just her first year, the number of Cooperative Research and Development Agreements (CRADAs) negotiated between the DOE and academia, industry, and others doubled those negotiated while under Secretary Watkins tenure.

Since the Cold War had ended, and given the focus on the environment, nuclear power had lost major attention by the DOE except for the ongoing nuclear waste cleanup. This changed with the election of President George W. Bush in 2001. President Bush was a proponent of both nuclear power and the oil industry, so during his administration the DOE had a renewed focus on nuclear and oil energy. The capstone of Bush's energy policy was the Energy Policy Act of 2005 (Public Law 109-58) that provided a broad range of subsidies for nuclear and oil companies.

When President Barack Obama was elected in 2008, he brought a renewed attention to how energy impacts the environment. *Clean energy* was the term coined to represent energy sources that have a much smaller negative impact to the environment than coal, oil, and nuclear. Under the Obama Administration's energy policy, several investments were made in clean energy including, tax credits for the solar and wind industries, funding for a smart grid, and subsidies to make low-income homes more energy efficient. The funding for these investments were provided through the American Recovery and Reinvestment Act of 2009 (Public Law 111-5). As stated in the Act, the purpose of this policy was for: "Making supplemental appropriations for job preservation and creation, infrastructure investment, energy efficiency and science, assistance to the unemployed, and State and local fiscal stabilization, for the fiscal year ending September 30, 2009, and for other purposes."

Current Organization of the DOE

As of late 2018, the DOE is led by Secretary James Richard Perry, the fourteenth Secretary of Energy. The Department is operating relatively similar to past year's departments under prior administrations. The Department's 2019 fiscal year budget request for $30.6 billion consists of six major programs. The National Nuclear Security Administration is the largest program by request amount of $15.1 billion of which $11 billion is designated for weapons activities. The next largest funding request of $6.6 billion is from the Environmental Management program to be used for continuing the cleanup of waste generated from 50 years of nuclear weapons development and public nuclear energy research. With a request of nearly $5.4 billion, the Office of Science uses funding to continue the DOE's long history of early-stage research and development in an effort to stay at the forefront of scientific innovation. The fourth major category of the budget requests comes from the Energy program. The Energy program uses its funding to promote technologies that will make the American energy supply more reliable, affordable, and efficient. The department's budget by major organization over the past several years is presented in Figure 2.1 below. Additionally, Figure 2.2 presents the extramural research budget of the DOE over the past several years.

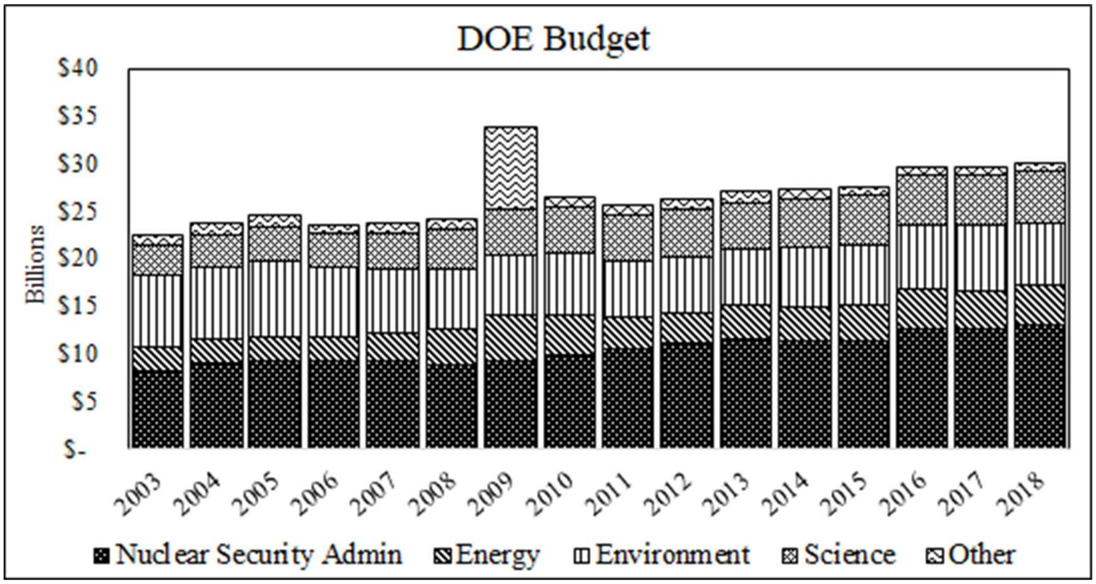

Figure 2.1: Department of Energy Budget by Major Organization:
Source: https://www.energy.gov/cfo/listings/budget-justification-supporting-documents

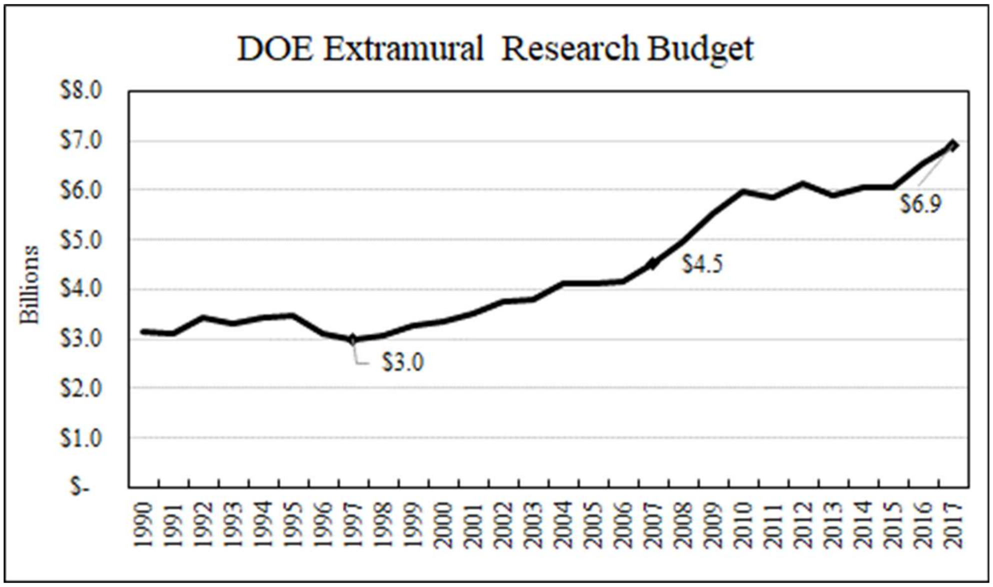

Figure 2.2: DOE Extramural Research Budget

Consistent with its origins, the DOE continues to engage in innovative research. According to its most recently released strategic plan (DOE, 2014, p. 10): "DOE will continue to pursue scientific discoveries that lay the technological foundation to extend our understanding of nature and create new technologies that support DOE's energy, environment, and security missions."

Seventeen DOE national laboratories are used to advance the Department's mission and aid in translating basic research to innovation. The national laboratories are critical to scientific innovation and possess unique instruments and facilities not found anywhere else in the world. The DOE, through its Office of Science, also funds user facilities that provide researchers from academia, industry, and the government with advanced scientific tools to perform new scientific research. In fiscal year 2015, over 32,000 researchers spanning all 50 states and Washington DC utilized a user facility (DOE, 2015).

Furthermore, 10 of the 17 national laboratories fall under the DOE's Office of Science. The Office of Science is "the lead federal agency supporting fundamental scientific research for energy and the Nation's largest supporter of basic research in the physical sciences", (DOE-OS, n.d., para. 1). The Office of Science administers eight programs, which includes the Small Business Innovation Research (SBIR) program; the DOE is currently one of 11 federal agencies that participates in the program. In addition to the Office of Science, seven additional DOE offices participate in the SBIR program.

Table 2.2 shows the DOE offices that participate and links to their mission statements. The DOE, consistent with the other ten federal agencies that participate in the SBIR program is currently required to set aside 3.2 percent of its extramural research budget to provide funding to the SBIR program. As of 2017, the extramural research budget at the DOE was $6.9 billion, therefore, the amount set aside for the SBIR program was $223.7 million.

Table 2.2: Department of Energy SBIR Program Participating Offices

DOE Office	Link to Mission Statement
Office of Cybersecurity, Energy Security, and Emergency Response	https://www.energy.gov/ceser/office-cybersecurity-energy-security-and-emergency-response
Office of Electricity	https://www.energy.gov/oe/office-electricity
Office of Energy Efficiency and Renewable Energy	https://www.energy.gov/eere/office-energy-efficiency-renewable-energy
Office of Environmental Management	https://www.energy.gov/em/office-environmental-management
Office of Fossil Energy	https://www.energy.gov/fe/office-fossil-energy
Office of Defense Nuclear Nonproliferation R&D	https://www.energy.gov/nnsa/missions/nonproliferation
Office of Nuclear Energy	https://www.energy.gov/ne/office-nuclear-energy
Office of Science	https://science.energy.gov/
Office of Advanced Scientific Computing Research	https://science.energy.gov/ascr/
Office of Basic Energy Sciences	https://science.energy.gov/bes/
Office of Biological and Environmental Research	https://science.energy.gov/ber/
Office of Fusion Energy Science	https://science.energy.gov/fes/
Office of High Energy Physics	https://science.energy.gov/hep/
Office of Nuclear Physics	https://science.energy.gov/np/

CHAPTER III: LEGISLATIVE HISTORY OF THE SBIR PROGRAM

The SBIR Program

Earlier than the legislative birth of the SBIR program, Congress recognized that small businesses were important to economic growth, and that they may require special treatment to remain competitive with larger enterprises. In 1953, Congress established the Small Business Administration (SBA) through the Small Business Act of 1953 (Public Law 85-536). As stated in the legislation the intent of the Act of 1953 is to:

> … aid, counsel, assist, and protect insofar as is possible the interests of small-business concerns in order to preserve free competitive enterprise, to insure that a fair proportion of the total purchases and contracts for supplies and services for the Government be placed with small-business enterprises, and to maintain and strengthen the overall economy of the Nation.

Over the next several years following the enactment of the Act of 1953, Congress provided assistance to small businesses through four primary programmatic functions: access to capital (e.g., direct business loans and guarantees on bank loans), education and counseling on the entrepreneurial process, government contracting (e.g., helping small business get government procurement contracts), and advocacy.

By the late 1970s, Congress was concerned that the United States was becoming less competitive in the global economy. There was also growing evidence that small businesses were becoming more important in job creation and the innovation process (NRC, 2008). For example, in 1979, a report from MIT's Neighborhood and Regional Change program was published that highlighted the significance of small business in the job creation process (Birch, 1979). Birch found that (1979, p. 29):

> On average about 60 percent of all jobs in the U.S. are generated by firms with 20 or fewer employees, about 50 percent of all jobs are created by independent small entrepreneurs. Large firms (those with over 500 employees) generate less than 15 percent of all net new jobs.

Small business's majority share in job creation at the time was, at least partially, driven by their entrepreneurial ability to adjust to the changing global economy. The early 1980s have been referred to as the Entrepreneurial Economy and according to Link and Scott, (2013, p. 14), "…smaller firms have a greater ability to be innovative, or to adopt and adapt others' new technologies and ideas, and thus quickly and efficiently appropriate investments in new knowledge that are made externally."

Although Congress had long recognized small businesses as being important for stimulating economic growth plus the then growing evidence of their importance in job creation, there was growing concern that this sector was being neglected. In 1977, an SBIR prototype program at the National Science Foundation (NSF), designed by Roland Tibbetts, began. Tibbetts, who worked in the private sector for several years before joining the NSF, foresaw a three-phase program structure:

> … in order to foster the R&D of small, high-tech businesses and push them to realize their commercial potential. He believed these firms were instrumental in converting government R&D into public benefit through technological innovation and commercial applications, therefore stimulating aggregate economic growth. (SBIR-STTR, n.d., para. 3)

Following the success of the prototype program, in 1982, Congress amended the 1953 Act, with the intent: "…to strengthen the role of the small, innovative firms in federally funded research and development…" In the 1982 amendment to the Act of 1953, Congress stated:

(1) technological innovation creates jobs, increases productivity, competition, and economic growth, and is a valuable counterforce to inflation and the United States balance-of-payments deficit;

(2) while small business is the principal source of significant innovations in the Nation, the vast majority of federally funded research and development is conducted by large businesses, universities, and Government laboratories; and

(3) small businesses are among the most cost-effective performers of research and development and are particularly capable of developing research and development results into new products.

The amendment to the Small Business Administration Act, specifically the Small Business Innovation Development Act of 1982 (Public Law 97-219), established the SBIR program. The objectives of the program are:

1. to stimulate technological innovation,
2. to use small business to meet federal research and development needs,
3. to foster and encourage participation by minority and disadvantaged persons in technological innovation, and
4. to increase private sector commercialization of innovations derived from federal research and development.

To be eligible for funding from the SBIR program, a firm must meet the following criteria:

1. employ fewer than 500 employees;
2. be independently owned with at least 51 percent ownership by U.S. citizens or lawfully admitted permanent resident aliens;
3. not be the dominant firm in the proposed projects field;
4. be a for profit organization;
5. be the primary employment of the project's principal investigator.

The proposing firm must also perform at least two-third of the R&D work in Phase I and at least one-half in Phase II.

The Amendment to the 1982 Act required that each federal agency with external research program budgets greater than $100 million for fiscal year 1982 and any subsequent year establish and fund their own SBIR programs. Regarding the amount each agency must reserve for the SBIR program, the Act stated each qualifying agency:

> … shall expend not less than 0.2 per centum of its extramural budget in fiscal year 1983 or in such subsequent fiscal year as the agency has such budget, not less than 0.6 per centum of such budget in the second fiscal year thereafter; not less than 1 per centum of such budget in the third fiscal year thereafter, and not less than 1.25 per centum of such budget in all subsequent fiscal years with small business concerns specifically in connection with a small business innovation research program which meets the requirements of the Small Business Innovation Development Act of 1982 and regulations issued thereunder.

To achieve the program objectives a two-phase competitive research awards program was established. The Phase I awards are a relatively small amount and generally covers a six-month period. The intent of the Phase I award is to aid domestic businesses in analyzing the technical merit (i.e., proof of concept) and feasibility of commercializing the proposed R&D effort. The Phase II award, which is based on the success of the Phase I research, is larger and the research typically lasts for about two years. The intent of the second phase is to continue the R&D efforts initiated in the first phase, ideally resulting in commercializable output. Only Phase I SBIR projects are eligible to apply for Phase II awards, but not all Phase I awarded firms receive a Phase II award. Beyond the two phases officially supported by the SBIR program, a third phase is defined, Phase III, which is unfunded by the SBIR program; it is intended to define that period of time when the small business pursues commercialization of the efforts from the first two phases. The expectation is that the funded firm will seek third-party financial support for this final phase.

The 1982 Act was not permanent therefore, it has been subject to several reauthorizations and a few amendments that modified the structure of the SBIR program. The first reauthorization was in 1986 through the Department of Defense Appropriation Act of 1986 (Public Law 99-443), which extended the 1982 Act through 1992. In 1992, the Small Business Research and Development Enactment Act, (Public Law 102-564), reauthorized the SBIR program until 2000. The 1992 reauthorization increased the maximum set-aside rate from 1.25 percent to 2.50 percent, re-emphasized the goal of increasing private sector commercialization of SBIR funded technologies, increase Phase I awards to $100,000 and Phase II awards to $750,000, and broadened the third program objective to include women. The Small Business Reauthorization Act of 2000 (Public Law 106-554) reauthorized the SBIR program until September 30, 2008, without modifications to the required set-aside rates or award amounts.

In 2008, Congress failed to reauthorize the SBIR program by the September 30 deadline date; however, Congress did extend it through March 20, 2009 through Public Law 110-235. On March 19, 2009, Public Law 110-10 extended the program through July 31, 2009, and it was again extended until September 30, 2009, by a Senate continuing resolution (S.1513). House bill (H.R. 3614) was passed on September 23, 2009, which extended the SBIR until October 31, 2009. On March 30, 2010, the Small Business Administration amended the SBIR Policy Directive. This amendment increased the available Phase I award amount to $150,000 and Phase II award amount to $1,000,000 as proposed in the failed Senate bill, S. 3029, from September 2008.

Senate bill, S. 1929, extended the program through April 30, 2010, and the Senate continued the trend with the short-term extension via S. 3253, which extended the program until July 31, 2010. The program was then extended again through September 30, 2010 by the House (H.R. 5849), and then again through January 31, 2011 by the Senate (S. 3839). The House followed suit by extending the SBIR program until May 31, 2011 (H.R. 366). On May 31, 2011, the Senate temporarily extended the program again through September 30, 2011 (S. 1802). Two consecutive house bills extended the program, first to November 18 (H.R. 2608) then to December 16, 2011 (H.R. 2112). H.R. 2112 was the last of the temporary extensions resulting from Congress's failure to reauthorize the SBIR program in 2008.

On December 31, 2011, President Obama signed the National Defense Authorization Act of 2012 (Public Law 112-81) which codified the reauthorization of the SBIR program through September 30, 2017. On December 23, 2016, President Obama signed the National Defense Authorization Act of 2017, which reauthorized the SBIR program through September 22, 2022. Table 3.1 summarizes the key legislation that has kept the SBIR program running since its inception.

Currently, there are eleven agencies participating in the SBIR program, and the set-aside rate is now 3.2 percent through 2022. The agencies participating in the program are: Department of Agriculture, Department of Commerce, Department of Defense, Department of Education, Department of Energy, Department of Health and Human Services, Department of Homeland Security, Department of Transportation, Environmental Protection Agency, National Aeronautics and Space Administration, and National Science Foundation. Of the eleven participating agencies, five account for approximately 97 percent of all SBIR funding, with the Department of Defense committing the largest share.

Table 3.1: SBIR Program Legislation

Legislation	Public Law	Authorization Period
Small Business Innovation Development Act of 1982	97-219	1982-1986
Department of Defense Appropriation Act of 1986	99-443	1986-1992
Small Business Research and Development Enactment Act of 1992	102-564	1992-2000
Small Business Reauthorization Act of 2000	106-554	2000-2008
Short-term extensions	---	2008-2012
National Defense Authorization Act of 2012	112-81	2012-2017
National Defense Authorization Act of 2017	114-328	2017-2022

Source: Based on Link and Scott (2013) Table 5.1 with additional information.

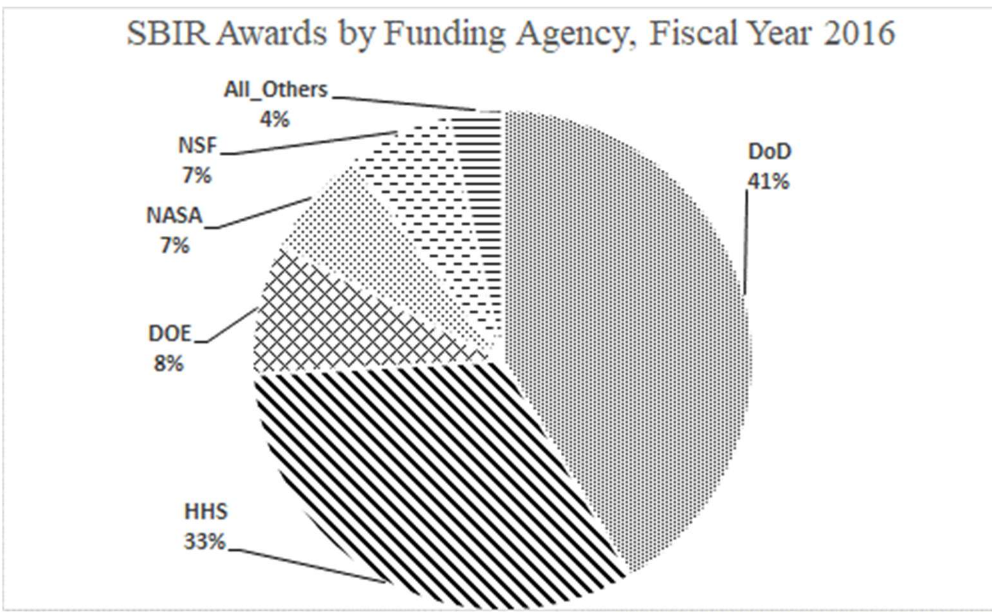

Figure 3.1: SBIR Program Funding by Major Department

Source: 2016 SBIR AND STTR ANNUAL REPORT

The Empirical Literature on the SBIR Program

As part of the SBIR Reauthorization Act of 2000 (S. 493, Sec 307), the National Research Council (NRC)[2] received a mandate to report on assessments of the SBIR program, to each funding agency, and required updates every four years. The intent of the assessments is to understand the economic benefits of the program. Prior to the 2000 mandate, there was a relatively limited body of literature that assessed the program (National Academies, 2016), especially given the size of the program. Since the first round of mandated assessments the literature has grown substantially. Today, there is a significant literature that has studied many facets of the SBIR program. Areas that have been studied include general policy evaluations (e.g., Link and Scott, 2009; Gicheva and Link, 2013), the SBIR programs association with employment growth (e.g., Link and Scott, 2012a; Link and Scott, 2012b), although creating employment opportunities is not part of the programs stated mission, spillover benefits (e.g., Audretsch et al., 2002; Allen et al., 2012), and the mechanism of the award system itself (e.g., Bhattacharya, 2018). In a recent assessment of the SBIR program at the DOE, the National Academies, (2020) expanded the focus of its assessment relative to the 2016 review (Academy, 2016). The recent review stated the objectives of the review were to examine

- A range of economic impacts including, to the extent practicable, the number of jobs created by these programs;
- The role of SBIR/STTR programs in stimulating technological innovation and contributing to DOE's research and development needs;
- Collaborations created between small businesses and research institutions on account of the programs;

[2] NRC refers to the National Research Council from this point forward as opposed to the National Regulatory Commission, unless otherwise noted.

- The effectiveness of DOE’s SBIR/STTR award-selection process and commercialization assistance; and

- Ways to improve outreach efforts to SBIR/STTR applicants, particularly to increase applications from small businesses that are (1) new to the programs, (2) from underrepresented states, (3) woman-owned, or (4) minority-owned. (Academy, 2020, p. 22)

As it relates to this dissertation, two areas of the empirical literature are focused on: the commercialization success or failure of funded projects and spillover benefits from the SBIR program.

Government intervention in markets should, theoretically, be designed to overcome or ameliorate a market failure. The market failure in the case of small firm technology development and commercialization is that there is an underinvestment in private R&D. Invoking market failure as the justification for the SBIR program suggests that the net social benefits associated with the program are positive. If public funding for private R&D increases private benefits to be at least equal to private costs, then society will be able to realize the social benefit, otherwise the R&D effort should not be undertaken.

Concerned with estimating the social rate of return from the SBIR program, Audretsch et al. (2002) analyzed data from interviews conducted by Link and Scott (2000) of DoD SBIR award recipients for 44 projects in 43 companies. Audretsch et al. (2002) found that, on average, across the 44 projects for which they had data, the expected private rate of return without SBIR funding was 25 percent while the lower bound of the expected social rate of return was 84 percent. The gap between the private return and social return is driven by a lower social required rate of return (hurdle rate) and difficulties appropriating the return on investment of the R&D. The private hurdle rate is higher than the social hurdle rate, therefore, the social return will always be greater than the private return for R&D projects. Allen et al. (2012) also performed an analysis to estimate the social benefit from the SBIR program. Using data from the top five government agency SBIR program participants, Allen et al. (2012) estimated the producer and consumer surplus from the population of Phase II funded awards between 1992 and 2001. They assumed the firm bringing a new technology to market would enjoy monopoly power for some time until others enter the market. Using these surplus estimates the authors found the demand elasticities associated with a cost-benefit ratio of unity for the projects. All five agencies had elastic demands at a cost-benefit ratio equal to 1, and the DOE's elasticity was estimated to be 1.518. Allen et al., (2012) state that there is no known elasticity of demand however, it is likely the actual demand elasticity is lower than 1.518 due to the firm enjoying monopolistic power for some time. This implies a social benefit-cost ratio greater than 1, hence a positive spillover from the SBIR program.

While Audretsch el al. (2002) and Allen et al. (2012) were concerned with identifying the presence and measure of social benefit from the SBIR program, Link and Ruhm (2009a) discuss the source of the societal spillover by analyzing the vocational background of entrepreneur's who received SBIR funding from the NIH. Link and Ruhm (2009a) explained that human capital from R&D projects can add to societies benefit through two competing channels; one public (research publications) and one private (patents). They found that entrepreneurs with business backgrounds have a 9.5 percentage point decrease in the probability that the intellectual capital will be disseminated through publications only. They also found that when an entrepreneur partners with a university there is an 11.3 percentage point increase in the probability that publication is the only source to propagate intellectual capital.

In a study using data from the NIH SBIR program, Toole and Czarnitzki (2009) analyze the association between the human capital of scientists with a biomedical academic background and firm performance. The authors found, "that academic scientific knowledge has an institutional specificity that limits its transferability or applicability to a commercialization environment…" (Toole and Czarnitzki, 2009, p.112). This result is consistent with Link and Ruhm (2009a) and further points to the idea that the source of the knowledge spillover is more likely to be from publications than from patents. Toole and Czarnitzki (2009) further explain that the former result is most prevalent when the principal investigator is more adept at basic research or idea generation as opposed to applied research.

Commercialization is only one of the objectives of the SBIR program; however, discussions about the success of the program often cite commercialization activity as the success metric. Phase III, albeit a phase without official support from the SBIR program, is when commercialization is supposed to occur. The program does not award funds past Phase II so any additional capital needed to bring the R&D to market must come from alternative sources than the SBIR program. Therefore, it is quite possible that a small business will be awarded both Phase I and II awards but fail to bring their efforts to market.

In a study using data from NIH SBIR Phase II funded projects, Link and Ruhm (2009b) estimated the probability a project will commercialize as a function of receiving additional funding plus other control variables. The dependent variable was a binary indicator equal to one if the firm commercialized their research. The authors found that if a firm received additional funding above the Phase I and II awards, then the probability of commercializing was approximately 35 percentage points higher than without. Link and Ruhm (2009b) also found that when a university is involved with the project, the probability of commercializing increases by 12 percentage points over those that did not have university involvement.

In a similar study, Siegel and Wessner (2012) were concerned with how university involvement is associated with the commercialization success of SBIR award recipients. Instead of a binary indicator of success as mentioned previously, Siegel and Wessner (2012) define seven measures related to aspects of commercialization: (1) actual sales,

(2) expected sales, (3) new employees, (4) patents applied for, (5) copyrights applied for, (6) trademarks applied for, and (7) licensing agreements consummated. The authors regressed each of the seven metrics separately onto several factors including an indicator for university involvement and a variable for the amount of additional funding other than from the SBIR. In all seven models the parameter estimate on the university involvement indicator was positive and relatively large in magnitude. However, the estimates were not statistically significant in the models for new employees or trademarks applied for. None of the models had a significant parameter estimate on the additional funding variable and the signs of the estimates were not consistent.

Link and Scott (2010), provided further evidence to the discussion surrounding successful commercialization of SBIR funded projects. Link and Scott evaluated the probability of commercialization at the five largest SBIR participating agencies using a binary dependent variable of sales. The binary indicator registers a value of one if there had been some sort of commercialization such as sales of products, processes, services, rights to technology, or spin off companies. They found that the average of the predicted probabilities of commercialization, by the firms sampled, at each agency, were all slightly less than 50 percent.

The SBIR program, which was initially passed in 1982 and renewed several times, provides an opportunity for small businesses to conduct R&D projects that they would not be able to take on without the funding. Small businesses are crucial in bringing innovative technologies to market, however, often lack the funding required to do so. The SBIR program makes it possible for many small businesses to pursue R&D projects that result in a new technology that generates social benefit. In total, the social benefit generated from the SBIR program is much greater than the cost. The importance of the SBIR program in stimulating R&D among small businesses is confirmed through the continued renewal of the program. Much of the literature examining the SBIR program has largely focused on defining and measuring the success of the SBIR program as it relates to outcomes of the programs stated objectives. However, there is a very limited body of research that examines the factors associated with publicly funded project failure; this dissertation begins to fill that gap.

CHAPTER IV: R&D PROJECT FAILURE

Failure is often defined in terms of the lack of success of an undertaking. By this definition, the definition of failure is not independent of the definition of success. There may be varying degrees of failure coupled with varying degrees of success. This situation may arise in many ways especially ifn the undertaking is able to be measured for completeness at distinct intervals or by independent project components/ goals. However, failure can also be thought of as a binary descriptor to describe the situation when the initial undertaking was not fully successful in terms of the original plan. Therefore, measures of success or failure can be thought of in multiple ways and often the data available to analyze these metrics determine how the success or failure metric is defined.

The metrics for success that have been studied have generally focused on the purposeful output or outcome of a business or project; and from an empirical perspective success has been modeled to be a function of project and firm characteristics. Only a few researchers have considered how key individuals contributed to success.

As an example of a study of how key individuals contributed to success, Mansfield and Wagner (1975) collected detailed data on three firms in the industrial R&D sector and defined three measures of the probability of success. They classified the projects in their sample as either technology push or demand-pull projects[3] and they found that technology-push projects are likely riskier and less likely to succeed than demand-pull projects. Using semi-structured interviews of key personnel collected from a two-phase sampling of 103 projects from six firms from 1969-1973, Rubenstein, Chakrabarti,

[3] Technology push projects typically do not have a current market demand whereas demand pull projects are typically initiated in response to a current market demand.

O'Keefe, Souder, and Young (1976) defined several measures of success. The study elaborates that measures of success are specific to each project and factors associated with success encompass human, social, and communication factors. The authors stated that success cannot be achieved by the organization as a whole, but in an overwhelming number of cases a key individual was critical to the project's success.

Siegel and Wessner (2012) used data from the NRC database of Phase II SBIR funded projects to define seven output measures of success and study factors associated with each measure. Two of their defined measures of success were expected sales and actual sales, which were shown to be positively related to the age of the project, entrepreneurial experience of the founder, and size of the award. In a study looking to understand how behaviors of key individuals, namely project managers, shape the success of a project, Nixon et al. (2012, p. 210) found that "…research, leadership style and personal traits have also been identified as a critical success factor, determining either the success or failure of a project."

As mentioned above, understanding factors associated with a particular key individual involved with the success of a project or business has been recognized by only a few researchers thus is an area of research that should be further developed. Similarly, understanding how individuals may contribute to the failure of a project should be further developed, and such studies are even more limited than studies of project success.

Project failure could be thought of as a perfect complement of success; however, that logic may not always hold. Using survey data of 97 project managers to explain why projects fail, Pinto and Manuel (1990) suggested that failure is not a binary outcome; it can vary across projects as well as in various phases of the project. They suggested that there are three distinct benchmarks to measure project performance: the implementation process itself; the perceived value of the project; and client satisfaction with the delivered project.

Shepherd and Wiklund (2006) reviewed literature aimed at answering why businesses fail. They discussed that failure is hard to define, should be studied as a process as opposed to an instantaneous event, and that economic reasons should define a business failure. They defined three causes of business failure: liability of newness, overconfidence, and lack of human capital including experience. In this sense, failure is defined as a binary outcome as opposed to a more fluid measure.

Liability of newness can be associated with the business itself. Gicheva and Link (2016) consider such liability in a study designed to estimate the probability of an SBIR project resulting in commercialization conditional on not failing. They used data from the NRC database on Phase II funded SBIR projects to derive their estimates and found that nascent firms were 20 percent more likely to fail than a non-nascent firm.

Overconfidence and lack of human capital are factors that link human characteristics to failure but not necessarily a specific individual trait, given groups of people, such as a management team, can exert similar traits. For example, using data on 18 R&D projects that failed from the Israeli bio-medics electronic sector, Spiller and Teubal (1993) examine behaviors that are associated with firms' failed R&D projects. They found that project failure can be brought on by inappropriate firm behavior or because of uncertainty or both. Their study elaborated that choice of program and faulty program execution are examples of inappropriate firm behavior, both of which are likely undertaken by some form of management or project team. Similarly, Sauser, Reilly, and Shenhar (2009) analyzed information from the National Aeronautics and Space Administration's (NASA's) Mars Climate Orbiter project with a particular focus on managerial decisions impact on project failure. They found that in many cases it is not technical details, mishaps, or poor designs that lead to project failure; it often results from managerial ineffectiveness.

As suggested by Rubenstein et al. (1976), a key individual may possess certain characteristics that ultimately determine the failure or success of a project. Link and Wright (2015) conducted a study to understand what drivers lead to SBIR project failure. One of their explanatory variables was gender of the principal investigator assigned to the project. They found that if the principal investigator was a woman, there was a reduction in the probability of project failure. One explanation of this result may be that women have inherent characteristics, such as higher risk aversion compared to their male counterparts, which results in them failing less often on average. In a similar study, Andersen et al. (2017) considered why SBIR projects fail. They used data from a sample of 461 projects funded by the NIH SBIR program and found gender to be a significant factor, too. Specifically, they found a negative correlation between project failure and if the founder of the small business was a woman. They also found a negative correlation between project failure and if the business founders had a background in business.

The literature around project failure has often suggested that the reasoning for failure cannot be defined universally across all projects. Failure can be both a perfect complement to success or failure can be accompanied with partial success. However, the majority of the studies related to project failure have examined the reasons for project failure at the firm, managerial, or project level and have not explicitly focused on more micro-level dynamics within each project. Although each project may be unique in many facets, common across the majority of R&D projects is the presence of a principal investigator. For this reason, it follows that an understanding of the role PIs play in projects and various factors associated with them may provide further insight into understanding failure of projects. The literature on PIs is relatively small, though growing as the importance of PIs is becoming known; the performance of PIs may provide insight into understanding how likely it is that a project will fail. In the next chapter, I review the literature on PIs, which confirms there is a lack of research that examines key individual's association with project failure.

CHAPTER V: PRINCIPAL INVESTIGATORS

PIs play a critical role in the scientific community as lead scientists and more recently as effective managers. They are the leaders of R&D projects and, therefore, are critical individuals in the R&D process. It is important to deepen our understanding of PIs involvement in the innovation process since they are the people leading R&D projects that can bring new technologies to market that provide a large social benefit. Understanding PIs role in publicly funded R&D projects should shed light on how characteristics of them are associated with project failure. The remainder of this chapter reviews the relatively small but growing body of literature on PIs, which has a central focus of the importance and multifaceted responsibilities of PIs.

In a recent report by the Joint Research Centre (JRC), the authors highlight the dichotomous role of PIs being scientist and managers stating, "The PC [PI] has primary responsibility for creation of the project concept in almost 60% of projects surveyed. The PC [PI] also has the primary responsibility for selection of project partners and planning timelines and budgets in a majority of projects" (Cunningham, O'Reilly, Hooper, Nepelski, Roy, 2020, p.3). The behavioral importance of PIs, especially publicly funded PIs, has been growing as the institutional landscape evolves. Cunningham et al. (2016a), using survey data based on semi-structured interviews of the population of publicly funded PIs in Ireland over the years 2009-2014, examined the roles and activities of the scientists who are publicly funded principal investigators. They found that the roles of the principal investigator include being a project manager, an administrator, a science broker, and more recently as a boundary spanner (i.e., ability to bridge different areas and domains such as the academic sector and the private sector).

For publicly funded PIs acting as scientist, it is standard practice to share their research outcomes through the traditional channels such as scientific papers and conference presentations (Baglieri and Lorenzoni, 2014). However, PIs now face additional requirements outside those a traditional scientist would encounter. Public programs, especially those that are technology-focused, also expect the PI or the PI's funded organization to commercialize from their research. This paradigm has augmented the role and responsibilities of the traditional PI. Cunningham et al. (2016a, p. 67) discuss the growing importance of PIs stating that, "publicly funded PIs are key assets and the combination of their novel efforts and their capability to meet the expanding PI role means they are a core and critical actor in transforming scientific, economic and societal environments."

PIs have generally been referred to as *knowledge brokers* (e.g., Kidwell, 2013), and they are key actors in bringing their innovations to market. Using data from a survey of 135 universities, Thursby et al. (2001) found that 71 percent of early stage inventions required the inventor's cooperation to successfully commercialize their invention. They found that industry partners required the specialized knowledge only the inventor possessed to be able to move the innovation from early stage development to a product able to be commercialized. With reference to Mangematin, O'Reilly and Cunningham (2014) and Cunningham et al. (2016b), the latter (p. 779) sum up the importance of publicly funded PIs, stating that "…publicly funded principal investigators are the linchpin of knowledge transformation through articulation of research programmes, the shaping of research avenues and the bridging of academia and industry." Further, in a paper that examined the social origins of innovation failure, Pedraza (2017, p. 441) discussed the importance of building teams stating, "…bridging large cognitive distances—often a prerequisite for breakthrough innovation—requires the frequent, face-to-face interaction of members from the relevant distant communities." While the author does not specifically discuss PIs, as discussed previously, PIs are the team members who carry this responsibility. Therefore, Pedraza's finding further supports the notion that PIs are critical participants in the innovation process.

Because PIs are the scientists who generate the ideas for innovations and are in large part responsible for the success of their R&D projects, public funding agencies are de facto choosing to fund specific PIs. In fact, according to the SBIR program:

> Every SBIR … proposal must designate a single individual who will serve as the principal investigator on the proposed project. The PI has overall responsibility for the project, and therefore must be credible in terms of his/her education, work and project management experience (SBIR-STTR, 2018b, p. 1).

Having overall responsibility of a research project requires the PI to oversee the day to day operations of the project, provide updates to stake holders, manage staff, sign off on budgets and financial plans, ensure deadlines are met, and submit technical documentation (Cunningham et al., 2016a). When a funding agency allocates resources to an R&D project, it is de facto trusting the PI to accomplish the mission of the project successfully.

The designation of PI may be viewed as an accomplishment that recognizes a scientist as reaching a certain level or milestone in their career. Being a PI conveys status within the academic community and with that accreditation, additional resources may be allocated to the PI to assist in endeavors that add both economic and non-economic value to the research (Cunningham et al., 2017). Because becoming a PI does not happen by chance, and given their high rank in the scientific community, it is useful to understand how or why a person is elevated to PI. In a case study of thirty projects in Ireland's science, engineering, and technology sector from 2009-2014, Cunningham et al. (2016b) found that scientists tended to become PIs because of either a pull factor or a push factor. The three pull factors identified were control over the project, motivation or career advancement, and ambition/ personal drive. The two push factors identified were lack of other options or project dependencies and institutional pressures.

No matter the reason or reasons that a person becomes or is designated as a PI, being a PI results in additional responsibility beyond that of a research scientist. As stated above, the PI has the overall responsibility for an R&D project and therefore must be multifaceted in their abilities. Using survey data based on semi-structured interviews of the population of publicly funded PIs in Ireland over the years 2009-2014, Cunningham et al. (2016a), found that PIs must act as project managers, administrators, science brokers, and have the ability to bridge the gap between multiple domains such as the private and academic sectors. Kidwell (2013) echoed the notion of PIs being boundary spanners through a case study of four PIs, involved in nanotechnology research funded by the SBIR program, that have successfully commercialized their research. Similarly, Boehm and Hogan (2014) collected data from semi-structured interviews of 82 stakeholders involved in 17 collaborative research projects in German and Irish universities, 25 of the interviews were with PIs. Using these data, they found PIs must take on multiple roles such as project manager, negotiator, resource acquirer as well as the traditional academic.

PIs, as boundary spanners, play an important role in commercialization-related activities associated with R&D projects. PIs are at the center of the entrepreneurial network system that includes funding agencies, venture capitalists, banks, entrepreneurs, and high growth small and medium enterprises (SMEs) (Cunningham et al., 2017). Each participant in the entrepreneurial process seeks to maximize their return on investment, albeit a monetary or non-monetary investment. The PI’s role becomes even more challenging when participants in the process have competing interests. Cunningham et al. (2014) discussed the inhibiting factors associated with PIs leading publicly funded research programs. They found a key tension between the entrepreneurial and scientific outcomes. The PIs employer and other stake-holders may pressure the PI to commercialize their research, but as a scientist the PI may be less interested in capitalizing on the research and more interested in moving the science forward (these objectives may not be mutually exclusive).

Commercialization of the firm’s output requires the PI to engage in entrepreneurial activities. The push by the PI’s employer and other stakeholders to commercialize their research does not necessarily translate to the PI having a strong desire to be a successful entrepreneur. PIs, as project lead, have some autonomy when it comes to how they allocate their time across the various boundary spanning tasks. Del et al. (2017) used data from the Eurobarometer survey and a questionnaire to PIs in Europe to understand what factors are associated with PIs preferences towards entrepreneurial activities and their performance. They found that PIs still lean toward research over entrepreneurial activities but that a country’s culture towards entrepreneurship may influence a PI to have a greater preference towards entrepreneurial activities. PIs may prefer research activities over entrepreneurial activities; however, the ability to acquire external funding is increasingly being viewed as a core competency (Geuna and Nesta, 2006). Further, since PIs are at the center of the entrepreneurial ecosystem, they are by default key actors in transferring knowledge and commercialization activities (Cunningham et al., 2016; Menter, 2016; O’Kane, 2016). For these reasons, commercialization is an activity growing in importance that PIs may have to embrace.

When forming a research proposal, the PI must have an agenda for the project including whether to attempt to commercialize the research. With any innovative work there will be risk, uncertainty, or both associated with achieving the project’s goals. The presence of either risk or uncertainty should not alter a projects goals or deter the project itself from being undertaken as long as the risk or uncertainty are not prohibitive. O’Kane et al. (2017) discuss particular risk factors associated with commercialization of publicly funded R&D projects. Using data from semi-structured interviews with 24 funded health science PIs in New Zealand, the authors found four factors that inhibit PIs from incorporating or completing commercialization as a part of their research plan. The factors are (2017, p. 216):

(1) PI-funding body trust; (2) disconnects between universities and funding bodies expectations; (3) deficiencies in TTO [technology transfer office] resourcing; and (4) levels of conflict/ complementarity between publication and commercialization activities in funded science.

Using ten case studies of PIs from Irish universities, O'Reilly and Cunningham (2017), examined the barriers and enablers to successful technology transfer to SMEs from university research and the role university plays in the success. They found asset scarcity as a barrier to successful technology transfer with SMEs. Also considered was the geographic proximity of the SME to the PI but this was not referenced as barrier to commercialization. However, social and cultural proximities were deemed significant. Further, an SME's perceptions of bureaucracy within university TTOs was cited as a barrier, and in some cases SME research relationships were undervalued because of the expectation of low financial returns.

When a PI oversees an R&D project that has received outside funding, the funding party expects the PI to deliver a successful project. If a PI fails to deliver a successful project, the funding party may begin losing trust in the PIs capabilities. The commercialization success of a research project has been studied as a barometer for measuring PIs successfulness. Recognizing success can have many different faces, Del et al. (2017) identified four key performance indicators (KPI) to measure PIs entrepreneurial intentions and performance in a cross-country comparison. The KPI's are, networking and resources acquired, innovations realized, technology transfer activities, and new spin-offs and start-ups. Kidwell (2013) analyzed the characteristics associated with PIs involved in nanotechnology who successfully commercialized their research. Kidwell found that prior success in commercializing their research has a strong correlation with future success. Further, successful PIs build trust with stakeholders by presenting solutions to a problem even when the industry is not initially aware of the problem. They build trust by anticipating the future and managing issues or conflicts. Essentially, successful PIs find potential industry partners and build a good relationship with them. Further, highlighting the importance of PIs reputation or track record of success, Boehm and Hogan (2014) found that industry partners may favor a specific PI regardless of the university that employs them.

The literature to-date on PIs has largely been focused on identifying their role and responsibilities in publicly funded R&D projects. PIs have been shown to be critical to the process and are generally required to perform a variety of duties in their role. In some sense, they are the gate keepers of new technology to market, which implies they have a large responsibility for delivering social benefit. As shown above, there is limited research on how characteristics of PIs are associated with project failure. Further, there has not been a theoretical formulation provided in the literature to explain how characteristics of PIs are associated with project failure. In the next chapter, I begin closing that gap by providing a microeconomic theoretical model to explain how characteristics of PIs may associate with R&D project failure.

CHAPTER VI: A THEORETICAL MODEL OF R&D PROJECT SUCCESS / FAILURE

In the following chapter, I propose a theoretical framework for thinking about how characteristics of a key individual, in a firm, involved in the R&D process may be associated with project failure; such construct is new to the literature. The model considers success and failure to be perfect complements and PIs are defined as the key individual within the firm.

When a firm, along with the PI, undertakes an R&D project, there is uncertainty about the success of the project as well as about any potential revenues if the project leads to a commercialized technology that enters the market as an innovation. Uncertainty results from many factors; in this chapter, the focus is on a particular factor, namely the ability of the project PI. The firm's PI is the one, within the R&D process, that has the ultimate decision-making power to drive the direction of the project. I posit that experience, E, of the PI is related to the success or failure of an R&D project—more experience is associated with a greater likelihood of success and less experience is thus associated with a greater likelihood of failure.

The PI, in concert with the firm, forms a team, and ultimately a technology is chosen to pursue (Leyden and Link, 2015); these actions—the formation of the team and the choice of a technology to pursue—define the R&D project. The experience of the PI is thus reflected in the selection of the team and the project to pursue, and thus the experience of the PI, along with available resources from the firm, is ultimately the factor that will be related to the success of the project pursued. Given the resources from the firm that are available for the selected R&D project, a PI with greater experience should tend to influence the selection of a portfolio of inputs that result in a project with higher likelihood of success relative to a lesser experienced PI.

Choosing the members of the R&D team is one of the most important decisions the PI makes. Without a team, or with a team that has insufficient ability, the PI may not have the necessary human capital to perform the required R&D successfully and/or to bring any resulting technology to market. PIs with more experience may have a larger and more relevant network—an internal to the firm network and an external network—of available team members; a larger network provides the PI with a greater potential supply of human capital to choose from. This point was emphasized by Schott and Sedaghat (2014, p. 472): "…that the size of the network around entrepreneurs positively affects innovation…" and "The more an entrepreneur networks, overall, the more innovative the entrepreneur is likely to be…"

Thus, the overall resource base available to the PI may be thought of as input to the R&D process; let Q represent a measure of quantity of the R&D-related inputs available to the project. With Q as a measure of input quantity, $p(Q, E)$ thus represents the probability of a new marketable technology brought to market. A success is defined as new marketable technology with positive expected profits. I assume that the $p(Q, E)$ function is a positive concave function that exhibits diminishing returns, therefore, $\frac{\partial p}{\partial Q} > 0$, $\frac{\partial^2 p}{\partial Q^2} < 0$, $\frac{\partial p}{\partial E} > 0$, and $\frac{\partial^2 p}{\partial E^2} < 0$. [4]

Let $R(q)$ represent a concave function that represents a mapping of quality of the resulting commercializable technology, that is the quality of the resulting innovation (i.e., the technology brought to market), q, to the revenues received by the firm that are generated from the sale of the innovation. $R(q)$ exhibits diminishing marginal returns,

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[4] It is possible that eventually Q could become too large, therefore reducing p at the margin, that is ∂p/∂Q<0, although this set of Q is not relevant under the assumption that the PI would never construct a project at that input quantity.

therefore, $\frac{\partial R}{\partial q} > 0$ and $\frac{\partial^2 R}{\partial q^2} < 0$. The quality of the resulting innovation is assumed to be a concave function of the quantity of the R&D inputs and PI input to the project, $q(Q, E)$, such that $\frac{\partial q}{\partial Q} > 0$ and $\frac{\partial q}{\partial E} > 0$.

The quality of the innovation is a measure of how much consumer surplus the innovation provides those who purchase it. For example, an innovation that cost less relative to a substitute product has a higher quality (q) than that of the substitute, since consumers would prefer to pay less when choosing between comparable products. Likewise, a product that has superior features that provides greater utility, sufficiently high to compensate for a possible higher price, is another example of higher quality. Thus, the expected revenues, R^e, from the innovation will be:

$$R^e = p(Q, E) * R(q(Q, E)), \tag{6.1}$$

and expected marginal revenues, with respect to either Q or E, will be

$$MR^e = p'(Q, E) * R(q(Q, E)) + p(Q, E) * R'(q(Q, E)) * q'(Q, E). \tag{6.2}$$

Naturally, there is cost associated with the R&D process. Leyden and Link, (2015) describe the entrepreneurial process as a two-step iterative process that incurs cost at each step. They posit that costs are funded by both personal endowments and capital markets depending on the phase of the process. Following Audretsch, Leyden, and Link, (2012), costs may be intellectual or physical and are both fixed and variable. In this construct, greater Q increases total cost, at an increasing rate, thus cost is a function of inputs. The cost function can be written as:

$$c = c(Q) \ni c(0) > 0, c'(Q) > 0, c''(Q) > 0. \tag{6.3}$$

The firm looking to maximize profits will choose an optimal combination of inputs, $Q*$, such that it maximizes expected profit:

$$\pi^e(Q,E) = p(Q,E) * R(q(Q,E)) - c(Q). \tag{6.4}$$

The optimal quantity of inputs conditional on the experience of the PI, $Q*$, is achieved by equating expected marginal revenue, MR^e, to marginal cost, MC, of the R&D project (Figure 6.1):

$$p(Q,E) * R'(q(Q,E)) * q'(Q,E) + p'(Q,E) * R(q(Q,E)) = c'(Q). \tag{6.5}$$

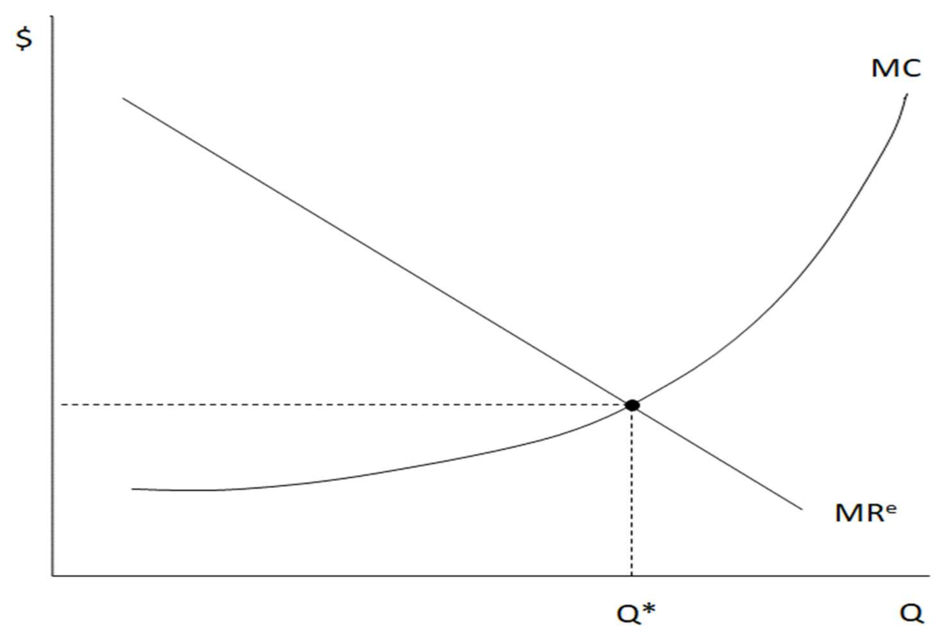

Figure 6.1: Profit Maximizing Choice of Experience

As mentioned previously, at the onset of an R&D project there is uncertainty around the ultimate success of the project. The PI's experience determines the ability of the quantity of inputs, Q, to generate a given quality, q, of the innovation, and ultimately the maximum expected profit. To illustrate this point, Figure 6.2 presents the expected profit curves as a function of project quality for two alternative projects, and Figure 6.3 presents the densities of the projects expected profits. From the two figures it is clear that the project with PI experience E_2, (project 2) has profits $\pi_2^e(Q, E_2)$ that are negative even at the profit maximizing choice of quality. The project with expected profits $\pi_1^e(Q, E_1)$ (project 1) has positive expected profits at the optimal quality level.

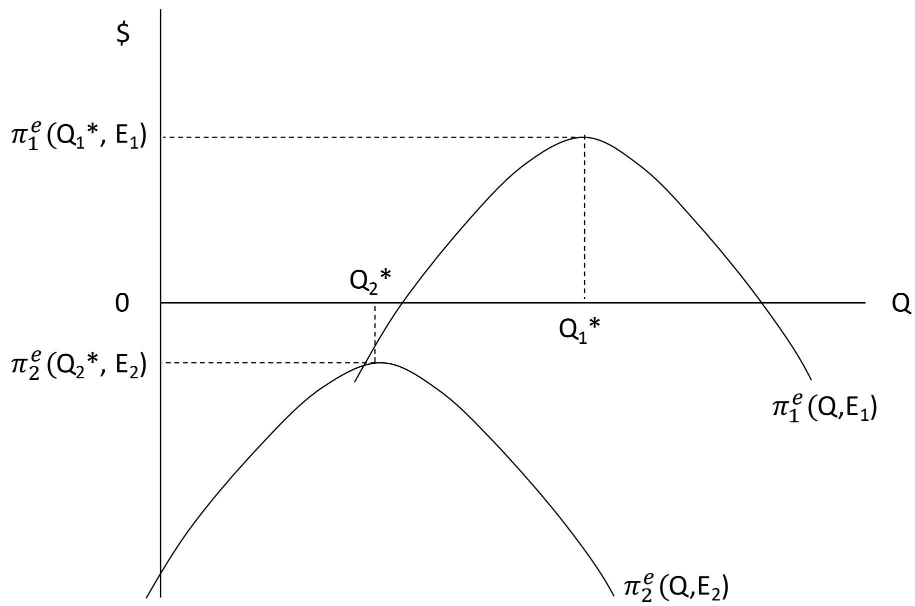

Figure 6.2: Profit Maximization Success and Failure

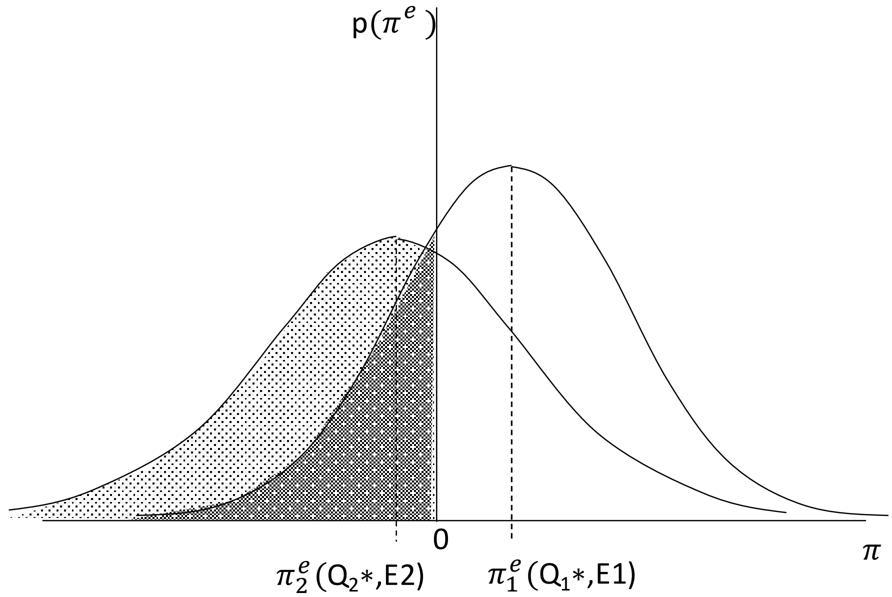

Figure 6.3: Expected Profit Distributions

Project 2 has negative expected profits because the quantity of inputs, Q*, that the PI is able to transform into a marketable product can only be sold at a price less than the average cost. Defining negative expected profits as the indicator of failure, $\pi^e(Q^*, E) \geq 0$, must hold true for the project to be categorized as a success. Therefore, project 1 would be one worth pursuing and project 2 would not.

From this conclusion it can be inferred, *ceteris paribus*, that the PI associated with project 1 has greater experience than the PI associated with project 2. Thus, my model suggests that the experience base of the R&D project's PI is positively related to project success. It follows then that the experience base of the R&D project's PI is negatively related to project failure.

CHAPTER VII: DOE SBIR DATA

Small businesses contribute substantially to the U.S. economy. As of 2014 (the most recent year complete data are available), small business5 share of private nonfarm gross domestic product was approximately 43.5 percent of the total, and as of 2014 contributed to just under half of the total number of employees in the U.S. in terms of nonfarm payrolls (Kobe and Schwinn, 2018). Of this important sector in the economy, the "Small Business Innovation Research (SBIR) program remains the nation's largest innovation program for small business" (National Academies, 2016, p.1). Hence, the data used in this dissertation are information gathered from recipients of a Phase II SBIR award. Specifically, the data are a random sample of 225 Phase II projects (referred to later as the full sample) funded by the DOE's SBIR program in the years 2001 through 2010.

The data were collected in 2014 through a survey (second-round survey) conducted by the Academy. The Academy is a "private, nonprofit institutions that provide expert advice on some of the most pressing challenges facing the nation and the world" (Academy, n.d.). As a result of legislation written in the SBIR reauthorization of 2000 (Public Law 106-554) and further emphasized by the 2011 SBIR program reauthorization (S. 493), the Academy was tasked with conducting an evaluation of the SBIR program. The reauthorization that occurred in 2000 states that,

> … each Federal agency with a budget of more than $50 million for its SBIR Program for FY 1999 to enter into an agreement with the National Academy of Sciences for the National Research Council

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[5] Small business in this case is defined as having fewer than 500 employees. According to the Small Business Administration size standard most small businesses qualify as small businesses under this rule. See https://www.sba.gov/sites/default/files/files/Size_Standards_Table.pdf.

> to: (1) conduct a study of the value and benefits achieved by the Program; and (2) make appropriate recommendations for Program improvement (Sec 108).

The research conducted as a result of the reauthorization of 2000, which included a similar survey (first-round) as the second-round survey, led to a series of Academies reports published from 2004-2009. These reports focused on the SBIR program at the largest five agencies (based on SBIR budgets), which included the DOE (Academy, 2016).

When the Senate reauthorized the SBIR program in 2011, the legislation reemphasized the requirement to evaluate the program by amending,

> … the Small Business Reauthorization Act of 2000 to continue NAS [National Academies of Sciences] evaluation of the SBIR program, as well as reports on such evaluation from the National Research Council to participating agency heads and the small business committees (Sec. 307).

Therefore, the Academies conducted a second-round assessment which included a survey in 2014 that was, "…sent to every PI who received a Phase II award from DOE, FY 2001-2010" (National Academies, 2016, p.3). This dissertation draws on a random sample of 225 responses, of which 170 were from a PI, to the second-round survey to explore the role PIs play in project failure.

In this dissertation, two separate binary measures of failure are defined. As mentioned previously, failure may not always be binary, however, the data used for this dissertation provides the opportunity to look at failure as a binary measure as opposed to others. The first measure captures a general measure of failure and is defined as a Phase II funded project that was discontinued with no sales from the developed technology or any additional funding (*Failure*). *Failure* may occur due to any of the following issues:

1. the level of technical risk was too high
2. the principal investigator left
3. technical failure or difficulties
4. market demand was too small
5. the firm shifted priorities
6. or inadequate sales capability.

Of the 225 DOE Phase II funded projects studied here, 45 failed in this dimension, which translates to a 20 percent failure rate. A similar measure of failure was used by Link and Wright (2015) who used a random sample of 1,878 Phase II projects, across five agencies, from the first-round survey to estimate the probability an SBIR funded project fails. Of the 1,878 Phase II projects studied by Link and Wright (2015), 624 failed, representing a 33 percent failure rate.[6] Likewise, Andersen et al. (2017) define a similar measure of failure and used a random sample of 461 SBIR projects funded by the NIH, from 1992 through 2001, to estimate the probability a project fails. The failure rate of the 461 NIH funded projects was found to be 21.5 percent. Thus, the failure rate identified in the data for this dissertation is not out of line with two of the studies that are most relevant to the scope of the dissertation and the analysis that follows.

The second dependent variable is a narrower measure of failure, namely failure for technical reasons (*TechFailure*). Specifically, ones that failed for technical reasons or because technical risk was too high are defined as failing for technical reasons. This more specific measure of project failure is considered in this dissertation because having a narrower understanding of reasons that a project may fail can help policy makers develop more pointed policy that may be more effective for guiding firms that are susceptible to a specific type of failure. Of the 45 projects that failed for any reason, 14 or 31 percent of

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[6] There are 154 DOE Phase II projects in the 1,878 sample. Although the failure rate by agency is not provided in Link and Wright (2015), if available it would have allowed a comparison to the DOE sample studied here.

those failed for technical reasons. This dissertation is the first study known to analyze covariates with SBIR project technical failure.

Further, it is assumed that reducing the probability of failure is an objective of the SBIR program. The SBIR program has limited funds to allocate, therefore should want to allocate as efficiently as possible to maximize the programs social return on investment. When appropriating funds to a firm, the SBIR expects the firm to succeed and generate some social benefit else the award would not be given. Nonetheless, this is not a strong assumption since it is clear the SBIR program would certainly prefer a positive social return on the awards granted over the alternative.

Table 7.1: Dependent Variables Descriptive Statistics (n = 225)

Variable	Mean	StdDev	Range
Failure	0.200	0.401	0/1
TechFailure	0.062	0.242	0/1

CHAPTER VIII: INITIAL EMPIRICAL FINDINGS

Initial Probit Model

According to the structural model laid out in Chapter VI, the experience, *E*, of the PI impacts the probability of bringing a new technology to market, the expected revenues a firm can earn as a function of q (quality of the innovation), and the cost associated with the project. However, due to the data available, a reduced form specification is used where project failure is a binary outcome as opposed to the continuous formulation using expected profits as the measure of failure. Thus, R&D inputs, *Q*, and experience, *E*, are used to estimate the probability of project failure as a binary model. Given the earlier work by Link and Wright (2015) and Andersen et al. (2017), and the similarities in the data they used with those used in this dissertation, the first model presented looks to those studies to identify variables in the data that represent *Q* and *E* and may be associated with project failure. That is, a simple probability model of failure is employed to identify sets of covariates that are associated with SBIR project failure. The model is defined as

$$failed = I(\boldsymbol{X}_i\beta + \epsilon_i > 0), \tag{8.1}$$

where *failed* $(Failure, TechFailure)$ is a binary variable, *I* is an indicator function, $\boldsymbol{X}$ is a vector of firm and project characteristics, and $\epsilon \sim N(0,1)$. Multiple constructs of $\boldsymbol{X}$ are also used to analyze the associations among different firm and project characteristics with $Failure$ and $TechFailure$.

Three independent variables that were used in Link and Wright (2015) are available in the DOE dataset used in this dissertation. In addition, three of the independent variables used in Andersen et al. (2017) are also used in this dissertation.

These variables are defined in Table 8.1 below, along with the definition of *Failure* (and technical failure, *TechFailure*, which is again discussed below).

Table 8.1: Variable Definitions

Variable	Definition
Failure	= 1 if project was discontinued with no sales or additional funding received; 0 otherwise
TechFailure	= 1 if *Failure* = 1 and the reason for failure was of a technical nature; 0 otherwise
FemalePI	= 1 if the principal investigator is a female; 0 otherwise
FemaleOwner	= 1 if the owner of the firm is a female; 0 otherwise
Employees	Number of employees in the firm the time the Phase II award was received
SimAwardsDummy	= 1 if received Phase II award for a similar technology previously; 0 otherwise
ProfInvolved	= 1 if university faculty worked on the project; 0 otherwise
DEE	= 1 if project was in the energy or environmental sector only
DEng	= 1 if project was in the engineering sector only
Other	= 1 if project was in only one sector and not in *DEE* or *DEng*
DMT	= 1 if project was in multiple sectors

The first variable considered, *FemalePI,* is hypothesized, based on the literature, to have a negative relationship with *Failure*. If a firm has a female PI, then it is expected that the project is less likely to fail, on average, than a firm with a male PI; this relationship has been shown to be statistically significant in Link and Wright (2015). Inherent differences in the nature of males versus females, such as a female PI tending to be, “more innovative and critical thinking in problem solving” (Link and Wright 2015, p. 445) may provide context to this result. Similarly, Andersen et al. (2017) considered the gender of the owner as opposed to the gender of the PI in their study and found a statistically significant relationship between SBIR project failure and female ownership. They also found this relationship to be statistically significant even when controlling for possible endogeneity of the variable. Given the findings from Andersen et al. (2017), *FemaleOwner* is used as an alternative measure to *FemalePI* in conjunction with the other covariates specified below. Thus, based on the literature, the hypothesized relationship of *FemaleOwner* with *Failure* is negative.

No hypothesis is offered for the variable *Employees*, which is a proxy for firm size. On the one hand, larger firms might take on more complex projects. As a project becomes more complex, the probability it will fail might increase. On the other hand, larger firms might have more resources to draw on in the event that unexpected events occur during the Phase II research. Thus, in this case, the probability that a project will fail decreases with firm size.

SimAwardsDummy is a binary variable that indicates whether any prior similar awards have been received and is expected to have a negative relationship with *Failure*, as shown in prior studies. *SimAwardsDummy* is a proxy for research experience, specifically, experience in researching a related technology. Having at least some past research experience is expected, on average, to reduce the likelihood that the firm's project would fail.

ProfInvolved is a binary indicator for whether university faculty were involved in the project. This variable is used as an additional measure of human capital. Having university faculty involved in the project, likely brings some level of expertise or experience that should increase the level of human capital involved in the project. Greater human capital, *ceterus paribus,* should reduce the probability of project failure. Thus, *ProfInvolved* is hypothesized, based on the literature, to have a negative relationship with *Failure*.

Moving beyond the variables suggested by the literature, fixed effect controls for the SBIR projects technology sector are also considered. The data indicate that for some firms sampled, the technology currently being funded falls into multiple technology sectors; these projects are captured by a dummy variable *DMT* for projects in multiple technology sectors. Thus, as a measure of project complexity, *DMT*, is hypothesized, *ceteris paribus*, to be positively associated with SBIR project failure.

Further, the relationship between each of the previously mentioned variables and failure is expected to have the same directional relationship with both *Failure* and *TechFailure*, with the exception of *Employees.* Since no hypothesis is proposed for *Employees*, I do not speculate as to whether the relationship between *Employees* and *Failure*, and, *Employees* and *TechFailure,* should be the same.

Descriptive Statistics

Descriptive statistics for the variables used in equation (8.1) are presented in Table 8.2 below. The number of observations used is 169 of the 225 Phase II projects due to some firm's non-response to one or more of the survey questions used to calculate the independent variables. The mean value of *Failure* in this sample is 0.213 compared to 0.20 in the full sample of 225 projects (see Table 7.1). Thus, 21.3 percent of the projects in the sample failed. The mean value of *TechFailure* in this sample is 0.071 compared to 0.062 in the full sample (see Table 7.1), thus 7.1 percent of the projects in the sample failed for technical reasons. The mean number of projects with a *FemalePI* is 5.3 percent, and the mean number of projects with a *FemaleOwner* is 5.9 percent. The number of *Employees* within a firm at the time the Phase II project was received is, on average, just over 36. The share of firms that had at least one past award in a similar technology, *SimAwardsDummy*, is 60.4 percent. The mean number of projects with a *ProfInvolved* is 0.29. The energy and environment sector (*DEE*) accounts for 20.7 percent of the projects in the sample, the share of projects in the engineering sector (*DEng*) is 14.2 percent, projects in one sector other than energy and environment or engineering (*Other*) account for 16.6 percent, and projects in multiple technology sectors (*DMT*) represent 48.5 percent of the sample.

Table 8.2: Descriptive Statistics on Variables Used in Equation (8.1)

Variable	Mean	StdDev	Range
Failure	0.213	0.411	0/1
TechFailure	0.071	0.258	0/1
FemalePI	0.053	0.225	0/1
FemaleOwner	0.059	0.237	0/1
Employees	36.124	49.106	1-300
SimAwardsDummy	0.604	0.491	0/1
ProfInvolved	0.290	0.455	0/1
DEE	0.207	0.406	0/1
DEng	0.142	0.350	0/1
Other	0.166	0.373	0/1
DMT	0.485	0.501	0/1

To explore the relationship among the independent variables and *Failure* using the model in equation (8.1), I examined descriptive statistics on the variables being considered. I segmented the 169 Phase II projects into those that failed (n=33) and those that did not fail (n=133) based on the variable *Failure*. As shown in Table 8.3, 2.8 percent of the projects that failed had a female PI compared to 6 percent of the projects that did not fail. Similarly, 2.8 percent of the projects that failed had a female owner compared to 6.8 percent of the projects that did not fail. The mean number of employees in projects that failed is 40, which is relatively close to the mean number of employees in the projects that did not fail, namely 35. Considering the binary indicator of having received a past similar award in a related technology field, *SimAwardsDummy*, about 31 percent of the projects that failed had at least one previous award compared to about 68 percent of the projects that did not fail. Further, of the projects that experienced *Failure*, approximately

11 percent had university faculty involved, compared to nearly 34 percent of firms with *ProfInvolved* that did not experience *Failure.* These initial findings are consistent with my original hypotheses.

Moving to technology sector fixed effects, projects that failed and that are categorized into a single sector, the *DEE*, *DEng*, and *Other* account for 3.0, 3.6 and, 5.9 percent of the sampled projects, respectively. For the projects that did not fail, the *DEE*, *DEng*, and *Other* represent 17.8, 10.6, and 10.6 percent of the sample, respectively. Projects that are classified in multiple sectors and failed represent 8.9 percent of the projects sampled and those that did not fail account for 39.6 percent. Thus, the share of projects classified into multiple technology sectors that did not fail is much greater than its share of projects that did fail which does not support the original hypothesis of this variable's expected association with *Failure.*

To explore the relationship among the independent variables and *TechFailure* using the model in equation (8.1), I segmented the 169 Phase II projects into those that failed for a technical reason (n=12) and those that did not fail (n=157). As shown in Table 8.4, none of the projects that failed for technical reasons had a female PI compared to 5.7 percent of the projects that did not fail for technical reasons. Similarly, none of the projects that failed for technical reasons had a female owner, while 6.4 percent of the projects that did not fail for technical reasons had a female owner. This finding is consistent with the earlier findings for the *FemalePI* and *FemaleOwner* indicators grouped by *Failure*.

Table 8.3: Independent Variables Grouped by *Failure*

Variable	Mean	StdDev	Range
***Failure:* 1 (n=36)**			
TechFailure	0.333	0.478	0/1
FemalePI	0.028	0.167	0/1
FemaleOwner	0.028	0.167	0/1
Employees	40.083	60.259	1-300
SimAwardsDummy	0.306	0.467	0/1
ProfInvolved	0.111	0.319	0/1
*DEE**	0.030	0.351	0/1
*DEng**	0.036	0.378	0/1
*Other**	0.059	0.454	0/1
*DMT**	0.089	0.500	0/1
***Failure:* 0 (n = 133)**			
TechFailure	0.000	0.000	0-0
FemalePI	0.060	0.239	0/1
FemaleOwner	0.068	0.252	0/1
Employees	35.053	45.835	1-224
SimAwardsDummy	0.684	0.467	0/1
ProfInvolved	0.338	0.475	0/1
*DEE**	0.178	0.419	0/1
*DEng**	0.106	0.343	0/1
*Other**	0.106	0.343	0/1
*DMT**	0.396	0.502	0/1

*Since these are fixed effects controls, n = 169 so that the means represent the share of each sector in each group relative to the total sample as opposed to the within group share.

The mean number of employees in projects that failed for technical reasons is just greater than 26, compared with the mean number of employees in the projects that did not fail for technical reasons of nearly 37. Therefore, there are 11 less *Employees,* on average, that worked on a project that experienced *TechFailure* than those that did not. This association is opposite of the relationship between *Employees* and *Failure*, which resulted in about 5 more *Employees*, on average, that experienced *Failure* than not. This result, perhaps, implies a non-linear relationship between *Employees* and projects that fail, for any reason as will be discussed below.

Considering past experience, as measured by *SimAwardsDummy*, 25 percent of projects that failed for technical reasons received a past award while approximately 63 percent of projects that did not fail for technical reasons received a past award. These finding are consistent with the earlier findings of *SimAwards* segmented by *Failure*.

Of the firms that experienced *TechFailure*, approximately 8 percent had university faculty working on the project, compared to nearly 31 percent of firms with *ProfInvolved* that did not experience *TechFailure.* These findings are consistent with the earlier findings of *ProfInvolved* segmented by *Failure.*

Moving to technology sector fixed effects, projects that failed for technical reasons and are categorized into a single sector, the *DEE*, *DEng*, and *Other* groups, account for 1.2, 0.0 and, 3.0 percent of the sampled projects, respectively. For the projects that did not fail for technical reasons, the *DEE*, *DEng*, and *Other* groups, represent 19.5, 14.2, and 13.6 percent of the sample, respectively. Further, projects that were classified in multiple sectors and experienced *TechFailure* represent 3.0 percent of the projects sampled and those that did not fail for technical reasons account for 45.6 percent. Thus, the share of projects classified into multiple technology sectors that did not experience technical failure is much greater than its share of projects that did experience technical failure, similar to the *DMT* results when grouped by *Failure.*

Table 8.4: Independent Variables Grouped by *TechFailure*

Variable	Mean	StdDev	Range
***TechFailure:* 1 (n=12)**			
FemalePI	0.000	0.000	0/1
FemaleOwner	0.000	0.000	0/1
Employees	26.083	14.286	5-56
SimAwardsDummy	0.250	0.452	0/1
ProfInvolved	0.083	0.289	0/1
*DEE**	0.012	0.389	0/1
*DEng**	0.000	0.000	0-0
*Other**	0.030	0.515	0/1
*DMT**	0.030	0.515	0/1
***TechFailure:* 0 (n=157)**			
FemalePI	0.057	0.233	0/1
FemaleOwner	0.064	0.245	0/1
Employees	36.892	50.736	1-300
SimAwardsDummy	0.631	0.484	0/1
ProfInvolved	0.306	0.462	0/1
*DEE**	0.195	0.409	0/1
*DEng**	0.142	0.361	0/1
*Other**	0.136	0.355	0/1
*DMT**	0.456	0.501	0/1

*Since these are fixed effects controls, n = 169 so that the means represent the share of each sector in each group relative to the total sample as opposed to the within group share.

INITIAL PROBIT MODEL RESULTS

Parameter estimates and marginal effects from the estimation of equation (8.1) using different project and firm characteristics are shown in Tables 8.5-8.11 below. Each of the table's present findings from three separate models; two models with *Failure* as the response and one model with *TechFailure* as the response. The two models for *Failure* have the same specifications except either *FemalePI* or *FemaleOwner* is used in the estimation. Further, the random sample size for all models presented here forward is 169.

The variables used in the first estimations of equation (8.1), shown in Table 8.5, are those that are suggested by the literature. Focusing first on the models of *Failure,* as shown in Table 8.5, both *FemalePI* and *FemaleOwner* parameter estimates support their hypothesized relationships with *Failure*. That is, both *FemalePI* and *FemaleOwner* parameter estimates are negative and the two estimates have similar values. However, these estimates are not statistically significant. The coefficients on *Employees* are positive in the two *Failure* models and when *FemalePI* is included the coefficient is slightly greater than when *FemaleOwner* is used the model. Due to the potential non-linear association between *Failure* and *Employees,* a relationship was not hypothesized, thus, these estimates support the notion that marginally, larger firms are more likely to experience project failure. However, neither of the estimates of *Employees* are statistically significant. The *SimAwardsDummy* variable is used to analyze whether having received any past awards in a related technology is associated with SBIR project failure. The coefficient on *SimAwardsDummy* is negative in the two *Failure* models and both are significant at the 0.001-level. The marginal effects of *SimAwardsDummy* on *Failure* are significant at the 0.001-level. The marginal effect of *SimAwardsDummy* in the *FemalePI* specification is -0.242 and when *FemaleOwner* is in the model is -0.241. These results infer a reduction of 24 percentage points in the probability of *Failure* if at least one similar award was received.

Table 8.5: Set One Probit Results from Equation (8.1)

	(1) *Failure*	Marginal Effects	(2) *Failure*	Marginal Effects	(3) *TechFailure*	Marginal Effects
FemalePI	-0.569 (0.568)	-0.120 (0.0931)			--†	--†
FemaleOwner			-0.585 (0.554)	-0.123 (0.0899)	--†	--†
Employees	0.00137 (0.00226)	0.000357 (0.000585)	0.00123 (0.00229)	0.000318 (0.000592)	-0.00389 (0.00219)	-0.000485 (0.000315)
SimAwardsDummy	-0.932*** (0.229)	-0.242*** (0.0525)	-0.928*** (0.229)	-0.241*** (0.0526)	-0.797* (0.313)	-0.0994* (0.0419)
Intercept	-0.342 (0.178)		-0.336 (0.180)		-0.984*** (0.200)	
Wald χ^2	17.92**		18.19**		15.49***	
Likelihood Ratio	18.15***		18.24***		7.512*	

Robust standard errors in parentheses
*p<0.05 ** p<0.01 *** p<0.001
† *FemalePI* and *FemaleOwner* are not used in the model due to lack of variation.

Moving to the model of *TechFailure*, as also shown in Table 8.5, neither *FemalePI* or *FemaleOwner* are included in the estimation due to lack of variation; there are no projects that experienced *TechFailure* and had a female PI or a female owner. The coefficient for *Employees* in the *TechFailure* model is negative, the opposite sign of its estimates in the *Failure* regressions. Although this parameter is not statistically significant, *Employees* negative relationship with *TechFailure* suggests that increasing the size of the firm by adding employees reduces the probability of *TechFailure*. The coefficient on *SimAwardsDummy* in the *TechFailure* specification is negative and statistically significant at the 0.05-level. The marginal effect of *SimAwardsDummy* on *TechFailure* of -0.0994 implies a nearly 10 percentage point reduction in the probability of *TechFailure* if any similar award was received as opposed to when zero similar awards were received. The marginal effect of *SimAwardsDummy* in the *Failure* model, discussed above, is more than twice the size of the marginal effect of *SimAwardsDummy* in the *TechFailure* model. Having received any past awards may have a greater impact on *Failure* than on *TechFailure* since *Failure* is a broader measure. The experience gained through the award process and resulting R&D work may provide experience such as budgeting or project management skills that reduce the likelihood of *Failure* but are not able to reduce the likelihood of *TechFailure*.

The next set of models augments the first set of estimations of equation (8.1) by including another project characteristic variable used as an additional measure of human capital, namely *ProfInvolved.* The results from including this additional measure of human capital are provided in Table 8.6. The parameter estimates for both *Failure* models are statistically significant at the 0.05-level and are negative. The marginal effect of *ProfInvolved* in the *FemalePI* specification is -0.171, and similarly in the *FemaleOwner* model is -0.170. These results suggest that having university faculty working on the project reduces the probability of *Failure* by 17 percentage points. The marginal effects of *SimAwardsDummy* in both *Failure* models are larger than the *ProfInvolved* marginal effects, implying that receiving at least 1 previous Phase II award translates to a larger reduction in the probability of *Failure* than having university faculty working on the project. The parameter estimate of *ProfInvolved* in the *TechFailure* regression is negative, however, is not statistically significant.

Table 8.6: Set Two Probit Results from Equation (8.1)

	(1) *Failure*	Marginal Effects	(2) *Failure*	Marginal Effects	(3) *TechFailure*	Marginal Effects
FemalePI	-0.599	-0.123			--†	--†
	(0.565)	(0.0896)				
FemaleOwner			-0.609	-0.125	--†	--†
			(0.544)	(0.0860)		
Employees	0.00224	0.000565	0.00205	0.000516	-0.00394	-0.000485
	(0.00241)	(0.000599)	(0.00244)	(0.000607)	(0.00268)	(0.000368)
SimAwardsDummy	-0.847***	-0.213***	-0.843***	-0.212***	-0.709*	-0.0873*
	(0.232)	(0.0522)	(0.232)	(0.0523)	(0.301)	(0.0387)
ProfInvolved	-0.678*	-0.171*	-0.676*	-0.170*	-0.507	-0.0625
	(0.322)	(0.0778)	(0.320)	(0.0772)	(0.453)	(0.0552)
Intercept	-0.267		-0.261		-0.925***	
	(0.181)		(0.182)		(0.211)	
Wald χ^2	19.22***		19.75***		13.40**	
Likelihood Ratio	23.45***		23.53***		8.93*	

Robust standard errors in parentheses

* p<0.05 ** p<0.01 *** p<0.001

† *FemalePI* and *FemaleOwner* are not used in the model due to lack of variation.

To introduce another measure of project complexity into the analysis, the former set of models are each augmented with *DMT,* a fixed effect control variable that indicates when the technology being developed by each project should be classified into multiple technology sectors. Table 8.7 provides the model results with *DMT* as an additional regressor to the specifications shown in Table 8.6. The parameter estimates for *DMT* in both *Failure* specifications are negative, however, not statistically significant. The hypothesized relationship between *DMT* and *Failure* was positive, based on the notion that a technology that falls in more than one technology sector could be more complex than one classified in a single sector, thus these estimates do not support the original hypothesis.

As shown in Table 8.7, the coefficient on *DMT* in the *TechFailure* model is positive, opposite that found in the *Failure* specifications, though not statistically significant. This result is in line with the hypothesis that projects classified into multiple technology sectors are more complex on average, and *ceteris paribus*, have higher failure rates.

Table 8.7: Set Three Probit Results from Equation (8.1)

	(1) *Failure*	Marginal Effects	(2) *Failure*	Marginal Effects	(3) *TechFailure*	Marginal Effects
FemalePI	-0.601	-0.123			--†	--†
	(0.559)	(0.0885)				
FemaleOwner			-0.601	-0.123	--†	--†
			(0.541)	(0.0867)		
Employees	0.00231	0.000582	0.00208	0.000524	-0.00397	-0.000489
	(0.00245)	(0.000607)	(0.00248)	(0.000616)	(0.00280)	(0.000382)
SimAwardsDummy	-0.839***	-0.211***	-0.839***	-0.211***	-0.711*	-0.0875*
	(0.226)	(0.0514)	(0.227)	(0.0516)	(0.296)	(0.0385)
ProfInvolved	-0.673*	-0.170*	-0.673*	-0.169*	-0.511	-0.0628
	(0.322)	(0.0779)	(0.319)	(0.0773)	(0.441)	(0.0539)
DMT	-0.0588	-0.0148	-0.0260	-0.00654	0.0210	0.00259
	(0.233)	(0.0584)	(0.234)	(0.0587)	(0.306)	(0.0378)
Intercept	-0.247		-0.252		-0.932***	
	(0.199)		(0.200)		(0.246)	
Wald χ^2	19.75**		21.03***		13.80**	
Likelihood Ratio	23.51***		23.54***		8.93	

Robust standard errors in parentheses

* p<0.05 ** p<0.01 *** p<0.001

† *FemalePI* and *FemaleOwner* are not used in the model due to lack of variation.

Finally, variance inflation factors (VIF) for the group of firm and project characteristics that were used in the prior 3 sets of estimations of equation (8.1) (Tables 8.5-8.7) are shown in Table 8.8. As shown in Table 8.8, the VIF on each variable is only slightly greater than 1; this suggests that there is little concern for multicollinearity between these variables. Since these sets of variables encompass all the variables used in the 3 sets of estimations of equation (8.1), then multicollinearity is not a concern for any of the prior estimations of equation (8.1).

Table 8.8: Variance Inflation Factors

	VIF	
FemalePI	1.002	
FemaleOwner		1.013
Employees	1.044	1.050
SimAwardsDummy	1.049	1.049
ProfInvolved	1.066	1.067
DMT	1.057	1.063

CHAPTER IX: PRINCIPAL INVESTIGATOR EMPIRICAL FINDINGS

Many of the studies related to project failure have examined the reasons for project failure at the firm, managerial, or project level and have not explicitly focused on more micro-level dynamics within each project. Thus, there is a notable absence of literature that examines characteristics of PIs and their association with research failure. This dissertation contributes to the literature by analyzing disaggregated demographic factors of the PI's, beyond gender, who are involved in the random sample of 169 SBIR Phase II funded projects as discussed in prior chapters.

Equation (8.1) is employed once again to estimate the relationship between each measure of SBIR project failure (*Failure* and *TechFailure*) and the firm and project characteristics discussed in Chapter VIII augmented with additional measures of PI experience. Therefore, $\boldsymbol{X}$, from equation (8.1), represents a vector of firm and project characteristics plus measures of the PI's experience as drawn from the random sample. The $\boldsymbol{X}$ vector used in the reduced form specifications of the structural model (laid out in Chapter VI) contains elements of both $\boldsymbol{Q}$ (R&D inputs) and $\boldsymbol{E}$ (experience of the PI and/or firm). The models used in the following chapter build on those examined in Chapter VIII by providing a richer formulation of $\boldsymbol{E}$ through additional measures of PI experience.

The following chapter examines three additional dimensions to measure PI experience; demographic factors, PIs role as firm leaders and chief executives, and the homophilic relationship between PIs and firm owners. Four types of demographic variables are available in the data; gender, ethnicity, age, and immigration status or nationality. Considering firm leadership characteristics, the data provide information from which it can be determined if the PI was also the CEO, a firm founder, or both CEO and a founder. Additional information about founders is available, such as the number of founders with a business or academic background. Further, as discussed in Chapter VIII, the data provide information on the gender of both the owner and PI which is used to analyze the homophilic relationship between firm owners and PIs. Table 9.1 provides definitions of the PI experience variables.

As discussed previously, gender has been identified in prior studies as having significant explanatory power of project failure. Although the results of the initial probit estimations (Tables 8.5-8.7) for the variable *FemalePI* are not statistically significant at conventional levels, the negative association with project failure is directionally consistent with prior studies. Therefore, it is expected for the inverse relationship between project and failure and *FemalePI* to remain unchanged after including additional experience measures.

Table 9.1: PI Variable Definitions

Variable	Definition
FemalePI	= 1 if the principal investigator is a female; 0 otherwise
MinorityPI	= 1 if the principal investigator is a minority; 0 otherwise
Age30DecilePI	= 1 if the principal investigator is between 30 and 39 years old; 0 otherwise
Age40DecilePI	= 1 if the principal investigator is between 40 and 49 years old; 0 otherwise
Age50DecilePI	= 1 if the principal investigator is between 50 and 59 years old; 0 otherwise
AmerPI	= 1 if the principal investigator is an American-born U.S. citizen; 0 otherwise
PICEO	= 1 if the principal investigator is the CEO of the firm; 0 otherwise
PIFounder	= 1 if the principal investigator is a founder of the firm; 0 otherwise
PIFounderCEO	= 1 the principal investigator is a founder and the CEO of the firm; 0 otherwise
PIOneFounder	= 1 if the principal investigator is the only founder of the firm; 0 otherwise
PIOneFounderCEO	= 1 if the principal investigator is the only founder and the CEO of the firm; 0 otherwise
BizBackground	Number of founders with a background in business
AcademicBackground	Number of founders with an academic background

The relationship between ethnicity of the PI and project failure has not been established in the literature. The factors that distinguish ethnicities do not intuitively suggest a differing relationship among ethnicities and project failure. Therefore, no assumption is offered in this dissertation about the association between ethnicity and failure.

The relationship between age of the PI and failure has not been established in the literature. Age, often used as a proxy for experience, does not have a clear linear relationship with project failure. It is possible that older PIs have more experience and through this experience tend to fail less often than their younger counterparts. However, at some point it is possible that being too old, or having too much experience, results in a greater likelihood of project failure. This may come to fruition due to increased risk taking by older more experienced PIs that have had significant success in the past. Therefore, no assumption is offered in this dissertation about the association between ethnicity and age of the PI.

Similar to ethnicity of the PI, immigration status of the PI has not been established in the literature. It is not obvious whether a certain immigration status of the PI should increase the likelihood of project failure compared to another. Hence, no assumption is offered about the association between immigration status of the PI and project failure.

The relationship between project failure and whether the PI was also the CEO or a firm founder has not been established in the literature. However, using similar data as those used in this dissertation, Bednar et al. (2019), control for the situation when the PI was also the CEO when estimating the probability of commercialization. They found a statistically significant negative relationship between the probability of commercialization and if the PI was also the CEO. This relationship loosely implies a positive relationship between firms with a PI CEO and project failure. Therefore, based on this implication, I expect a positive relationship between *PICEO* and *Failure*. Similarly, I expect *PIFounder* to also have a positive relationship with failure. One explanation for this hypothesis is that intuitively, PIs may be more likely to hold multiple leadership roles in smaller firms where resources are less abundant, and the demands of multiple top leadership positions do not allow the PI to succeed as either a scientist or firm founder. Firms where the PI is performing triple duty, that is PI, founder, and CEO, are also hypothesized to have a positive relationship with *Failure* due to the previous expectations of *PICEO* and *PIFounder*. The rationale behind these hypotheses suggests firms with a *PIFounderCEO* should have a greater probability of *Failure* than either those with a *PICEO* or *PIFounder.* Similarly, firms that were founded solely by the PI, *PIOneFounder*, are expected to be positively associated with *Failure* and have a greater probability of *Failure* than those with a *PIFounder.* Finally, firms with a *PIOneFounderCEO* are expected to have the highest probability of *Failure* in accordance with the hypotheses discussed above.

Data are available on the background of the firm founders; either business or academic. Andersen et al. (2017), using similar data, considered the business background of firm owners when estimating the probability of SBIR project failure and found a statistically significant inverse relationship with failure. However, this dissertation uses a slightly different measure of vocational experience. Because the focus of this dissertation is on the PI's role in project failure and not necessarily a founder or CEO, founders that were also the PI (as well as PI CEO's) are used in the experience vector as opposed to firm founders unconditional on being a PI. Nonetheless, given the closeness in measures between Andersen et al (2017) and those used in this dissertation, I expect a negative relationship between PI founders with a business background and project failure. I expect firms with PI founders that have an academic background to be inversely related with failure given the significant negative relationship estimated between *Failure* and university faculty involvement in the project (see Table 8.6).

Additionally, Bednar et al. (2019) examined the homophilic relationship between firm owners and PIs, and found that females PIs tend to perform better as measured by the probability of commercializing when the firm owner is also female; this association will also be explored in this chapter however, the measure of concern is project failure. Hence, I expect the relationship among homophilic firms (measured by owner and PI) and project failure to be directionally consistent with the relationship found in Bednar et al. (2019).

PI Demographics

Descriptive Statistics

The distributions of PIs conditional on each of the four demographic categories from the random sample of 169 SBIR Phase II funded projects are presented in Table 9.2. Female PIs comprise 5.3 percent of the sample and minority PIs make up 10.1 percent of the sample. The remaining 85 percent of projects had non-female, non-minority PIs.

Considering a further disaggregation of the minority binary variable, PIs of the Asian-Indian ethnicity represent 7.1 percent of the 169 randomly sampled projects and 70.6 percent of the minority PIs. PIs of the Asian-Pacific ethnicity comprise 2.4 percent of the random sample and 23.5 percent of the minority PIs. The remaining proportion of minority PIs are Hispanic, making up less than 1 percent of the random sample and 5.9 percent of the minority PIs. There are no PIs in the sample that fall into the Black, Native American, or Other ethnicities.

There are 10 age brackets for PIs; the youngest category being less than 25 years of age and the oldest greater than 65. There are no PIs in the sample that were less than 25 years old at the time of the survey and less than 1 percent of PIs were between 25-29 years old. PIs that were between 30-34 years old represent 4.1 percent of the random sample and PIs between 35-39 make up 16.6 percent of the sample. PIs between the ages of 40-44 are the most frequent in the sample, representing 18.9 percent and PIs between 45-49 years old make up 14.8 percent of the sample. The age group 50-54 comprises 14.2 percent of the sample and PIs between 55-59 years old comprise 18.3 percent of the random sample, the second most frequent age range of PIs. PIs between the ages of 60-64 represent 6.5 percent of the sample and PIs ages 65 and older comprise 5.9 percent of the random sample.

The most frequent immigration status of PIs in the random sample is that of American-born U.S. citizens: these PIs represent 62.1 percent of the sample. PIs that were naturalized U.S. citizens made up 20.1 percent of the sample and those that held a green card comprised 16.0 percent. Finally, PIs that held an H1 visa make up 1.8 percent of the sample and there were no PIs that had an immigration status other than those mentioned above.

Table 9.2: Descriptive Statistics of PI Demographic Variables

Characteristic	Number	Percent of Sample (n=169)
Gender/Ethnicity of PI		
Female PI	9	5.3254
Minority PI	17	10.0592
Neither Female nor Minority PI	144	85.2071
Ethnicity of Minority PI		
Asian-Indian	12	7.1006
Asian-Pacific	4	2.3669
Black	0	0
Hispanic	1	0.5917
Native American	0	0
Other	0	0
Age of PI		
<25	0	0
25-29	1	0.5917
30-34	7	4.1420
35-39	28	16.5680
40-44	32	18.9349
45-49	25	14.7929
50-54	24	14.2012
55-59	31	18.3432
60-64	11	6.5089
65+	10	5.9172
Immigration Status of PI		
American-born U.S. citizen	105	62.1302
Naturalized U.S. citizen	34	20.1183
U.S. Green card	27	15.9763
H1 visa	3	1.7751
Other	0	0

To begin to explore the relationship among PI demographic variables and *Failure* I've segmented the random sample of 169 Phase II funded projects by those that failed (n=36) and those that did not (n=133). As shown in Table 9.3, less than 1 percent of firms with a female PI experienced *Failure,* the smallest percent of *Failure* among the gender/

ethnicity dimension. Further, conditional on a firm having a female PI (n =9), 11 percent experienced *Failure*. Firms with a minority PI (n=17) and that experienced *Failure* comprise 2.96 percent of all firms in the sample, while 29 percent of firms that had a minority PI experienced *Failure.* Firms with a non-female, non-minority PI (n =144), and experienced *Failure* comprise 17.6 percent of the random sample and experienced a 21 percent *Failure* rate within the sub-sample of firms that had a non-female, non-minority PI.

Moving to the age groups of the PI, there is not a firm within the random sample that had a PI in the age range of 30-34 (n=7) and that experienced *Failure,* though PIs in this age bracket account for about 4 percent of the total random sample. Firms with a PI in the 35-39 age range (n=28) and that encountered *Failure* comprise nearly 3 percent of the sample though almost 18 percent of PIs within the 35-39 age bracket experienced *Failure.* Firms with a PI that was between 40 and 44 years old (n=32) and that met *Failure* account for 5.3 percent of the total sample, the largest share of *Failure* by age indicator. Further, 28 percent of PIs 40-44 years old experienced *Failure*, which is the third highest failure rate within an age cohort. Firms with a PI age 45-49 (n=25) and that encountered *Failure* comprise 4.7 percent of all firms in the sample, the second largest share of firms that failed conditional on age of the PI. The *Failure* rate of 32 percent among PIs 45-49 years old is the second highest rate across all age cohorts. Firms with a PI between 50-54 years old (n=24) and that experienced *Failure* represent 1.2 percent of the total sample. Within this age range, less than 1 percent of PIs failed which is the second lowest *Failure* rate within an age cohort. Firms with a PI between 55-59 years old (n=31) and that experienced *Failure* make up almost 3 percent of the random sample, though conditional on firms with a PI in this age bracket 16 percent of them failed. The second to the oldest age cohort of PIs, those between 60-64 years old (n=11) and that encountered *Failure,* were PIs for 2.4 percent of all firms in the sample and experienced the highest failure rate within an age cohort; 36 percent of PIs ages 60-64 experienced

Failure. The oldest cohort of PIs, ages 65 years and older (n=10) and that witnessed *Failure* represent 1.2 percent of all PIs in the sample which translates to a 20 percent *Failure* rate among the oldest PIs in the sample.

The last demographic variable considered in this dissertation is the immigration status of the PI. Again, as shown in Table 9.3, PIs that are American-born U.S. citizens (n=105) and whose firms experienced *Failure,* represent 10.6 percent of the total sample, the largest share of PIs conditional on immigration status. Within the American-born U.S. citizen PIs, 17 percent of their projects failed. PIs that are naturalized U.S. citizens (n=34) and that experienced *Failure,* account for 5.3 percent of all PIs in the sample and have a *Failure* rate among this immigration cohort of 26.5 percent. PIs that held a U.S. Green card (n=27) and encountered *Failure*, represent 5.3 percent of PIs in the full sample, while they have a within cohort *Failure* rate of 33.3 percent. Finally, PIs that held an H1 visa (n=3) did not have any cases of *Failure*.

Table 9.3: Distribution of PI Demographics by *Failure*

Characteristic	Failure				
	1	0	1	0	1/ (0,1)
	Count		Percent (n=169)		Rate
Gender/Ethnicity of PI					
Female PI	1	8	0.6%	4.7%	11.1%
Minority PI	5	12	3.0%	7.1%	29.4%
Neither Female nor Minority PI	30	114	17.8%	67.5%	20.8%
Ethnicity of Minority PI					
Asian-Indian	2	10	1.2%	5.9%	16.7%
Asian-Pacific	3	1	1.8%	0.6%	75.0%
Black	0	0	0.0%	0.0%	0.0%
Hispanic	0	1	0.0%	0.6%	0.0%
Native American	0	0	0.0%	0.0%	0.0%
Other	0	0	0.0%	0.0%	0.0%
Age of PI					
<25	0	0	0.0%	0.0%	0.0%
25-29	1	0	0.6%	0.0%	100.0%
30-34	0	7	0.0%	4.1%	0.0%
35-39	5	23	3.0%	13.6%	17.9%
40-44	9	23	5.3%	13.6%	28.1%
45-49	8	17	4.7%	10.1%	32.0%
50-54	2	22	1.2%	13.0%	8.3%
55-59	5	26	3.0%	15.4%	16.1%
60-64	4	7	2.4%	4.1%	36.4%
65+	2	8	1.2%	4.7%	20.0%
Immigration Status of PI					
American-born U.S. citizen	18	87	10.7%	51.5%	17.1%
Naturalized U.S. citizen	9	25	5.3%	14.8%	26.5%
U.S. Green card	9	18	5.3%	10.7%	33.3%
H1 visa	0	3	0.0%	1.8%	0.0%
Other	0	0	0.0%	0.0%	0.0%

Considering the relationship among PI demographic variables and *TechFailure,* I've also segmented the random sample of 169 Phase II funded projects by those that failed for technical reasons (n=12) and those that did not (n=157). As shown in Table 9.4, no firms with a female PI experienced *TechFailure.* Firms with a minority PI (n=17) and that experienced *TechFailure* represent 1.8 percent of the random sample while 17 percent of minority PIs failed for technical reasons. Firms with a non-female, non-minority PI (n =144), and that experienced *TechFailure* comprise 5.3 percent of the random sample and had a *TechFailure* rate of 6.5 percent among non-female, non-minority PIs.

Moving to the age bins of the PI, there was no firm that had a PI less than 35 years old and experienced *TechFailure*. Firms that had a PI in any one of the age buckets 35-39, 40-44, or 45-49 and that experienced *TechFailure*, each comprised 1.8 percent of the full sample. In terms of *TechFailure* prevalence, 10.7 percent of 35-39-year-old PIs, 9.4 of the 40-44-year-old PIs, and 12 percent of the 45-49-year-old PIs failed for technical reasons. There were no firms with a PI between 50-54 years old and that experienced *TechFailure.* Firms with a PI between 55-59 years old and that experienced *TechFailure* make up less than 1 percent of the full sample, though conditional on firms with a PI in this age bracket, 3.2 percent of them failed for technical reasons. PIs between 60-64 years old and that encountered *TechFailure,* make up 1.2 percent of all PIs which translates to an 18.2 percent *TechFailure* rate among this age cohort. The oldest cohort of PIs, ages 65 years and older did not have any cases of failure for technical reasons.

Table 9.4: Distribution of PI Demographics by *TechFailure*

Characteristic	*TechFailure*				
	1	0	1	0	1 / (0, 1)
	Count		Percent (n = 169)		Rate
Gender/Ethnicity of PI					
Female PI	0	9	0.0%	5.3%	0.0%
Minority PI	3	14	1.8%	8.3%	17.6%
Neither Female nor Minority PI	9	135	5.3%	79.9%	6.3%
Ethnicity of Minority PI					
Asian-Indian	1	11	0.6%	6.5%	8.3%
Asian-Pacific	2	2	1.2%	1.2%	50.0%
Black	0	0	0.0%	0.0%	0.0%
Hispanic	0	1	0.0%	0.6%	0.0%
Native American	0	1	0.0%	0.6%	0.0%
Other	0	0	0.0%	0.0%	0.0%
Age of PI					
<25	0	0	0.0%	0.0%	0.0%
25-29	0	1	0.0%	0.6%	0.0%
30-34	0	7	0.0%	4.1%	0.0%
35-39	3	25	1.8%	14.8%	10.7%
40-44	3	29	1.8%	17.2%	9.4%
45-49	3	22	1.8%	13.0%	12.0%
50-54	0	24	0.0%	14.2%	0.0%
55-59	1	30	0.6%	17.8%	3.2%
60-64	2	9	1.2%	5.3%	18.2%
65+	0	10	0.0%	5.9%	0.0%
Immigration Status of PI					
American-born U.S. citizen	5	100	3.0%	59.2%	4.8%
Naturalized U.S. citizen	2	32	1.2%	18.9%	5.9%
U.S. Green card	5	22	3.0%	13.0%	18.5%
H1 visa	0	3	0.0%	1.8%	0.0%
Other	0	0	0.0%	0.0%	0.0%

Finally, considering the immigration status of the PI segmented by *TechFailure*, as shown in Table 9.4, PIs that are American-born U.S. citizens and whose firms experienced *TechFailure* represent almost 3 percent of the full sample. Within the American-born U.S. citizen PIs, 5 percent of their projects failed for technical reasons. PIs that are naturalized U.S. citizens and that experienced *TechFailure,* account for 1.2 percent of all PIs in the sample and have a *TechFailure* rate among this immigration cohort of 5.9 percent. PIs that held a U.S. Green card and encountered *TechFailure*, represent almost 3 percent of PIs in the full sample, while they have a within cohort *TechFailure* rate of 18.5 percent. Finally, PIs that held an H1 visa did not have any cases of *TechFailure*.

MODEL RESULTS

Leveraging the reduced form model from Chapter VIII, equation (8.1), the following estimations include additional factors of PI experience. In terms of the structural form of this model, as presented in Chapter VI, the additional variables represent a richer experience vector, ***E***, through the addition of demographic type information. The additional information on PIs experience provides more evidence in understanding how variations in PIs experience are associated with project failure. Further, the focus of the following discussion is on demographic variables of PIs, therefore discussion of estimation results for other variables will be limited unless the there is a meaningful change in a variables' output from previous results.

The first additional PI variable examined is the minority status of the PI. This variable is used to augment the model results presented in Table 8.7. Results from the estimation for both *Failure* and *TechFailure* measures including the *MinorityPI* measure are provided in Table 9.5. The estimated parameters for *MinorityPI* in both the *Failure* and *TechFailure* regressions are not statistically significant nor are the estimated marginal effects. These results are in-line with the hypothesis that variation between PIs based on ethnicity do not have a significant relationship with SBIR project failure.

Continuing to build on the experience vector, model results from the inclusion of age indicators of the PI are provided in Table 9.6. As shown in Table 9.2, the survey data used in this dissertation provide age indicators in approximately five-year intervals. To use in the model, the age brackets were collapsed into decile bins so that there was a meaningful mass of observations within each bin. The reference age bucket represents PIs that were age 60 and greater. As shown in Table 9.6, the three age indicators all have a negative parameter in the *Failure* estimation, indicating that they are less likely to experience *Failure* relative to PIs at least 60 years old (the oldest cohort), however, only *Age30DecilePI* is statistically significant at conventional levels (0.05-level). *Age50DecilePI* has a p-value of 0.052 which is marginally outside the threshold of reported significance in this dissertation, however, is suggestive of a significant relationship. Further, none of the age parameters are statistically significant in the *TechFailure* specification.

Table 9.5: PI Probit with *MinorityPI*

	(1)		(2)	
	Failure	Marginal Effects	*TechFailure*	Marginal Effects
FemalePI	-0.700	-0.137	--†	--†
	(0.578)	(0.0830)		
MinorityPI	0.559	0.158	0.829	0.143
	(0.357)	(0.107)	(0.429)	(0.0926)
Employees	0.00219	0.000545	-0.00407	-0.000484
	(0.00236)	(0.000575)	(0.00255)	(0.000354)
SimAwardsDummy	-0.903***	-0.246***	-0.832*	-0.102*
	(0.232)	(0.0631)	(0.333)	(0.0409)
ProfInvolved	-0.641*	-0.144*	-0.476	-0.0471
	(0.320)	(0.0604)	(0.470)	(0.0364)
DMT	-0.0592	-0.0147	0.0171	0.00203
	(0.235)	(0.0581)	(0.312)	(0.0372)
Intercept	-0.272		-1.008***	
	(0.200)		(0.261)	
Wald χ^2	20.29**		18.54**	
Likelihood Ratio	25.57***		12.35*	

Robust standard errors in parentheses

*p<0.05 ** p<0.01 *** p<0.001

† *FemalePI* is not used in the model due to lack of variation.

The *Age30DecilePI* marginal effect of -0.179 in the *Failure* specification is significant at the 0.01-level and suggests that PIs that are in their thirties are expected to experience a probability of *Failure* 17.9 percentage points less relative to the oldest cohort. Similarly, PIs that fall into *Age50DecilePI* have a probability of *Failure* that is 16.1 percentage points less relative to PIs that are at least 60 years old as shown by the estimated marginal effect. The marginal effect of *Age50DecilePI* is significant at the 0.05 level.

Age is a traditional proxy for experience since often one acquires experience over time. Therefore, it is straightforward that younger PIs are likely less experienced than older PIs as they've had less time to have accumulated human capital. With less experience, the typical projects that younger PIs work on may be inherently less risky than those more experienced PIs would be involved with. Further, younger PIs with less experience should have a higher marginal rate of human capital accumulation than their older cohorts due to diminishing marginal returns on experience. The higher marginal rate of human capital accumulation of younger PIs may can translate to a form of motivation in the PI that results in higher productivity. Simonton (1988) and Simonton (1991) found that scientific productivity peaks at an age just shy of 40 years old then begins to gradually decline. The decline in productivity may also coincide with human capital depreciation in the oldest cohort of PIs. While the oldest cohort of PIs may have achieved success in their earlier years, being toward the end of their career could lessen the motivation to maintain their skills up-to the level required for continued success. Additionally, the projects the most experienced cohort of PIs are typically involved with may be riskier than those of younger PIs. Thus, in summary, younger PIs may have higher levels of motivation while working on less risky projects than the oldest cohort which helps explains why the younger cohorts of PIs with less experience have lower probabilities of *Failure* relative to the oldest cohort.

The age decile indicator parameters are not statistically significant in the *TechFailure* regression, nor their marginal effects. Given the nature of *TechFailure,* it is reasonable that the typical experience gained that is attributable to the age of the PI does not necessarily translate to experience that helps reduce the likelihood of *TechFailure*.

Moving forward, the last demographic variable considered here to augment the experience vector is the nationality of the PI. Table 9.7 below presents the model results with *AmerPI* as an additional regressor to those presented in Table 9.6. As expected, the parameter estimate for the nationality of the PI is not statistically significant nor is the marginal effect in either the *Failure* or *TechFailure* specifications. Although, Del et al. (2017) found that a country's culture can influence a PI to have a greater preference towards entrepreneurial activities, the country a PI comes from does not necessarily equip a PI with the experience needed to reduce the probability of failure.

Table 9.6: PI Probit with Age Decile Indicators

	(1)		(2)	
	Failure	Marginal Effects	*TechFailure*	Marginal Effects
FemalePI	-0.856 (0.616)	-0.149* (0.0746)	--†	--†
MinorityPI	0.671 (0.378)	0.177 (0.108)	0.714 (0.428)	0.112 (0.0812)
Age30DecilePI	-0.948* (0.422)	-0.179** (0.0632)	-0.201 (0.500)	-0.0217 (0.0506)
Age40DecilePI	-0.0603 (0.374)	-0.0137 (0.0846)	0.0391 (0.456)	0.00450 (0.0527)
Age50DecilePI	-0.756 (0.390)	-0.161* (0.0756)	-0.751 (0.578)	-0.0697 (0.0427)
Employees	0.00186 (0.00234)	0.000427 (0.000526)	-0.00512 (0.00281)	-0.000586 (0.000393)
SimAwardsDummy	-1.027*** (0.245)	-0.258*** (0.0623)	-0.785* (0.330)	-0.0931* (0.0372)
ProfInvolved	-0.749* (0.340)	-0.172* (0.0740)	-0.544 (0.449)	-0.0622 (0.0512)
DMT	0.0689 (0.256)	0.0158 (0.0586)	0.0810 (0.304)	0.00932 (0.0352)
Intercept	0.165 (0.342)		-0.800 (0.458)	
Wald χ^2	33.38***		18.65*	
Likelihood Ratio	35.94***		15.64*	

Robust standard errors in parentheses

*p<0.05 ** p<0.01 *** p<0.001

† *FemalePI* is not used in the model due to lack of variation.

Table 9.7: PI Probit with Nationality Indicator

	(1)		(2)	
	Failure	Marginal Effects	*TechFailure*	Marginal Effects
FemalePI	-0.855	-0.147	--†	--†
	(0.651)	(0.0779)		
MinorityPI	0.428	0.106	0.538	0.0777
	(0.396)	(0.106)	(0.436)	(0.0753)
Age30DecilePI	-1.077*	-0.195**	-0.296	-0.0311
	(0.427)	(0.0595)	(0.479)	(0.0461)
Age40DecilePI	-0.0867	-0.0194	0.00284	0.000324
	(0.382)	(0.0846)	(0.457)	(0.0521)
Age50DecilePI	-0.824*	-0.171*	-0.817	-0.0749
	(0.398)	(0.0740)	(0.605)	(0.0434)
AmerPI	-0.421	-0.0991	-0.305	-0.0359
	(0.263)	(0.0631)	(0.304)	(0.0356)
Employees	0.00143	0.000323	-0.00586*	-0.000669
	(0.00233)	(0.000519)	(0.00291)	(0.000405)
SimAwardsDummy	-0.964***	-0.238***	-0.741*	-0.0866*
	(0.242)	(0.0587)	(0.321)	(0.0350)
ProfInvolved	-0.753*	-0.170*	-0.537	-0.0612
	(0.339)	(0.0727)	(0.454)	(0.0514)
DMT	0.0466	0.0105	0.0599	0.00687
	(0.255)	(0.0576)	(0.301)	(0.0346)
Intercept	0.488		-0.544	
	(0.414)		(0.493)	
Wald χ^2	30.91***		16.36	
Likelihood Ratio	38.22***		16.27	

Robust standard errors in parentheses
*p<0.05 ** p<0.01 *** p<0.001
† *FemalePI* is not used in the model due to lack of variation.

PIs as CEO's/ Firm Founders

DESCRIPTIVE STATISTICS

Summary statistics for PIs that are also a firm leader are provided in Table 9.8 below. As shown, PIs that are also the CEO, *PICEO,* represent 22.5 percent of the random sample of Phase II funded SBIR projects used in this dissertation. PIs that were also a founder, and not necessarily the only founder, make up 29.6 percent of the sample. PIs that were the CEO and a firm founder, *PIFounderCEO*, comprise 21.3 percent of the sample. Summary statistics are also provided for a subsample of *PIFounder,* specifically, PIs that were the sole founder of the firm, *PIOneFounder.* PIs that were the sole firm founder represent 13.6 percent of the sample. Similarly, PIs that were the CEO and the sole firm founder, *PIOneFounderCEO,* represent 11.2 percent of the sample.

As mentioned previously, the second-round survey also provides information on firm founders' background, specifically the number of founders with a business or academic background. As shown in Table 9.8, the mean number of firm founders with a background in business is slightly less than one, at 0.7574. The standard deviation is slightly greater than 1 founder and within the sample the number of founders with a business background ranged between 0 and 5. The mean number of founders with an academic background is slightly more than one at 1.0592 founders, with a standard deviation of 1.3615. The number of founders with an academic background ranged between 0 and 10 founders within the random sample of firms.

Table 9.8: Descriptive Statistics of PIs as Firm Leaders

Indicator	Mean	StdDev	Range
PICEO	0.2249	0.4187	0/1
PIFounder	0.2959	0.4578	0/1
PICEOFounder	0.213	0.4107	0/1
PIOneFounder	0.1361	0.3439	0/1
PIOneFounderCEO	0.1124	0.3168	0/1
BizBackground	0.7574	1.0552	0-5
AcademicBackground	1.0592	1.3615	0-10

To begin exploring the relationship between the firm leadership experience variables and *Failure,* descriptive statistics of the firm leadership variables are segmented by those that experienced project failure (*Failure* = 1) and those that did not (*Failure* = 0). As shown in Table 9.9 below, 5.9 percent of the sample were a *PICEO* that experienced *Failure*, while *PICEO* that did not fail made up 16.6 percent of the sample. Therefore, firms with a *PICEO* had a failure rate of 26.3 percent. Firms with a *PIFounder* and that experienced *Failure*, comprise 5.9 percent of the sample, while their counterparts that did not experience *Failure* comprise 23.7 percent of the firms sampled. Firms with a *PIFounder* have a *Failure* rate of 20.0 percent, the lowest rate of failure among the firm leadership experience variables. Firms with a *PIFounderCEO* and that experienced *Failure* also make up 5.9 percent of the sample, although *PIFounderCEO* firms that did not fail hold 15.4 percent of the sample. This translates to a 27.8 percent *Failure* rate for *PIFounderCEO* firms. *PIOneFounder* firms that had *Failure* comprise 4.7 percent of the random sample and those that did not, 8.9 percent. Thus, *PIOneFounder* firms had a *Failure* rate of 34.8 percent, which is 14.8 percentage points greater than *PIFounder* firms. Firms that were founded and managed by the PI, *PIOneFounderCEO,* and that experienced *Failure* comprise 4.7 percent of the sample and those that did not fail comprise 6.5 percent, which translates to the highest *Failure* rate among the various firm leadership experience types of 42.1 percent. These statistics are suggestive with my hypothesis that the more concentrated the leadership experience is within a firm, the more likely they are to experience *Failure*.

The mean number of firm founders with a business background, *BizBackground*, conditional on having experienced *Failure* is 0.6389 which is less than the mean *BizBackground* of the firms that did not fail of 0.7895. This is consistent with my hypothesis that *BizBackground* is negatively associated with *Failure*. Similarly, the mean *AcademicBackground* for firms that failed is 0.8611 which is less than those that did not fail of 1.1128. This also is consistent with my hypothesis that *AcademicBackground* is negatively associated with *Failure.*

Table 9.9: Descriptive Statistics of PIs as Firm Leaders Grouped by *Failure*
(standard deviations in parenthesis)

Indicator	***Failure***				
	1	**0**	**1**	**0**	**1 / (0, 1)**
	Count		**Percent (n = 169)**		**Rate**
PICEO	10	28	5.9%	16.6%	26.3%
PIFounder	10	40	5.9%	23.7%	20.0%
PIFounderCEO	10	26	5.9%	15.4%	27.8%
PIOneFounder	8	15	4.7%	8.9%	34.8%
PIOneFounderCEO	8	11	4.7%	6.5%	42.1%
			n = 36	**n = 133**	
*BizBackground**	--	--	0.6389 (0.8669)	0.7895 (1.1013)	--
*AcademicBackground**	--	--	0.8611 (1.3342)	1.1128 (1.3688)	--

**Values are means of the variable*

To begin exploring the relationship between the firm leadership experience variables and *TechFailure,* descriptive statistics of the firm leadership variables are also segmented by those that experienced project failure for technical reasons (*TechFailure* = 1) and those that did not (*TechFailure* = 0). As shown in Table 9.10 below, 1.2 percent of the sample were a *PICEO* that experienced *TechFailure*, while *PICEO* firms that did not fail made up 21.3 percent of the sample. Therefore, firms with a *PICEO* had a failure for technical reasons rate of 5.3 percent. Firms with a *PIFounder* and that experienced *TechFailure*, comprise 1.2 percent of the sample, while their counterparts that did not experience *TechFailure* comprise 28.4 percent of the firms sampled. Firms with a *PIFounder* have a *TechFailure* rate of 4.0 percent, the lowest rate of *TechFailure* among the firm leadership experience variables. Firms with a *PIFounderCEO* and that experienced *TechFailure* also make up 1.2 percent of the sample, while *PIFounderCEO* firms that did not fail hold 20.1 percent of the sample. This translates to a 5.6 percent *TechFailure* rate for

PIFounderCEO firms. *PIOneFounder* firms that had *TechFailure* comprise 1.2 percent of the random sample and those that did not, 12.4 percent. Thus, *PIOneFounder* firms had a *TechFailure* rate of 8.7 percent, which is more than twice the rate of firms with a *PIFounder*. Firms that were founded and managed by the PI, *PIOneFounderCEO,* and that experienced *TechFailure* also comprise 1.2 percent of the sample and those that did not fail comprise 10.1 percent, which translates to the highest *TechFailure* rate among the various firm leadership experience types of 10.5 percent. These results are consistent with my hypothesis: less variability of the human capital in key leadership roles for the firm results in a greater likelihood that the firm will experience project failure.

The mean number of firm founders with a business background conditional on having experienced *TechFailure* is 0.75 which is marginally less than the mean *BizBackground* of the firms that did not fail of 0.758. Given the lack of variation between these two means, it is not clear whether *BizBackground* has a meaningful association with *TechFailure*. The mean *AcademicBackground* for firms that failed for technical reasons is 0.6667 which is less than those that did not fail of 1.0892. This also is consistent with my hypothesis that *AcademicBackground* is negatively associated with *TechFailure.*

Table 9.10: Descriptive Statistics of PIs as Firm Leaders Grouped by *TechFailure*
(standard deviations in parenthesis)

Indicator	*TechFailure*				
	1	0	1	0	1 / (0, 1)
	Count		Percent (n = 169)		Rate
PICEO	2	36	1.2%	21.3%	5.3%
PIFounder	2	48	1.2%	28.4%	4.0%
PICEOFounder	2	34	1.2%	20.1%	5.6%
PIOneFounder	2	21	1.2%	12.4%	8.7%
PIOneFounderCEO	2	17	1.2%	10.1%	10.5%
			n = 12	**n = 157**	
*BizBackground**	--	--	0.75 (0.866)	0.758 (1.0706)	--
*AcademicBackground**	--	--	0.6667 (0.8876)	1.0892 (1.3885)	--

**Values are means of the variable*

MODEL RESULTS

The following set of models continues to build on the reduced form specification discussed previously by augmenting the model with the PI firm leadership measures of experience. In terms of the structural formulation discussed in Chapter VI, adding the information about leadership of the firm represents experience of both the firm and the PI. This final set of models that incorporates the firm's leadership experience provides the richest experience vector to understand covariates of project failure. Further, the focus of the following discussion is on the firm leadership variables, therefore discussion of estimation results for other variables will be limited unless the there is a meaningful change in a variable's output from previous results.

Table 9.11 presents the model results of three estimations of *Failure* with additional regressors to those presented in Table 9.7. The first specification includes *PIFounder* which has a positive coefficient though the parameter nor the marginal effect are statistically significant at conventional levels.

The second model results shown in Table 9.11 adds *BizBackground* to the estimation. The parameter of *BizBackground* is not statistically significant, but the estimate is directionally consistent with my hypothesis of a negative relationship with *Failure.* The marginal effect of *BizBackground* is not statistically significant at the reported levels with a p-value of 0.088, which is outside the bounds of statistical significance used in this dissertation. An interaction term between *PIFounder* and *BizBackground* was also included. The coefficient on the interaction term has a p-value of 0.051, marginally outside the reported significance levels, and has a negative relationship with *Failure.* The interaction term does not provide a direct link to the background of the PI since there may be co-founders, however, the term still provides useful information. It suggests that when a firm has a *PIFounder,* having founders with a background in business at least partially offsets the positive effect on *Failure* from having a *PIFounder.*

The third model results shown in Table 9.11 includes *AcademicBackground* and its interaction with *PIFounder*, however, neither the interaction term nor *AcademicBackground* parameter estimates are statistically significant. The marginal effect of *AcademicBackground* has a p-value of 0.064 which is marginally outside the bounds of the reported significance levels in this dissertation, though may be suggestive of a significant relationship. Nonetheless, the marginal effect of *AcademicBackground* on *Failure* of -0.0501 suggests a 5.0 percentage point reduction in the probability of *Failure* for each additional firm founder that had an academic background, *ceteris paribus*.

The next two model specifications consider a subset of the *PIFounder* variable using a dichotomous indicator, *PIOneFounder,* to indicate when the PI was the sole founder of the firm. Model results from the inclusion of *PIOneFounder* are shown in Table 9.12. The parameter estimate for *PIOneFounder* is positive as expected and though not statistically significant at the reported levels, has a p-value of 0.058. The marginal effect of *PIOneFounder* has a p-value of 0.080, again outside the thresholds of reported statistical significance in this dissertation. Although the statistical significance of the marginal effect of *PIOneFounder* is outside the threshold for reporting, the effect is relatively large. Firms which the PI is the sole founder have a 17.4 percentage points increase in the probability of *Failure* compared to firms that do not have a *PIOneFounder*.

The second model shown in Table 9.12 includes *AcademicBackground* as an additional measure as well as the interaction between *PIOneFounder* and *AcademicBackground.* Because *PIOneFounder* indicates the sole founder was also the PI, the interaction term provides a direct link to the PI's background. However, the parameter estimates for *PIOneFounder*, *AcademicBackground,* and the interaction term between the two are not statistically significant.

Table 9.11: PI as Founder *Failure* Probit

	(1)		(2)		(3)	
	Failure	Marginal Effects	*Failure*	Marginal Effects	*Failure*	Marginal Effects
PIFounder	0.112	0.0256	0.394	0.00950	0.425	0.0165
	(0.295)	(0.0679)	(0.367)	(0.0653)	(0.361)	(0.0663)
BizBackground			-0.0443	-0.0506		
			(0.137)	(0.0297)		
PIFounder x *BizBackground*			-0.692			
			(0.355)			
AcademicBackground					-0.107	-0.0501
					(0.149)	(0.0271)
PIFounder x *AcademicBackground*					-0.433	
					(0.271)	
FemalePI	-0.857	-0.148	-0.707	-0.125	-1.014	-0.161*
	(0.658)	(0.0785)	(0.653)	(0.0877)	(0.733)	(0.0746)
MinorityPI	0.426	0.106	0.384	0.0904	0.505	0.122
	(0.392)	(0.105)	(0.388)	(0.0974)	(0.418)	(0.108)
Age30DecilePI	-1.069*	-0.194**	-1.157**	-0.203***	-1.159**	-0.202***
	(0.430)	(0.0602)	(0.438)	(0.0586)	(0.423)	(0.0561)
Age40DecilePI	-0.0831	-0.0186	-0.114	-0.0245	-0.113	-0.0243
	(0.384)	(0.0850)	(0.401)	(0.0850)	(0.370)	(0.0786)
Age50DecilePI	-0.838*	-0.174*	-0.924*	-0.181**	-0.989*	-0.195**
	(0.393)	(0.0728)	(0.410)	(0.0701)	(0.389)	(0.0682)
AmerPI	-0.417	-0.0982	-0.420	-0.0949	-0.368	-0.0831
	(0.263)	(0.0626)	(0.268)	(0.0612)	(0.263)	(0.0602)
Employees	0.00170	0.000386	0.00203	0.000441	0.00229	0.000499
	(0.00246)	(0.000546)	(0.00246)	(0.000525)	(0.00264)	(0.000563)
SimAwardsDummy	-0.980***	-0.241***	-0.956***	-0.225***	-0.991***	-0.234***
	(0.247)	(0.0594)	(0.252)	(0.0581)	(0.255)	(0.0579)
ProfInvolved	-0.765*	-0.173*	-0.748*	-0.163*	-0.773*	-0.169*
	(0.348)	(0.0744)	(0.356)	(0.0728)	(0.357)	(0.0730)
DMT	0.0731	0.0165	0.0800	0.0174	0.105	0.0228
	(0.258)	(0.0581)	(0.270)	(0.0585)	(0.265)	(0.0575)
Intercept	0.440		0.492		0.545	
	(0.430)		(0.452)		(0.423)	
Wald χ^2	30.42**		38.35***		36.31***	
Likelihood Ratio	38.37***		42.81***		43.23***	

Robust standard errors in parentheses
*p<0.05 ** p<0.01 *** p<0.001

Table 9.12: PI as Single Founder *Failure* Probit

	(1)		(2)	
	Failure	Marginal Effects	*Failure*	Marginal Effects
PIOneFounder	0.700	0.174	0.461	0.208
	(0.369)	(0.0997)	(0.489)	(0.154)
AcademicBackground			-0.177	-0.0244
			(0.139)	(0.0369)
PIOneFounder x *AcademicBackground*			0.354	
			(0.679)	
FemalePI	-0.713	-0.126	-0.827	-0.139
	(0.653)	(0.0870)	(0.708)	(0.0844)
MinorityPI	0.434	0.104	0.574	0.139
	(0.386)	(0.0994)	(0.397)	(0.102)
Age30DecilePI	-1.087*	-0.192**	-1.281**	-0.215***
	(0.437)	(0.0598)	(0.418)	(0.0521)
Age40DecilePI	-0.0816	-0.0177	-0.192	-0.0407
	(0.395)	(0.0849)	(0.371)	(0.0772)
Age50DecilePI	-0.963*	-0.188**	-1.103**	-0.209**
	(0.412)	(0.0702)	(0.396)	(0.0646)
AmerPI	-0.390	-0.0884	-0.352	-0.0787
	(0.267)	(0.0612)	(0.266)	(0.0599)
Employees	0.00251	0.000550	0.00304	0.000659
	(0.00231)	(0.000492)	(0.00255)	(0.000534)
SimAwardsDummy	-1.026***	-0.243***	-1.033***	-0.240***
	(0.252)	(0.0574)	(0.261)	(0.0565)
ProfInvolved	-0.731*	-0.160*	-0.716*	-0.155*
	(0.345)	(0.0709)	(0.361)	(0.0729)
DMT	0.115	0.0251	0.118	0.0256
	(0.265)	(0.0576)	(0.265)	(0.0571)
Intercept	0.324		0.569	
	(0.413)		(0.407)	
Wald χ^2	30.13**		28.73**	
Likelihood Ratio	42.40***		44.77***	

Robust standard errors in parentheses
*p<0.05 ** p<0.01 *** p<0.001

In Table 9.13 model results are shown for four separate estimations that consider the case where the PI was also the CEO. Also included in this set of models is the case where the PI was the CEO and at least one of the firm founders. The first model results shown in Table 9.13 include *PICEO* which has a positive parameter estimate though is not statistically significant at conventional levels with a p-value of 0.082. The marginal effect of *PICEO* on *Failure* is not statistically significant.

The second estimation results in Table 9.13 include *PIFounderCEO* as an additional measure of experience. The estimate for *PIFounderCEO* suggests a positive association with *Failure* and parameter estimate is significant at the 0.05-level. The marginal effect of 0.151 is not statistically significant at conventional levels, though has a p-value of 0.056. The marginal effect of *PIFounderCEO* suggests firms with a *PIFounderCEO* have a 15.1 percentage point increase in the probability of *Failure* over firms that do not.

Table 9.13: PI as CEO and PI as Founder and CEO *Failure* Probit

	(1)		(2)		(3)		(4)	
	Failure	Marginal Effects	*Failure*	Marginal Effects	*Failure*	Marginal Effects	*Failure*	Marginal Effects
PICEO	0.540	0.128						
	(0.310)	(0.0757)						
PIFounderCEO			0.629*	0.151	0.945*	0.123	0.848*	0.126
			(0.320)	(0.0789)	(0.397)	(0.0729)	(0.373)	(0.0788)
BizBackground					-0.0425	-0.0459		
					(0.136)	(0.0286)		
PIFounderCEO x *BizBackground*					-0.751			
					(0.392)			
AcademicBackground							-0.141	-0.0479
							(0.149)	(0.0273)
PIFounderCEO x *AcademicBackground*							-0.340	
							(0.330)	
FemalePI	-0.856	-0.146	-0.861	-0.146	-0.718	-0.125	-1.026	-0.160*
	(0.694)	(0.0822)	(0.705)	(0.0828)	(0.674)	(0.0890)	(0.799)	(0.0789)
MinorityPI	0.423	0.103	0.418	0.101	0.424	0.0982	0.500	0.118
	(0.389)	(0.101)	(0.390)	(0.100)	(0.392)	(0.0967)	(0.421)	(0.106)
Age30DecilePI	-1.089*	-0.195***	-1.123**	-0.198***	-1.227**	-0.207***	-1.273**	-0.213***
	(0.426)	(0.0590)	(0.428)	(0.0579)	(0.442)	(0.0555)	(0.414)	(0.0521)
Age40DecilePI	-0.114	-0.0250	-0.145	-0.0314	-0.207	-0.0431	-0.208	-0.0437
	(0.388)	(0.0842)	(0.390)	(0.0833)	(0.396)	(0.0807)	(0.370)	(0.0759)
Age50DecilePI	-0.962*	-0.192**	-1.002*	-0.197**	-1.099**	-0.203**	-1.178**	-0.221***
	(0.395)	(0.0690)	(0.399)	(0.0682)	(0.414)	(0.0639)	(0.379)	(0.0619)
AmerPI	-0.390	-0.0897	-0.392	-0.0895	-0.362	-0.0795	-0.349	-0.0774
	(0.264)	(0.0610)	(0.265)	(0.0608)	(0.275)	(0.0606)	(0.264)	(0.0589)

Table 9.13 Continued

Employees	0.00280	0.000624	0.00290	0.000640	0.00304	0.000647	0.00341	0.000732
	(0.00243)	(0.000522)	(0.00239)	(0.000509)	(0.00239)	(0.000491)	(0.00263)	(0.000540)
SimAwardsDummy	-1.052***	-0.252***	-1.069***	-0.255***	-1.052***	-0.240***	-1.063***	-0.245***
	(0.254)	(0.0574)	(0.258)	(0.0576)	(0.261)	(0.0559)	(0.261)	(0.0566)
ProfInvolved	-0.786*	-0.175*	-0.779*	-0.172*	-0.778*	-0.166*	-0.791*	-0.170*
	(0.352)	(0.0730)	(0.348)	(0.0718)	(0.359)	(0.0711)	(0.352)	(0.0699)
DMT	0.146	0.0324	0.181	0.0397	0.189	0.0400	0.232	0.0492
	(0.258)	(0.0570)	(0.265)	(0.0579)	(0.281)	(0.0591)	(0.265)	(0.0560)
Intercept	0.332		0.333		0.389		0.493	
	(0.417)		(0.413)		(0.440)		(0.407)	
Wald χ^2	30.44**		30.51**		33.64**		40.20***	
Likelihood Ratio	41.1***		41.96***		46.36***		45.59***	

Robust standard errors in parentheses
*p<0.05 ** p<0.01 *** p<0.001

The third model results shown in Table 9.13 augment the second model with the inclusion of *BizBackground* and its interaction with *PIFounderCEO.* The coefficient on *PIFounderCEO* is positive, as expected, and statistically significant at the 0.05-level. The coefficients on *BizBackground* and the interaction of *PIFounderCEO* and *BizBackground* are both negative, and the p-value on the interaction term is 0.055, which is suggestive of a significant relationship with *Failure*. However, the marginal effect of *BizBackground* on *Failure* is not statistically significant at reported levels. These results indicate that firms with a less diverse leadership structure, as measured by the multiple roles of a single person, will have a positive impact on *Failure.* Further, the experience gained from having an additional firm founder with a business background can offset (not necessarily completely) the positive impact on *Failure* from a concentrated leadership structure.

The last model results shown in Table 9.13 include *AcademicBackground* as opposed to *BizBackground* as in the prior estimation discussed. The coefficient on *PIFounderCEO* is positive and significant at the 0.05 level. The coefficients for *AcademicBackground* and the interaction term are not statistically significant.

The final firm leadership experience variable used within a model in this dissertation is *PIOneFounderCEO.* Firms with a PI as the sole founder and also the CEO represent the most concentrated firm leadership experience available within these data. As shown in the first model results in Table 9.14, the parameter estimate for *PIOneFounderCEO* is significant at the 0.05-level and has a positive relationship with *Failure.* The marginal effect of *PIOneFounderCEO* on *Failure* is also significant at the 0.05-level and is relatively large at 0.261. This indicates that firms with a *PIOneFounderCEO* have a 26.1 percentage point increase in the probability of *Failure* over firms that do not. This result is consistent with my hypothesis that the more concentrated the experience of the firm leadership, i.e. the more roles a single person plays, the more likely the firm will experience *Failure.* The second estimation results shown in Table 9.14 augment the first with the inclusion of *AcademicBackground* as well as its interaction with

PIOneFounderCEO. After controlling for *AcademicBackground,* the parameter estimate for *PIOneFounderCEO* is no longer significant at the 0.05-level. However, with a p-value of 0.063 the estimate is suggestive of a significant relationship. The marginal effect of *PIOneFounderCEO* is also no longer significant at the 0.05-level. The parameter estimates for *AcademicBackground* and the interaction term are not statistically significant at a reasonable confidence level.

Table 9.14: PI as Sole Founder and CEO *Failure* Probit

	(1)		(2)	
	Failure	Marginal Effects	*Failure*	Marginal Effects
PIOneFounderCEO	1.018*	0.261*	0.863	0.276
	(0.397)	(0.109)	(0.465)	(0.183)
AcademicBackground			-0.173	-0.0290
			(0.140)	(0.0356)
PIOneFounderCEO x *AcademicBackground*			0.220	
			(0.735)	
FemalePI	-0.657	-0.116	-0.761	-0.129
	(0.649)	(0.0900)	(0.701)	(0.0883)
MinorityPI	0.424	0.0990	0.564	0.132
	(0.389)	(0.0974)	(0.401)	(0.101)
Age30DecilePI	-1.171**	-0.200***	-1.350**	-0.219***
	(0.431)	(0.0562)	(0.413)	(0.0501)
Age40DecilePI	-0.130	-0.0275	-0.227	-0.0469
	(0.388)	(0.0806)	(0.369)	(0.0750)
Age50DecilePI	-1.072**	-0.200**	-1.215**	-0.219***
	(0.401)	(0.0644)	(0.375)	(0.0590)
AmerPI	-0.360	-0.0796	-0.321	-0.0697
	(0.271)	(0.0604)	(0.269)	(0.0590)
Employees	0.00301	0.000643	0.00362	0.000766
	(0.00231)	(0.000477)	(0.00256)	(0.000517)
SimAwardsDummy	-1.050***	-0.241***	-1.055***	-0.238***
	(0.254)	(0.0557)	(0.258)	(0.0544)
ProfInvolved	-0.771*	-0.165*	-0.765*	-0.162*
	(0.352)	(0.0699)	(0.367)	(0.0717)
DMT	0.170	0.0360	0.183	0.0383
	(0.268)	(0.0567)	(0.262)	(0.0548)
Intercept	0.307		0.526	
	(0.412)		(0.405)	
Wald χ^2	31.60***		33.92**	
Likelihood Ratio	45.78***		47.94***	

Robust standard errors in parentheses
*p<0.05 ** p<0.01 *** p<0.001

The next sets of model results use *TechFailure* as the dependent variable. Table 9.15 presents estimation results of two models; the first includes *PIFounder* and the second *PIOneFounder.* As shown in the first specification results presented in Table 9.15, neither the parameter estimate nor the marginal effect for *PIFounder* are statistically significant. However, after controlling for this type of leadership experience, the coefficient for *Employees* is negative and statistically significant at the 0.05-level, whereas in the initial estimates it was not significant at the reported alpha levels (see Table 8.7). The marginal effect is not significant at the 0.05-level, however, has a p-value of 0.065 which may be suggestive a significant relationship. The marginal effect of *Employees* on *TechFailure* is relatively small at -0.000850. This indicates that for each additional employee the probability of *TechFailure* is reduced by 0.0850 percentage points. While the marginal effect of *Employees* on *TechFailure* is relatively small after controlling for *PIFounder,* it is directionally intuitive. For the case when firm leadership experience is less varied, the experience gained from adding additional human capital to the firm offsets the lack of variation in experience of the firm leaders.

The second estimation results shown in Table 9.15 include *PIOneFounder* as the measure of firm leadership experience. In this specification neither the parameter estimate nor the marginal effect of *PIOneFounder* are statistically significant. The parameter estimate for *Employees* is negative and has a p-value of 0.058, which may suggest a significant relationship with *TechFailure*, however, the marginal effect of *Employees* on *TechFailure* in this model is not statistically significant.

Table 9.15: PI as Founder and as Sole Founder *TechFailure* Probit

	(1)		(2)	
	TechFailure	Marginal Effects	*TechFailure*	Marginal Effects
PIFounder	-0.338	-0.0353		
	(0.343)	(0.0323)		
PIOneFounder			0.327	0.0422
			(0.391)	(0.0587)
MinorityPI	0.528	0.0755	0.566	0.0817
	(0.435)	(0.0742)	(0.442)	(0.0771)
Age30DecilePI	-0.286	-0.0299	-0.307	-0.0319
	(0.477)	(0.0459)	(0.482)	(0.0461)
Age40DecilePI	0.0321	0.00365	-0.00563	-0.000636
	(0.459)	(0.0524)	(0.457)	(0.0516)
Age50DecilePI	-0.740	-0.0687	-0.901	-0.0801*
	(0.568)	(0.0415)	(0.562)	(0.0406)
AmerPI	-0.302	-0.0354	-0.304	-0.0354
	(0.303)	(0.0353)	(0.307)	(0.0357)
Employees	-0.00751*	-0.000850	-0.00491	-0.000555
	(0.00329)	(0.000461)	(0.00259)	(0.000342)
SimAwardsDummy	-0.689*	-0.0798*	-0.781*	-0.0904**
	(0.309)	(0.0338)	(0.317)	(0.0348)
ProfInvolved	-0.539	-0.0610	-0.491	-0.0555
	(0.453)	(0.0514)	(0.442)	(0.0488)
DMT	-0.0119	-0.00135	0.0795	0.00904
	(0.277)	(0.0314)	(0.294)	(0.0337)
Intercept	-0.429		-0.609	
	(0.514)		(0.516)	
Wald χ^2	17.02		17.82	
Likelihood Ratio	16.91		16.75	

Robust standard errors in parentheses

*p<0.05 ** p<0.01 *** p<0.001

The final set of estimation results are presented in Table 9.16 and augment those presented in Table 9.15 with the further conditioning on PIs that were also CEO. As shown in the first set of results in Table 9.16, the parameter estimate for *PICEO* and its marginal effect are not statistically significant. However, similar to the results in Table 9.15, the parameter estimate for *Employees* is negative and significant at the 0.05-level. The marginal effect is -0.000714 and has a p-value of 0.079 suggesting a small effect on *TechFailure*.

The second estimation results shown in Table 9.16 include an even more concentrated firm leadership structure with the use of *PIFounderCEO.* Although, *PIFounderCEO* is not a statistically significant estimator of *TechFailure*, after controlling for this variable, the coefficient on *Employees* is significant at the 0.05 level. The p-value of the marginal effect of *Employees* on *TechFailure* is 0.078. This marginal effect indicates an additional employee reduces the probability of *TechFailure* by 0.0692 percentage points.

The last model estimation results presented in Table 9.16 include the most concentrated firm leadership experience variable, *PIOneFounderCEO*. Similar to the prior two specifications, the coefficient and marginal effect for *PIOneFounderCEO* are not statistically significant.

Table 9.16: PI CEO and CEO Founder *TechFailure* Probit

	(1)		(2)		(2)	
	TechFailure	Marginal Effects	*TechFailure*	Marginal Effects	*TechFailure*	Marginal Effects
PICEO	-0.0868	-0.00964				
	(0.357)	(0.0382)				
PIFounderCEO			-0.0478	-0.00537		
			(0.361)	(0.0397)		
PIOneFounderCEO					0.483	0.0662
					(0.407)	(0.0694)
MinorityPI	0.535	0.0772	0.536	0.0775	0.579	0.0832
	(0.434)	(0.0749)	(0.434)	(0.0751)	(0.449)	(0.0780)
Age30DecilePI	-0.291	-0.0306	-0.291	-0.0306	-0.349	-0.0356
	(0.474)	(0.0458)	(0.471)	(0.0455)	(0.478)	(0.0447)
Age40DecilePI	0.0139	0.00158	0.0107	0.00123	-0.0355	-0.00397
	(0.454)	(0.0520)	(0.455)	(0.0521)	(0.452)	(0.0503)
Age50DecilePI	-0.792	-0.0730	-0.802	-0.0738	-0.973	-0.0843*
	(0.559)	(0.0409)	(0.557)	(0.0408)	(0.562)	(0.0398)
AmerPI	-0.306	-0.0360	-0.305	-0.0359	-0.292	-0.0338
	(0.304)	(0.0357)	(0.304)	(0.0356)	(0.312)	(0.0362)
Employees	-0.00626*	-0.000714	-0.00607*	-0.000692	-0.00454	-0.000510
	(0.00296)	(0.000406)	(0.00287)	(0.000393)	(0.00254)	(0.000329)
SimAwardsDummy	-0.725*	-0.0847*	-0.732*	-0.0856*	-0.801*	-0.0918**
	(0.314)	(0.0347)	(0.314)	(0.0348)	(0.324)	(0.0351)
ProfInvolved	-0.546	-0.0623	-0.543	-0.0619	-0.486	-0.0546
	(0.442)	(0.0499)	(0.441)	(0.0497)	(0.444)	(0.0487)
DMT	0.0466	0.00534	0.0515	0.00590	0.102	0.0116
	(0.280)	(0.0322)	(0.279)	(0.0321)	(0.289)	(0.0332)
Intercept	-0.523		-0.534		-0.615	
	(0.507)		(0.504)		(0.506)	
Wald χ^2	16.73		16.61		18.15	
Likelihood Ratio	16.3		16.28		17.22	

Robust standard errors in parentheses
*p<0.05 ** p<0.01 *** p<0.001

In summary, the findings of the analysis of firm leadership experience on project failure suggests that the more concentrated the human capital within the firm leadership, the more likely the project will fail. Further, the vocational background of the firm's leaders may have an impact on the probability of *Failure*. The human capital gained by firm leaders from having a business background or working in academia may translate to experience useful in reducing *Failure.* The concentration of firm leadership experience does not have a meaningful impact on failure for technical reasons. However, after considering the concentration of human capital of firm leaders, having more employees is a suggestive indicator for a reduction in the probability of *TechFailure*. By increasing the number of employees, the experience base of human capital is increased which may help with preventing issues that lead to technical failures.

Finally, variance inflation factors (VIF) for the group of firm and project characteristics that were used in the prior sets of estimations of equation (8.1) (Tables 9.5-9.7 and 9.11-9.16) are shown in Table 9.17. As shown in Table 9.18, the VIF on each variable is less than 2 except for the age decile indicators which are less than 3; this suggests that there is little concern for multicollinearity between these variables. Since these sets of variables encompass all the variables used in the models described in this chapter, then multicollinearity is not a concern for any of the prior estimations of equation (8.1).

Table 9.17: Variance Inflation Factors

	Table.Model_Number						
	9.11.2	**9.11.3**	**9.12.2**	**9.13.1**	**9.13.3**	**9.13.4**	**9.14.2**
PIFounder	1.7982	1.8035					
PIOneFounder			1.7744				
PICEO				1.1734			
PIFounderCEO					1.7245	1.6681	
PIOneFounderCEO							1.7222
Bizbackground	1.5276				1.4272		
AcademicBackground		1.4098	1.1312			1.2963	1.1187
FemalePI	1.0584	1.0610	1.0756	1.0473	1.0539	1.0611	1.0737
MinorityPI	1.3229	1.3297	1.3233	1.3177	1.3216	1.3407	1.3230
Age30DecilePI	2.3070	2.2995	2.2382	2.2027	2.2669	2.2446	2.2368
Age40DecilePI	2.5942	2.4972	2.4717	2.4744	2.6151	2.5170	2.4838
Age50DecilePI	2.4676	2.4484	2.4651	2.4390	2.5152	2.4863	2.4914
AmerPI	1.3351	1.3212	1.3187	1.3205	1.3376	1.3208	1.3250
Employees	1.1635	1.1803	1.1233	1.1601	1.1588	1.1738	1.1269
SimAwardsDummy	1.1200	1.1206	1.1143	1.1111	1.1172	1.1235	1.1099
ProfInvolved	1.0889	1.0814	1.1084	1.0770	1.0855	1.0792	1.0997
DMT	1.1516	1.1319	1.1035	1.0992	1.1290	1.1156	1.1103

Homophilic Gender Composition

The final PI and firm relationship considered here is the case when both the PI and firm owner are of the same gender. Bednar et al., (2019) found a statistically significant positive relationship between the probability of commercializing a technology and if the firm owner and PI were both female. In this light, the homophilic relationship between owner and PI is analyzed here using the data from the random sample of 169 Phase II funded projects discussed previously. Due to lack of variation in the data, i.e. no female owner/ female PI firms experienced *Failure*, I am not able to leverage the reduced form model described in Chapter VIII. However, I do offer insights drawn from the data. Table

9.18 below presents summary statistics of the project team and project outcomes by gender composition of the project team.

Table 9.18: Mean Values by Gender Composition
(standard deviations in parenthesis)

Variable	Project Composition			
	Female PI/ Female Owner	Female PI/ Male Owner	Male PI/ Female Owner	Male PI/ Male Owner
Failure	0	0.17	0.14	0.22
TechFailure	0	0	0	0.08
SimAwards	0.67	0.50	0.86	1.22
	(0.58)	(0.55)	(0.90)	(1.82)
Employees	9.67	53.17	27.71	36.36
	(5.77)	(57.13)	(49.79)	(49.31)
n	3	6	7	153

As shown in the table, female owned firms experienced *Failure* at a lower mean rate, than their male counterparts. Firms with a female PI and a female owner (n = 3) did not have any *Failure*, while the firms with a female PI and a male owner (n = 6) had mean *Failure* of 0.17. Using the count of similar awards for each firm, *SimAwards*, the female PI/ female owned firms received slightly more *SimAwards,* at the mean, 0.67, than female PI/ male owner firms, which received a mean of 0.5 *SimAwards*. Female PI/ female owner firms were much smaller, at the mean, with close to 10 employees, than female PI/ male owner firms, which had the largest number of employees on average with a mean of about 53 *Employees*. Using *SimAwards* as a measure of experience and *Employees* as a measure of project complexity, the female PI/ female owner firms were slightly more experienced than the female PI/ male owner firms, however, the female PI/ female owner firms are much smaller which may indicate the projects pursued by the female PI/ female owner firms were less complex than the female PI/ male owner projects. From these results it may be inferred that female PI/ female owner firms are more likely to take on small, perhaps less riskier projects than female PI/ male owner firms. It is commonly accepted that females tend to be more risk averse than their male counterparts, on average. Therefore, the homophilic female PI/ female owner relationship experiences *Failure* at a much lower rate than the female PI/ male owner firms but the projects are also likely less risky.

Further, male PI/male owner firms (n = 153) experienced *Failure* at the highest rate (0.22) among the four gender combinations. Male PI/ male owner firms had the largest mean *SimAwards* of 1.22, indicating that firms with this gender composition tend to have more experience than others, however, also tend to experience *Failure* more often. The mean number of *Employees* of the male PI/male owner firms is about 36, the second largest average firm size. Again, using firm size as a measure of project complexity, male PI/male owner firms typically engage in projects riskier than those of female owners with either male or female PI, but less risky than female PI/ male owner firms. Thus, female PI/ male owner firms may tend to undertake larger, riskier projects as measured by *Employees* and on average have less experience as measured by *SimAwards* than male PI/male owner firms however male PI/ male owner firms still have a higher mean *Failure.*

Male PI/female owner firms (n = 7) experience *Failure* at a mean rate of 0.14 which is just 3 percentage points lower than firms with a female PI/ male owner composition. Male PI/ female owner firms received a mean of 0.86 *SimAwards* compared to a mean of 0.5 *SimAwards* received by female PI/ male owner firms. Male PI/female owner firms had mean firm size of almost 28 employees, which is most similar to male PI/ male owner firms. Therefore, male PI/female owner firms may have a similar failure rate as female PI/male owner firms as these firms are typically smaller and slightly more experienced.

As shown, both homophilic compositions of firms hold the two boundaries of *Failure.* Female PI/female owner firms have the lowest mean rate of *Failure* while male PI/male owner firms have the highest mean rate of *Failure*. Although the female homophilic firm is typically less experienced than their male counterparts, they tend to have smaller firms indicating the lower *Failure* rate can at least be partially explained by risk aversion. Further, conditional on firms with female owners, firms with a female PI are less experienced, have smaller firm sizes, and have lower rates of *Failure* on average. Conditioning on firms with male owners, firms with a female PI are typically less experienced but have larger firm sizes, however, a lower mean rate of *Failure*, compared to firms with a male PI. All this together provides further evidence of a negative association between *FemalePI* and *Failure*, and evidence that the homophilic relationship of *FemalePI/ Female Owner* firms tend to experience lower rates of *Failure* than any other gender combination of firm owner and PI.

CHAPTER X: CONCLUDING DISCUSSION

Discussion

The DOE has a long-standing history of using technological innovation to achieve its goals. As discussed in this dissertation, the DOE descended from one of the best-known projects that involved public-private partnerships resulting in a new technology coming to fruition. Given the current size, and therefore budget of the DOE, the agency is one of the top contributors to the SBIR program. The SBIR program is the main source of public funding in the U.S. for small firms conducting innovative research with the goal of commercializing new technologies. Each firm that is funded through the SBIR program should have a principal investigator acting as the lead scientist for the project. As discussed previously, the role of the PI is critical in small innovative firms. Although a PI may be the lead scientist for an R&D project, PI's responsibilities can span beyond the typical day-to-day responsibilities of a research scientist and encompass duty's akin to those of a manager or leader of the firm. Given the relative importance of PIs in the innovation process it is important to understand what characteristics of PIs, if any, are associated with a greater likelihood of project failure.

The literature examining the determinants of SBIR project failure is limited and there are no studies that examine the breadth of characteristics of PIs and their association with failure as is done in this dissertation. As such, this dissertation provides several important contributions to the literature.

A complete literature review on R&D project failure that spans both the economics and management disciplines literature was conducted to understand past research that could be used as a steppingstone for the analysis in this dissertation. There is a notable lack of research that considers PIs or more generally an R&D project leader as a source of project failure. Further, there is not a theoretical model for research project failure in the literature. Therefore, this dissertation provides a new-to-the-literature theory that uses a structural form model to explain how firm and project characteristics, such as PIs experience, may impact the likelihood of R&D project failure.

Using the DOE SBIR data from the NRC second round survey, which has not been described in the literature outside of this dissertation, a set of initial models were estimated using a reduced form specification of the structural model. The results of these estimations provide support for previous studies findings. Given the results from Andersen et al., (2017) and Link and Wright, (2015) I had an a priori expectation that having received a previous award would be negatively associated with project failure. Having received previous awards is a measure of experience and that experience is beneficial for reducing the probability of project failure.

From the initial set of models, I found that having university faculty involved in the R&D project translated to a relatively large reduction in the probability a project failed. This result was in-line with my original expectation which was motivated by the findings in Gicheva and Link, (2016). Having university faculty involved in the project is a measure of human capital and given the nature of their work, university faculty provide research expertise that tends to reduce the probability of project failure. Knowing the effect of having university faculty involved in a Phase II funded SBIR project has on the likelihood of project failure is relevant information to program applicants. In terms of policy, SBIR program administrators could use this information to educate applicants and encourage or potentially incentivize applicants to involve university faculty in their project.

After confirming results found in previous studies (Link and Wright, 2015, Gicheva and Link, 2016 and Andersen et al., 2017), additional PI experience variables were added to the initial model's specification. Three general measures to describe PIs experience were analyzed: demographic characteristics, PIs as firm leaders, and the homophilic relationship between firm owners and PIs. From the demographic characteristics of PIs, using age decile bins, I found that younger PIs, those younger than the oldest cohort (PIs at least 60 years old), tend to have a lower probability of *Failure* than the oldest PIs in the random sample. This result may be because younger PIs take on less-complex projects that naturally are less likely to fail and because of higher levels of motivation driven by higher rates of marginal human capital accumulation. On the other hand, the oldest cohort of PIs may be less risk averse than their younger counterparts but also experience depreciating rates of human capital. The oldest PIs may have enjoyed past success and are willing to take on riskier projects because their opportunity cost of failing is lower than their younger counterparts.

Cunningham et al. (2016a) found that PIs take on multiple roles such as project manager, administrator, science broker, and boundary spanner (i.e., ability to bridge different areas and domains such as the academic sector and the private sector). I found that in addition to these roles, PIs may also be a founder of the firm and/ or CEO. When PIs are founders and/or CEO's of the firm, the leadership structure is more concentrated and the responsibilities of the PI are greater. I found that in general the more concentrated the leadership the greater the probability a project will fail. The case when the PI was the sole founder and the CEO had the largest marginal effect on the probability a firm will fail. This suggests that although PIs may have the ability to take on many responsibilities, there is a limit to number of roles a PI can assume and still have a project that does not fail. These results are more information that could be used to inform policy of the SBIR program. SBIR program administrators could inform award recipients, especially those that have a concentrated leadership structure, to consider creating a greater span of control by employing a CEO other than the PI.

I also found that the vocational background of PIs that were a founder or both a founder and the CEO have an impact on the probability of project failure. For the firms where the

PI was a founder and not the only founder, having founders with either a business background or academic background resulted in having a lower probability of project failure. Founders having a business or academic background also had a negative effect on project failure for firms that had a PI that was both a founder and the CEO. However, for the firms with the most concentrated leadership structure, the case when the PI was the sole founder and the CEO of the firm, the vocational background of the PI did not have a significant impact on failure.

Limitations

As with all studies this dissertation has limitations. While the data used in this dissertation are a random sample of Phase II funded SBIR projects from the DOE's SBIR program, it would be useful to have a larger sample size. Additionally, the data are from a single department's SBIR program, so the results may not be generalizable across all SBIR participating agencies. There is a notable lack of information on the Phase II award amount each firm received which has been shown to be a highly significant covariate with project failure (Link and Wright, 2015). Further, R&D projects progress through time across different phases, however, the data do not provide information about the timing of the failure of the projects in the random sample. This information would be useful to further understand and define a measure of failure and perhaps reasons that led to it. Finally, I was not able to produce an estimate of the probability of failure with the female homophilic relationship between owner and PI as a covariate due to the lack of representation of this type of relationship in the random sample.

Future Research

The analysis performed in this dissertation as well as the limitations associated with it gives rise to several avenues for future research. First, to test the robustness of the results found in this dissertation, future research may consider using additional data from other departments to conduct similar analyses to those performed here. This dissertation considered two measures of failure. However, framing failure across different measures would be interesting. For example, failure could be defined as not receiving a patent, not generating spinoffs, or not increasing employment over the duration of the project. Looking at different objectives of the firm may help uncover useful information or covariates that are beneficial for reducing failure across several objectives or perhaps covariates unique to a specific measure of failure.

Future research may look at the specific time or phase within the R&D projects life cycle that the project failed and this concept could potentially be incorporated to advance the theoretical model. With this information policy makers could inform program participants of the pitfalls associated with various phases of an R&D project and perhaps channel resources to help generate an overall lower probability of failure. Further, another expansion to the theoretical model could be to incorporate an additional measure for cost of the experience of the principal investigator. On average, the better the experience a principal investigator has accumulated, the more that principal investigator would cost since better experience should, at least partially, reduce the risk of failure.

Additionally, understanding or formulating a measure of risk associated with SBIR projects would provide another useful dimension to understand why projects fail or even a method for categorizing SBIR projects. Knowing the variation in risk between projects may also provide further insights into characteristics of principal investigators that may be associated with projects that bare certain risk profiles. One measure, as discussed in the Section 10.2, that could help in defining the risk of a project is the SBIR award amount. Since awards are given to help further the innovation, it is not known whether the project will succeed or fail when the award is given. Therefore, the amount of the award could be considered as a measure of risk, whereas the greater the monetary value of the award translates to greater potentially losses, hence greater risk.

Conclusion

In conclusion, in this dissertation I have provided a complete literature review on R&D project failure that spans both the economics and management disciplines literature. This review uncovered a notable lack of literature related to PIs and their association with project failure as well no theoretical model of research failure. Therefore, I provided a theoretical model for research project failure to help fill the void, which is used in its structural form to guide the empirical analysis conducted. Further, in this dissertation I have analyzed DOE data using NRC second round survey data and used these data to replicate the empirical probability of failure providing support for previous studies findings. I have presented PIs as a new-to-the-literature covariate with R&D project failure and found that certain characteristics of PIs lead to a lower probability of failure. Specifically, younger PIs have a lower probability of failure than the oldest cohort and PIs that are the sole founder of the firm and are also the CEO have a significantly higher probability of failure compared to PIs who are strictly PIs. As such, this dissertation contributes to a small but growing body of literature that considers the role PIs have in the failure of R&D projects.

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