

Picking Winners: Market Outcomes of Public Venture Capital

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Through the Small Business Innovation Research (SBIR) program, the U.S. government provides grants and sole-source contracts to small businesses demonstrating potential for productive innovation. The program is designed to correct market failures associated with research and development inappropriability and information asymmetries in startup financing. I use linked datasets combining SBIR award data with the National Establishment Time Series to reexamine previous case-study- and survey-based investigations that found positive effects of the program on firm performance. Empirical matching models compare program participants to control groups of similar firms and reveal significant underperformance of program participants in both employment and sales growth over a six-year period.

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The idea of market failure is common in the economic theory of research and development: firms do not invest in innovation at a socially optimal level due to technological spillover and the inappropriability of investment returns. With social returns to innovation exceeding private returns, there may be a role for public support of private research and development (Arrow 1962, Griliches 1992, Jones and Williams 1998). Other inefficiencies arise from the nature of new ideas and the people working to commercialize them. Moral hazard and information asymmetry between entrepreneurs and venture capitalists may prevent viable projects from finding the necessary financing. Structure of the venture capital industry itself and the regulations governing it may favor large, established firms at the expense of more innovative but less capitalized competitors (Hall 2002). Such concerns led to the Small Business Innovation Development Act of 1982 (P.L. 97-219), which established the Small Business Innovation Research (SBIR) program to be overseen by the Small Business Administration.

Founded on the idea that innovative small businesses are the engine of U.S. economic growth, the act directs federal agencies engaging in high levels of research and development to

set aside a portion of their funding for small businesses. The SBIR program office states on its website, “SBIR targets the entrepreneurial sector because that is where most innovation and innovators thrive. However, the risk and expense of conducting serious R&D efforts are often beyond the means of many small businesses.” Through a competitive, multi-phased sequence of investments, agencies select projects with high potential and attempt to bring them from concept development to commercialization through a series of grants and sole-source contracts. Phase I of the program provides limited funding to demonstrate commercial potential. Successful Phase I firms then progress to Phase II in which products are further developed for introduction to the marketplace. The program currently disburses about \$2 billion per year to small businesses (see Figure 1).

The literature on the potential for R&D market failure presents a strong theoretical case for the need to support R&D efforts in small businesses (Romer 1986, 1990; Jones and Williams 1998). However, public choice theory suggests that, whatever the market failures, public solutions must first provide evidence that government organizations are equipped to produce desired outcomes. In the case of the SBIR program, can federal agencies identify and successfully invest in undercapitalized firms with potential for high impact on the economic performance of the United States? Anecdotal evidence would seem to answer this question in the affirmative. Proponents cite success stories such as Apple, Compaq and Intel, all of whom were recipients of government startup funding in their early days (Audretsch 2003). However, broader evidence supporting the conclusion that the SBIR program has been a success arises primarily from interviews, surveys and case studies of participating firms, and is therefore susceptible to the challenge that it comes from those most likely to overstate the program’s impact (Lerner and Kegler 2000). Objectively derived datasets are largely absent in the

literature, and the paucity of rich data on the subject allows notable (and by definition, outlying) cases to drive the debate.

This study provides a counterpoint to common case-study analyses of government R&D intervention with a dataset larger than any previously used, and comes to sharply different conclusions. Since interest in evaluating the SBIR program peaked a number of years ago, large quantities of publicly available data on SBIR awards have been collected by the program office. The challenge has been pairing these awards with data on firm performance since most SBIR program recipients are not publicly traded firms. The only significant study to undertake such a pairing was Lerner (1999), who manually combined survey data with information from a variety of public sources to conduct the only econometric analysis of the program to date with a sample size large enough to be convincing. The study found support for the program's beneficial effects.

I use a similar approach, linking SBIR awardee firms with employment and sales data through DUNS numbers also reported in the National Establishment Time Series (NETS). Although consistent DUNS number matches are only possible beginning in approximately 2007 (government procurement data quality greatly improved following the Federal Funding Accountability and Transparency Act of 2006), the following six years are adequate to discern program effects. I first replicate previous studies such as Lerner (1999), generating treatment and control groups by matching participating firms to non-participants by limited sets of firm characteristics. I obtain similar results, suggesting that SBIR firms grow faster than similar firms not benefiting from financing.

I then modify the matching procedure to account for additional data not available at the time of the early study. A critical problem in identifying the SBIR program's effect on firm

performance is disentangling the economic effects of the targeted innovation from those of the funding itself. A firm whose business model focuses on capturing non-competitive government contracts may indeed grow larger, but the goal of stimulating broader economic development and innovation will not be met. Examination of a larger panel of award data suggests that this is likely a problem: the same firms consistently win repeated SBIR awards over the span of many years (see Table 1). Case studies examining follow-on effects from single awards do not account for this serial correlation. A common finding that individual award recipients consistently outperform non-recipients in subsequent years may reflect the simple fact that initially successful firms continue to win SBIR awards. However, the skill set required to win federal contracts is likely different from that required to create value through innovation. By matching awardee firms with control firms based on a more robust set of variables, the models presented here control for both the serial correlation problem and other issues identified in previous studies such as localized availability of private venture capital and other critical inputs (Audretsch and Feldman 1996).

I begin with a limited sample created by matching Phase II award recipients with firms who won Phase I funding but failed to move to Phase II and examine employment and sales of the resulting treatment and control groups. The positive effect found here, as reported in Lerner (1999) and many other case-study-type analyses, disappears when firms are more carefully matched in subsequent model specifications. Matching treatment and control firms on location or total federal funding in addition to industry and size eliminates or even reverses the effects found in previous studies. Rather than matching Phase II firms with Phase I firms, I next match them with non-SBIR firms which held other R&D contracts with the federal government. The larger sample size allows for more careful matching procedures, and the effect of SBIR

participation is strongly negative, with participants underperforming in employment and sales growth relative to their peers. Alternative specifications confirm the robustness of this finding.

Analysis of the effects of SBIR funding on individual firm performance does not address larger questions of beneficial knowledge spillovers and stimulation of private venture capital funding for research and development (Gans and Stern 2000). Most existing studies, however, are based on the premise that public venture capital programs indeed improve performance of the target firms (Audretsch 2003; Wessner 2000). They then explore how these salubrious effects spill over to the broader economy and whether the benefits are greater than the costs. Audretsch, Link and Scott (2002) go so far as to state, “We do not debate the appropriateness of the government’s support of [the SBIR program] but take that as a historical given and turn directly to evaluating the program’s results.” The following analysis suggests that a fruitful avenue of research is the assumed private beneficial effect itself. If government contracting officers are unable to “pick the winners” and succeed only in sustaining underperforming firms, then the proper question is not how much of the technology spills over, but rather whether a more effective mechanism should be used to allocate national R&D resources.

Underperformance of SBIR awardees is not the end of the story. As Wallsten (2000) points out, optimal government support for entrepreneurs should be targeted to marginal firms, not the high performers who could obtain financing through private-sector means. While private venture capitalists attempt to fund firms generating positive private benefits, public venture capital targets firms with positive social benefits. In the presence of knowledge spillovers, the social benefit is greater than the private benefit, leading private venture capital to require a higher net expected return. Venture capitalists of all types, however, cannot determine in advance which projects will be profitable. Empirical research suggests that they err significantly

on the side of funding many negative-net-return projects, relying on a few star performers to make up the difference.

The margin of private funding thus falls below the margin of private benefit on a continuum of possible net project returns (see Figure 2). If the private-funding margin is below the social-benefit margin, then the marginal socially beneficial project would be funded by the private sector in the absence of public support. In the presence of deadweight costs of taxation, it will be not only difficult for public venture capital to produce a net social benefit; it will be impossible. The study to follow does not attempt to identify the locations of these critical margins. It is important to note, however, that any innate inability of the public sector to identify productive investments will make it even more difficult to target firms in the possibly narrow gap between negative social returns and availability of private funding. And of course, program administrators give no indication that selecting subpar performers is deliberate or that their low level of performance is monitored to correspond with the margin between privately funded and unfunded projects. Publicly stated selection criteria include technical merit of proposed research subjects, firm qualifications, and potential for commercial success and benefit to society (www.SBIR.gov).

The SBIR program has objectives other than creating successful new firms, such as helping disadvantaged business owners and equitably sharing revenue among different constituencies. It is therefore possible that we can expect some level of underperformance. The results here are important nonetheless; they are at odds with common perceptions of the program's results and align more closely with traditional theories of regulatory capture (Stigler 1971, Becker 1983). The amount of funding provided to protected groups is also very small: of the nearly \$40B disbursed through the program since its inception, only about 0.5% has gone to

historically underutilized business zones, 1.3% to minority-owned businesses, and 3.1% to women-owned businesses.

The remainder of the paper is organized as follows. Section II examines the history of the SBIR program and provides a brief survey of the literature on subsidized R&D, as well as alternative research bearing on the subject such as confounding factors and the pitfalls of government intervention in the small business R&D environment. I describe the dataset and empirical approach in Section III and present results in Section IV. Section V concludes.

Section II: Background and Theory

The 1982 act of Congress establishing the SBIR program identified four broad goals: “(1) stimulate technological innovation; (2) use small business to meet Federal research and development needs; (3) foster and encourage participation by minority and disadvantaged persons in technological innovation; and (4) increase private sector commercialization of innovations derived from federal research and development.” Participating businesses must be for-profit organizations with less than 500 employees and more than 50% ownership by United States citizens. Following precursor programs in the 1950’s and 1960’s, an early pilot program in the 1970’s, and congressional action in 1982, SBIR was subsequently strengthened and expanded over a number of years. The Small Business Technology Transfer (STTR) program was added ten years later, which is similar to SBIR but requires small businesses to partner with universities, federally funded research and development centers (FFRDC) and other non-profit institutions to encourage the transfer of technologies developed there into the private sector. The programs were reauthorized through 2008 by the Small Business Reauthorization Act of 2000

(P.L. 106-554) and have since been further extended and expanded, the most recent of which directs continuation through 2017.

The current law mandates that federal agencies with research and development budgets exceeding \$100 million set aside a percentage of this budget for small businesses. Under the SBIR/STTR Reauthorization Act of 2011, this percentage is set to rise each year, from 2.5% in Fiscal Year 2012 to 3.2% in 2017. The STTR program is smaller than SBIR, with funding of 0.35% in 2012 and similar incremental increases through 2016. Figure 3 shows funding totals by agency, with a large majority provided through the Departments of Defense (DoD) and Health and Human Services (HHS). Federal departments participating in the program also include Agriculture, Commerce, Education, Energy, Homeland Security, Transportation, the Environmental Protection Agency, National Aeronautics and Space Administration and National Science Foundation.

Each participating agency periodically publishes a list of designated R&D topics and selects awardees based on a competitive proposal process. The program has three phases (Small Business Administration 2014). Phase I is the proof of concept stage in which participating agencies award up to \$150,000 over 6-12 months to establish the feasibility and commercial merit of the winning project proposals. Small businesses awarded Phase I contracts continue to Phase II at the discretion of the awarding agency and may be non-competitively awarded up to \$1 million in additional funding to continue the R&D effort for up to two years. Agencies may exceed these caps by 50% at their own discretion, so effective limits in Phase I and Phase II are \$225,000 and \$1.5 million, respectively. The Small Business Administration can waive the limits, and awards frequently exceed these amounts, particularly for HHS medical R&D awards (see Figure 4 and Figure 5). Phase III is the commercialization phase; prior awardees do not

receive any further SBIR/STTR funding, but work to obtain private funding and may sell the products, processes or services developed in Phases I and II to the government through non-competitive, sole-source contracts.

A. Early Theory on the Inappropriability of R&D Returns

Not long after inception of the SBIR/STTR program, new economic models built support for the general consensus that government plays an important role in private sector R&D that had grown since formalization by Arrow (1962). Romer (1986) incorporated technological change into macroeconomic growth models and showed how innovation is critical to explaining the ability of high-capital regions to consistently outperform poorer areas. Later works by Romer (1990) and Grossman and Helpman (1991) highlighted the non-rival and only partially excludable nature of technology and intellectual property. Given the importance of human capital to long-run growth and the inability of innovators to capture the full returns, too few resources are devoted to research in equilibrium.

Griliches (1958) built empirical support for the large externalities involved in research and development. As early as 1979, however, Griliches pointed out problems with case studies in assessing the contribution of research and development to economic growth. He noted that econometric estimates of the production function may perform better than case studies by ignoring the detail of outlying events to focus on total output or total factor productivity as a function of past investments in innovation. But even these broader studies are questionable given the challenge of differentiating price changes driven by product improvements from those caused by changes in monetary factors or ordinary shifts in supply and demand. Even if such price measurement difficulties can be sorted out, new ideas influence other research in addition to having direct product effects. While some allocation of property rights is possible through the

patent system, resulting prices are non-linear and cannot be used to measure social returns (Griliches 1992).

The more practical problem of data availability arises when studying small SBIR/STTR firms that are not publicly listed; the absence of firm-level data on inputs, outputs, capital stocks and other key variables makes productivity calculations difficult. Whatever the measurement challenges, consensus has built that R&D generates a large social rate of return beyond any private benefits. Jones and Williams (1998) find that common empirical estimates represent a lower bound, and that optimal R&D as a percentage of GDP is two to four times actual investment.

B. Support for the SBIR/STTR Program

A growing body of work specifically investigates the SBIR/STTR program and its performance as a vehicle for public venture capital provision to small businesses. Audretsch, Link and Scott (2002) conclude from their analysis of SBIR/STTR participant survey data and case studies that the program indeed stimulates innovation and the commercialization of technologies developed using federal resources. Case studies also suggest that award recipients would not have carried out the funded research without government support and that their efforts resulted in substantial spillover effects with broad benefit to society. A later similar study uses survey data from the US National Academies' division on Science, Technology, and Economic Policy, which gathered information from founders, owners and employees of SBIR/STTR firms (Audretsch 2003). Evidence from the survey supports the position that SBIR/STTR helps create high-technology companies and strengthens the competitiveness of the US economy. Gans and Stern (2000) take a different approach, using survey data from 100 SBIR/STTR projects to examine the relationship between the appropriability of technology across various industries and

the activity of private venture capital. Their findings suggest that policy makers can play a role in addressing challenging appropriability regimes facing small firms, such as intellectual property or antitrust rules which restrict access to assets required for successful commercialization. Lerner (1999) uses GAO survey data to construct treatment and control groups of SBIR participants and non-participants, using a variety of sources to determine sales and employment of awardees and matched firms. Phase II awardees performed significantly better over the approximately seven year period than non-awardees in each control group.

Lerner and Kegler (2000) and Lerner (2002) examine the role of administrators of R&D subsidy programs like SBIR/STTR and methods of assessing their performance. The authors point out that “survey methods interview those with interest in continuing the project” and that owners of SBIR/STTR firms have even formed a lobbying organization to advocate the program to lawmakers. The program may nevertheless provide net benefits. Due to financing challenges and information asymmetries, venture capital firms may be too big for small projects to be worth their time, and agency conflict may lead to Akerlof’s (1970) lemons problem in the venture capital market. Technological spillovers may be particularly acute for small businesses ill-equipped to defend intellectual property or leverage market power to extract rents from the products they develop. Public venture capital may then play a valuable role in certifying the viability of small businesses to investors and incentivizing innovators to produce social gains that cannot be privately captured (Meuleman and De Maeseneire 2012; Soderblom, et al., 2015).

Private sector investors maintain rigorous methods to select and protect their investments. They thoroughly scrutinize business plans, less than 1% of which are accepted. They require partners to certify the attractiveness of the investment as well as conferral of preferred stock with restrictive covenants and representation on the board of directors. Funds are provided in stages,

each of which includes close monitoring. Lerner and Kegler (2000) describe these functions and ask why SBIR/STTR administrators should perform them better than private agents. The paper notes a number of reasons why they may not. Political connections may become more important than technical promise. Past recipients may develop experience navigating red tape or relationships with administrators that facilitate future selection processes. Project technical proposals may not address many factors important to a firm's success that would be evaluated by a private venture capitalist, such as an entrepreneur's experience, legal troubles, or side projects that may distract from core areas of expertise.

C. International Evidence

Early empirical support for the importance of R&D to growth, and its under-provision by the market, led to widespread government subsidies for innovative activities around the world. In examinations of international programs the results are mixed, and point to several problems with practical application of R&D support. One study of 2,000 Spanish manufacturing firms receiving subsidies found that while some of these firms would cease their R&D activities in the absence of government support, most of the funding goes to firms that would continue without it (Gonzalez, Jaumandreu and Pazo 2005). Other evidence from Finland suggests that, while social returns to subsidized research projects are as high as 30-50%, technological spillovers from these projects are smaller than their effects on the profits of the targeted firms (Takalo, Tanayama and Toivannen 2013). Bronzini and Iachini (2014) look at Italian investment subsidies and find differential effects by firm size, with small businesses increasing their own investment by approximately the amount of the subsidy while spending at larger businesses is not affected. Montmartin and Herrera (2015) account for the strong spatial dependence of R&D

support programs across 25 OECD nations between 1990 and 2009 and find that, while tax incentives increase business-funded R&D, subsidies are more likely to substitute for it.

D. Geographical Effects of R&D Subsidies

Krugman (1991), following Marshall (1920), models patterns of development based upon transportation costs, economies of scale and manufacturing as a share of national income, and emphasizes spillovers and increasing returns that drive localized growth. Building on this theory, Jaffe, Trajtenberg and Henderson (1993) use patent citations to identify patterns of related research and development activity. Patent citations are more likely to come from the same state and metropolitan statistical area as the cited patents, suggesting that local synergies in innovation are important. Regional effects are also found in industry-specific knowledge spillovers: the degree to which an industry is geographically concentrated is directly related to the importance to the industry of new economic knowledge (Audretsch and Feldman 1996). Most SBIR/STTR firms reside in either California or Massachusetts (see Figure 6), with highly concentrated funding in such places as Los Angeles, Boston and Washington, DC (Figure 7). Localized synergies can be a blessing and a curse for subsidy programs. They may magnify beneficial effects by providing a network of support for new business owners within their local community (Huggins and Thompson 2015), but they also create political challenges for programs funded by tax dollars at the federal level, which generate pressure to fund less innovative businesses in other districts.

E. Firm Age, Size, and the Contribution of Small Businesses to Growth

A key assumption of lawmakers developing the SBIR/STTR program was that externalities in the market for innovative products are particularly acute for small businesses, and that these externalities hurt a portion of the economy that is especially important to economic

development and growth. A growing body of research, however, calls into question early assumptions about the economic role of small businesses. Several confounding factors are often cited. Davis, Haltiwanger and Schuh (1996) point out that while gross rates of job creation are significantly higher for small businesses, survival rates are poor, resulting in a net level of job creation that is far lower. Studies find a vital role in overall job growth played by a few very small firms (Anvadike-Danes, et al. 2015), but these studies are challenged by others which note that age, not size, is the operative characteristic.

Covariance between age and size makes the issue a difficult one to resolve. Decker, et al. (2014), finds that startups currently generate 20% of new jobs, but most exit within 10 years. A small fraction of young firms grow strongly and make up for most of the job losses created by those that don't survive. This highly skewed distribution is important to understanding the challenge of subsidy programs illustrated in Figure 2. While the diagram depicts a continuous range of potential project returns, empirical evidence suggests that the underlying distribution displays strong positive skew. In addition to the locations of the social-benefit and private-funding margins, the location of the modal return may increase or decrease the number of firms falling target range for optimal public subsidies.

If age is indeed the key factor, and is correlated with size, then the focus of the SBIR/STTR program on small firms may be justifiable: targeting small firms will incidentally have disproportionate effects on young firms, a few of which are likely to become star performers. Of 6,967 businesses receiving SBIR/STTR awards between 2007 and 2012 and matched to the NETS database, approximately 25% were established prior to 1997. These older firms received 42% of the total funding. More than 40% of 2007-2012 awardees started prior to 2002; these firms received 63% of the funding. Small businesses that have remained small (and

hence eligible for the SBIR/STTR program) for more than five to ten years are likely not the star performers ostensibly targeted by the program, but they receive a majority of the subsidies.

A criticism that underlies many of those discussed so far is that public solutions to inefficiencies in private markets face challenges of their own. Program administrators are likely no more skilled than private venture capitalists at selecting productive firms and viable projects, and have weaker incentives to do so. Stigler (1971), Peltzman (1976) and Becker (1983) examine the nature of competition for government subsidies, asking whether market failures in the provision of R&D financing to small businesses can be corrected by government action. The presence of externalities does not by itself justify intervention. I now turn to this question.

Section III: Dataset and Empirical Approach

The SBIR/STTR program office publishes all past awards. I use firm names and DUNS numbers to match awardees with detailed firm information in the NETS. The procedure generates a list of 6,967 matched firms that received awards between 2007 and 2012. Matching SBIR/STTR awards with NETS firm performance data by DUNS number is a challenge due to reporting practices of federal agencies. Awards are reported directly by the SBIR/STTR program office, but DUNS number/firm name pairs are reported separately from funding data, and inconsistent firm name structures make it difficult to automatically pair DUNS numbers with funding lines. I paired firm DUNS numbers with SBIR/STTR-reported award data by manually matching similar firm names across the 34,553 distinct names reported by the program office. (For example, a firm name reported in one funding line may differ from another by an omitted comma or period.) DUNS numbers then provided the means to match SBIR/STTR funding to firm performance data in the NETS.

A. Obstacles to Unbiased Analysis

Analysis of the program presents a number of other challenges. First, we would expect the effects of regulatory capture to vary over time as firms learn to manipulate administrative processes. Second, only a small number of the many relevant differences between firms are observable, potentially leading to omitted variable bias. Third, the effects of funding on firms in different categories, such as industry or geographic location, are likely to operate with different lags. Fourth, awards are correlated over time, with recipient firms far more likely to continue to win awards than their unsuccessful peers. Fifth, firms must be measured consistently: more accurate data are likely available for older and larger firms, leading to bias in datasets derived from heterogeneous sources. I address each of these concerns in turn.

Early examinations of SBIR were limited by the recent establishment of the program. Firms were unlikely in the first few years to have been able to capture regulators to a degree sufficient to generate rents. If regulatory capture is indeed a problem, we would expect early positive results to reverse in later years as firms paid less attention to market success and more attention to government subsidy. Indeed, the statutory size limit of 500 employees required to keep receiving subsidies incentivizes firms to remain small as their competitors grow, although the precise effects of this threshold are difficult to quantify given the heavily skewed distribution of firm sizes. The dataset here begins 25 years after the program started, which accounts for potentially delayed effects of regulatory capture. Figure 1 illustrates that the program achieved a relatively steady state in overall funding levels over the past 10 to 15 years.

Another problem is missing data and the infeasibility of using fixed effects to account for it. Simple regression analysis fails to account for significant unspecified differences between regions, industries, and firms, while heterogeneous lag structures associated with industry-unique

varieties of innovation limit the usefulness of panel data (as do substantial data entry errors, which create amplified attenuation bias in fixed-effects analysis). Problems associated with data unavailability are described in more detail in Griliches (1992) and Zuniga-Vicente, et al. (2014). This analysis confronts these challenges by aggregating awards across a six-year period to address heterogeneous lag structures, and applying various firm matching techniques to generate treatment and control groups addressing non-temporal heterogeneities across observations. Aggregation also overcomes lags in data reporting procedures used in compilation of the NETS database. The drawback to examining the six-year period in aggregate is that it underestimates the effect: awards received in the last month of the period are treated the same as those received in the first month, though program participation has clearly had insufficient time to take effect. Advantages are the model's parsimony and tendency to underestimate rather than overestimate the effect of SBIR/STTR participation on firm performance.

Aggregation of awards over the six-year period also addresses what is perhaps the most significant challenge to program assessment: the tendency of the same firms to consistently win SBIR/STTR awards over many years. Serial correlation of awards makes it difficult to distinguish growth due to innovation from growth due to regulatory capture. Accounting for this correlation is a challenge across potential specifications. Limiting the analysis to only those firms that won no further awards after the period in question cuts the sample size to an unworkably small number of firms. A snapshot in time with a follow-up many years later ignores the intervening period over which growth may have been achieved through product innovation or through further subsidies: the two cases are not distinguished, and which is driving firm growth is left undetermined. The analysis here lengthens the interval over which independent variables are captured to correspond with a period of time long enough to observe

their effects. As mentioned before, this leads to underestimation by treating early awards the same as later awards, but it solves the problem of serial correlation that leads to confounding of innovation and regulatory capture effects. Funding levels are matched across treatment and control groups, eliminating unspecified government intervention as a possible source of positive bias in estimates of firm growth due to innovation and market success.

Consistent measurement of firm performance across the full range of data is also critical to eliminating bias in the estimation. Distinct data sources provide more or less accurate data on different categories of firms. For example, larger, listed firms are well represented in SEC filings while data on smaller, independent firms are often gathered from surveys or newspaper accounts of noteworthy events like bankruptcies. Discrete data sources contain unique biases that will be applied non-uniformly across the dataset, potentially resulting in biased estimates. As discussed above, surveys present particular challenges given the incentive of participants to bias answers in ways that encourage continuation of program funding. Structural or cultural variation between industries may also lead to inconsistent reporting practices between subgroups of firms with correlated performance measures. Data collection for this investigation was uniform across firms, relying upon NETS employment and sales data gathered outside the context of the SBIR/STTR program. While the NETS dataset is more uniform and objective, it suffers from problems of lagged and incremental reporting. It may take up to two years for changes in firm size to be reported in the data, and firms tend to report employment and sales levels in round numbers that jump sharply at arbitrary thresholds (such as 100 employees). Again, aggregation across a lengthy period of time helps to ensure important medium-term effects are captured and short-run variability adequately smoothed.

B. Dataset and Analytical Approach

The sample generated in this manner allows for more robust analysis than previously possible. The large dataset makes it possible to construct closely matched control groups based on detailed firm data. I examine three general model specifications. The first compares firms that only received Phase I awards (the control) to those that progressed to Phase II (the treatment). The second allows for an improved matching procedure by expanding the set of potential controls to the 37,465 non-SBIR/STTR firms that had active R&D contracts with the federal government between 2007 and 2012 (as reported in the Federal Procurement Data System); of these, complete data are available for 35,172 firms. I examine Phase I firms in more detail by comparing SBIR/STTR firms that received only Phase I awards during the 2007 to 2012 period (the treatment) with non-participating firms (the control). The third specification again uses the expanded control candidate set and improved matching procedure, but compares control firms to successful SBIR/STTR participants who won Phase II awards. Two additional variations examine the robustness of the findings by duplicating the second and third specifications while removing the requirement for a geographic match. This modification expands the sample size and develops the picture of program effects and sources of bias.

Specification 1 replicates previous studies that compare firms progressing normally through public venture capital programs with those that begin but do not continue on to subsequent program phases (Lerner 1999; Soderblom, et al. 2015). Eliminating firms with missing data reduces the original 6,967 SBIR/STTR firms to 6,794. Of these, 3,138 received only Phase I funding and failed to progress to Phase II; 3,656 of the firms received Phase II funding. I do not apply propensity score matching in this specification due to the limited size of the population of potential control firms; rather, I trim the dataset to Phase II treatment firms that

have precise matches with Phase-I-only firms. I match Phase II awardees to firms of the same 8-digit Standard Industrial Classification (SIC) code with the closest level of employment (required to be within 10 employees) and annual sales (required to be within \$500,000). The annual sales requirement combined with similar employment levels proxies for firm labor productivity in addition to serving as another measure of overall size. The large size of the full sample allows firms with insufficiently precise matches to be dropped, resulting in a final sample size of 3,098 firms (1,555 in the treatment group and 1,543 in the control group).

Table 2 displays summary statistics for each group. Treatment firms received positive SBIR/STTR Phase II awards, while control firms received Phase I awards only. By construction, mean employment levels match at approximately 3.5 employees and annual sales at approximately \$350,000. Using only this limited number of matching variables, firms in the treatment group received significantly more Phase I award funding over the seven-year period. This makes sense: firms progressing to Phase II performed better than their counterparts who did not advance and went on to win more future Phase I awards as well. The propensity of initially successful firms to win more Phase I contracts in future years makes them systematically different from matched control firms leading to the biased results described below.

I build on this procedure in Specifications 2 and 3 making use of the larger data set that includes non-participating federal R&D contractors. To improve the quality of the matches without reducing the sample to an unacceptable size, I match treatment firms to similar firms that did not participate in the SBIR/STTR program, but did have government R&D contract vehicles active in the Federal Procurement Data System (FPDS). Research and development contracts are defined by an FPDS Product/Service Code prefix of A or particular M-prefix codes associated with operation of government-owned, contractor-operated R&D facilities (see General Services

Administration 2011). The universe of firms included as candidates for the control group contains 35,172 private-sector firms with active federal R&D contract vehicles in FPDS between 2007 and 2012 that could be matched to NETS entries by DUNS number and do not have significant missing data. The research discussed in Section II suggests that SBIR/STTR participation may serve a certification function for firms seeking private sector venture capital financing; receipt of non-SBIR/STTR R&D funding would serve a similar function, making other federal R&D contractors plausible matches for SBIR/STTR treatment firms along this dimension.

In Specifications 2 and 3, I include additional criteria in matching treated SBIR/STTR recipient firms to control firms. In the models requiring precise characteristic matches, control firms must be in the same industry as the corresponding treatment firm (defined by 8-digit SIC code), within 10 employees in size and within \$500,000 in annual sales, as in Specification 1. In addition, they must be located in the same core-based statistical area (CBSA) as the treatment firm. Geographic matching is important for the reasons discussed in Section II such as network externalities and supply chain synergies in addition to the hypothesis in Lerner (1999) that venture capital tends to disproportionately affect local firms. The treatment and control groups thus contain similar numbers of firms by SIC and CBSA, with similar levels of employment and annual sales. All firms come from the general pool of federal R&D contractors.

I also apply propensity score matching to the samples in Specifications 2 and 3, which allows inclusion of more matching variables without imposing unacceptable limits on sample size. The expanded set of explanatory variables is included in the probit model estimating probability of treatment. The model uses the number of firms in the same 4-digit SIC and CBSA rather than requiring firms to be in the same city and industry. Employment and the logarithm of

annual sales are included along with firm age and total federal funding (SBIR/STTR funding or otherwise for non-participating firms). Non-SBIR/STTR federal funding by firm was extracted from FPDS. These additional variables are not included in the precise-match models since they would unacceptably reduce the sample size. Summary statistics for the full population of Phase I and Phase II firms and the population of potential control firms are provided in Table 3. SBIR/STTR firms employ an average of 8 to 12 people and have annual sales of \$1.2M to \$2.0M. They are 10-13 years old on average. Phase II firms tend to be larger and older. Non-participating federal R&D contractors are also included in Table 3; as expected, they tend to be significantly older and larger than SBIR/STTR firms, with averages of 115 employees, \$17.1M in annual sales, and 23 years of age. I match treatment firms in each specification with their three nearest neighbors by propensity scores estimated in the probit model to form the control group (in contrast to the precise-match model, no caliper restrictions are included).

I then compare treatment and control groups by growth in employment and growth in annual sales over the six-year period using two distinct methods. A difference-in-difference model uses raw reported values of employment and sales at the beginning and end of the period to estimate the treatment group change relative to that experienced by the control group. In the second method, estimation of the average treatment effect on the treated (ATT) combines the beginning and ending values into an overall growth variable, calculated as $(\text{Value}_{2012} - \text{Value}_{2007}) / \text{Value}_{2007}$. I adjust sample variances of propensity score matching estimators of the ATT for the first-stage estimation procedure using distributions derived by Abadie and Imbens (2012). Firms that are not in business in either 2007 or 2012 have values of employment and sales coded to zero in that year, with firms coming into existence showing growth of 100%

and firms going out of business showing growth of -100%. A model specification that drops these entering and exiting firms from the dataset (not presented here) produces similar results.

Table 4 displays treatment and control group summary statistics for the second specification. Treated firms in Specification 2 received an average of \$244,037 in Phase I awards between 2007 and 2012. Their average 2007 employment level of 2.32 employees matches that of the control group as does their mean 2007 sales of \$221,497. A total of 1,902 firms met the precise matching criteria and are included in the model (885 treatment firms and 1,017 control firms). The probit regression estimating treatment propensities is presented in column 1 of Table 5.

The theory presented above does not provide a clear prediction for how these firms will perform. Winning a Phase I award may indicate that the firm was judged highly innovative by competent panels of experts in their field and can therefore be expected to perform well. It may also serve as a certification function to outside investors, allowing the firm greater access to private-sector financing. On the other hand, failing to progress to Phase II may suggest that these firms have trouble translating innovative ideas into practical applications and are therefore likely to perform poorly relative to non-participant firms.

Specification 3 matches full participants in the SBIR/STTR program – recipients of both Phase I and Phase II funding – to firms that did not participate. I use the same matching criteria as Specification 2 along all other dimensions. As Table 6 shows, these firms tend to be slightly larger than Phase-I-only firms in Specification 2. The treatment group averages 4.36 employees and \$454,356 in annual sales, versus 4.01 employees and \$418,065 in sales for the control group. Treated firms received an average of \$462,057 in total Phase I awards and \$1,826,980 in Phase II awards between 2007 and 2012. The sample includes 828 firms in the control group and 963

firms in the treatment group. The probit regression estimating treatment probabilities is included column 3 of Table 5.

For Specification 3 firms that participated successfully in the SBIR/STTR program from beginning to end, predictions of the conventional analysis and those of the regulatory capture hypothesis are sharply different. The conventional analysis suggests that public venture capital provides the startup funding required to turn innovative ideas into salable goods, and that government subsidies will stimulate growth as participating businesses commercialize the products developed during the program. How much of this benefit is captured by the awardee and how much spills over to other firms, thus producing larger social benefits, is an open question, but we should nevertheless see some degree of above-average growth at the firm level. Regulatory capture, on the other hand, implies that participating firms will specialize not in innovation, but in obtaining subsidies. The program may even attract losers in the competition for private venture capital, further decreasing the quality of the talent pool and lowering growth levels below the overall average.

C. Robustness of Estimated Effects

Two additional specifications test the robustness of the analysis by changing the matching criteria and expanding the sample size. In Specifications 4 and 5, I remove the requirement that firms must match to a similar firm in the same CBSA. Table 7 and Table 8, respectively, display the summary statistics. Specification 4 uses a control group that is not matched by CBSA to test the effect on treatment firms of receiving positive Phase-I-only funding. Firms are of similar size, with about 3.5 employees and \$370,000 in annual sales at the beginning of the period in 2007. The sample size of precise-match firms is 1,955 in the treatment group and 2,448 in the control group. Specification 5 also uses non-CBSA matching,

but compares control firms to full program participants receiving Phase II funds. The firms are slightly larger on average than Specification 4 firms, with about 6 employees and \$700,000 in annual sales. The sample includes 1,933 treatment firms and 2,390 control firms. The propensity score matching models are similar to those in Specifications 2 and 3, but remove the geography variable from the probit estimation of propensity scores, which instead includes the total number of firms in the same 4-digit SIC code across the United States rather than in the same CBSA. This probit estimation is included in columns 2 and 4 of Table 5.

Theory reviewed in Section II suggests that any bias introduced to the model by removing geography from the matching procedure is likely to be positive. SBIR/STTR funding is highly concentrated geographically (see Figure 7), and firms residing within industry clusters are likely to affect one another through knowledge spillovers, shared supply chains, concentrated customer bases, and other such agglomeration effects. Matched treatment and control firms from the same CBSA will experience similar geographic synergies, making the difference in their performance levels smaller. Control group firms from other cities, however, will not share industry cluster characteristics. We would expect the difference in performance between these control firms and SBIR/STTR participants to be larger.

D. Model Specification

I first use a difference-in-difference model to compare the employment and sales growth of treatment firms with those of control firms between 2007 and 2012. This model is applied to both the limited precise-match samples as well as the broader treatment and control groups matched using propensity scores. With the matching procedure designed to account for non-orthogonal differences between groups, I use ordinary least squares to estimate

$$y_{i\tau} = \alpha + \beta t_i + \gamma a_\tau + \delta t_i a_\tau + \varepsilon_{i\tau}$$

where $y_{i\tau}$ is the level of sales or employment for firm i in period τ , t_i is a dummy variable indicating treatment status of firm i , a_τ is a dummy variable indicating either 2007 or 2012 values of the dependent variable, and $\varepsilon_{i\tau}$ is an error term that is assumed orthogonal. The coefficient of interest is δ , which is the difference-in-difference estimator:

$$\hat{\delta} = (\bar{y}_{(treat)(after)} - \bar{y}_{(treat)(before)}) - (\bar{y}_{(control)(after)} - \bar{y}_{(control)(before)})$$

Robust standard errors are clustered by 6-digit North American Industrial Classification System (NAICS) code. Other specifications, not reported here, used alternatives such as CBSA to cluster the standard errors; this had no significant effect on the results.

The probit model used to estimate propensity scores is specified as

$$t_i = \alpha + \beta X + \varepsilon_i$$

where t_i is a treatment status dummy and X is a matrix of independent variables including the number of firms in the same CBSA and/or industry, employment in 2007, log of sales in 2007, firm age in 2012 and the log of total federal funding to the firm. I estimate ATT using propensity-score-matched treatment and control groups according to

$$E[Y_{1i} - Y_{0i} | D_i = 1] = E[Y_{1i} | D_i = 1] - E[Y_{0i} | D_i = 1]$$

where $E[Y_{1i} | D_i = 1]$ is the estimated value of the treatment group outcome (change in employment or annual sales) given treatment and $E[Y_{0i} | D_i = 1]$ is the counterfactual control group outcome assuming treatment. Matched controls supply counterfactual outcome estimates.

In addition to robustness checks using the non-geographically matched sample, I also include ordinary and weighted least squares estimates of the form

$$y_i = \alpha + \beta t_i + \gamma X + \varepsilon_i$$

where y_i is either the percent growth in employment or the percent growth in annual sales for firm i between 2007 and 2012. The treatment dummy, t_i , indicates SBIR/STTR participation

with β the coefficient of interest. The independent variables included in the propensity scoring probit regression model are also included here as controls in the matrix X . Error is again captured in ε_i and is assumed orthogonal. In addition to OLS, the model is estimated using frequency weights generated by the propensity score matching procedure. I weight each treatment and control observation by the number of corresponding matches from the other group, giving greater weight to firms possessing broader similarities to their peers.

Section IV: Results

The objective of the three primary model specifications is to answer several questions about the performance of the U.S. government's public venture capital program. Is the government, at a large scale and over a long period of time, capable of stimulating productive investment in R&D by small, innovative firms? Has it been successful at replicating the private venture capital industry at a national scale using bureaucratic structures? Does the US economy perform better when agencies deliberately stimulate R&D investment at the most basic level of the small business? There are two primary competing hypotheses. The consensus in the literature examining the SBIR/STTR program is that it has indeed been a success, and that subsidies create innovation and growth that spills over into the broader economy, providing social benefits beyond the impact to individual firms. A second body of literature focuses on public choice theory and the economics of rent seeking; it leads to the conclusion that such programs are unlikely to drive sustained high levels of performance given the weak and even perverse incentives offered to program participants and administrators.

A. Specification 1: Phase II Recipients versus a Phase-I-Only Control Group

Specification 1 replicates what is arguably the most convincing technique employed to date that suggests the program has been a success. Lerner (1999) supplements the large number of case-study-based analyses of the SBIR/STTR program with a broad look at the data. A comprehensive dataset was unavailable at the time the study was conducted, but the results can be replicated using modern data and similar methods. Table 9 displays t-tests for equality of means across the full treatment- and control-firm candidate populations in each model specification. The mean employment level for the 3,138 Phase-I-only firms increases by 71% between 2007 and 2012, compared to 66% for the 3,656 Phase II firms; this difference is not statistically significant. A broad look at sales growth produces a similar result: Phase-I-only firms experienced mean growth in annual sales of 125% (in constant 2012 dollars) compared to 120% for the treatment group. This difference in means is again insignificant.

A treatment sample matched to control group candidate firms by industry, sales and employment, however, produces more interesting results. Table 10 (columns 1 and 2) presents the results of the precise-match difference-in-difference model comparing employment and sales growth of treated firms receiving Phase II awards to control firms that did not progress beyond Phase I. As in Lerner (1999), the treatment group outperforms the control group. Mean annual sales rises by \$83,600 between 2007 and 2012 for Phase II firms compared to Phase-I-only firms, and the result is highly significant, with a p-value of 0.004. These treated firms also experience average relative growth of 0.377 employees over the period, but the result is not statistically significant (p-value 0.165). (Sort order is important to the matching procedure, and some re-sorted specifications achieve a positive result significant at the 10% level.) Figure 8 graphically depicts the difference-in-difference relationship. There are a number of reasons,

however, why these results are suspect. Industry-, sales- and employment-level matching is insufficient to capture all of the relevant differences between the groups. More awards, rather than any resulting innovation and commercialization, may have produced the observed growth.

Geography, and the accompanying network effect, is a significant factor not captured in the analysis that likely leads to bias. Columns 3 and 4 of Table 10 show a model that also requires firm matches to be in the same CBSA; including this matching variable reverses the sign of the results and eliminates statistical significance, though at a reduced sample size of 635 treatment firms and 657 control firms. Columns 5 and 6 report results of a similar model with firms also matched on total Phase I awards rather than CBSA (using both reduces the sample size to an unworkably small number of firms). Again, the signs reverse and the results lose statistical significance. Matching is more difficult in this case, with 1,276 treatment firms matched to only 463 control firms.

B. Specification 2: Phase I Recipients versus a Non-SBIR/STTR Control Group

Specification 2 examines in isolation the control group from Specification 1: firms that were awarded Phase I contracts but failed to progress to Phase II during the 2007 to 2012 period. In the overall sample, the 3,138 Phase-I-only firms experienced average employment growth of 71% compared to 134% in a full sample of 35,172 non-SBIR/STTR firms (see Table 9). A t-test that the latter exceeds the former rejects the null hypothesis at a level of significance of 0.0001. Annual sales growth also reveals underperformance of Phase-I-only firms, with a 125% increase in the treatment group and 252% for non-participants.

The Specification 2 precise-match difference-in-difference model compares treatment firms to other government R&D contractors that did not participate in the SBIR/STTR program by matching on CBSA in addition to the Specification 1 parameters of industry, sales and

employment. This model finds significant underperformance of Phase-I-only firms. Annual sales and employment decline by \$1.88M and 11.7 employees relative to the control group (Table 11, columns 1 and 2; and Figure 9). These declines are highly statistically significant, with p-values of 0.006 and 0.005, respectively.

Rather than limiting the sample to only those firms with precise control group matches, the propensity scoring method uses the probit model in Table 5 to estimate probabilities of inclusion in the treatment group based on a vector of firm characteristics. This technique finds the best matches available from the 35,172 potential control group firms that had active government R&D contracts over the period. Treatment and control groups are then used to estimate the ATT. Matching treatment to control firms based on propensity scores allows for matching on the additional characteristics of firm age and total federal funding without excessive reductions in sample size. It produces negative coefficients, as reported in Table 12. Employment growth in the Phase I treatment group is 383% lower than the control group over six years, but with an insignificant p-value of only 0.162. Sales growth is also lower (-312%) and lacking statistical significance, with a p-value of 0.196. I apply a difference-in-difference model similar to the precise-match model employed above, but using the treatment and control groups generated by propensity score matching. The results presented in Table 13 are even more dramatic than those from the smaller samples derived from precise matching on firm characteristics. Phase-I-only firms added 13.7 fewer employees and \$2,370,000 less in annual sales than the control group over six years, with p-values of 0.000 and 0.002, respectively. Unlike the ATT reported above, however, standard errors in this model do not account for propensity score estimation in derivation of the treatment and control groups.

Specification 4 is similar to Specification 2, without requiring that matched control firms be in the same CBSA as their treated paired firm. Here I examine the bias effect suggested by the inclusion of CBSA in the Specification 1 model. Based on the theory of agglomeration synergies, dropping the CBSA matching requirement should bias the results upward in absolute value. In the precise-match difference-in-difference model of Specification 4, Phase-I-only firms experience mean declines in annual sales and employment of \$1.95M and 10.6 employees relative to their peers, with highly significant p-values of 0.004 and 0.012, respectively (Table 11, columns 5 and 6; Figure 11). The propensity score matching model estimates the ATT for employment is a drop of 338%, with a p-value of 0.028. Sales growth is also poor, dropping by 298% relative to the control, with a p-value of 0.035 (Table 12). Difference-in-difference estimates calculated using the propensity-score-matched treatment and control groups again provide even more sharply negative results, as reported in Table 13, columns 5 and 6.

I contrast these results to those in Specification 2, in which firms required a geographically matching control firm to be included in the sample. Phase-I-only firms in Specification 4 performed at levels similar to the non-geographically-matched control group (\$1.95M and 10.6 employee mean decline) as compared to Specification 2, which did require a geographic match (\$1.88M and 11.7 employee mean decline). Thus, for Phase-I-only firms we do not see strong bias associated with the geography variable.

The finding that Phase-I-only firms underperform challenges the certification hypothesis that SBIR/STTR awards serve as a signal to outside investors, but it is not conclusive. Private venture capitalists may observe the failed attempt to progress to Phase II and choose not to invest. The early success and later failure may result from clever innovation combined with a

management team that is unable to capitalize on the opportunity. Such management difficulties would likely be observed by private investors. Ultimately the results are inconclusive.

C. Specification 3: Phase II Recipients versus a Non-SBIR/STTR Control Group

Specification 3 is more revealing. It examines successful SBIR/STTR participants who continued to progress through the program and finds they also performed significantly worse than similar firms over the six-year period. Compared to the full non-participant group of 35,172 firms growing at average rates of 134% in employment and 252% in sales over six years, the 3,656 firms receiving Phase II funding grew at only 66% and 120%, respectively (see Table 9). In the precise-match difference-in-difference model, annual sales declined by \$1.09M and employment by seven employees relative to the control group, with p-values of 0.049 and 0.067, respectively (Table 11, columns 3 and 4; and Figure 10). Propensity score matching provides additional evidence of underperformance for Phase II award recipients (Table 12), with an ATT of -217% growth in employment and -250% growth in sales (with p-values of 0.002 and 0.001, respectively). Difference-in-difference estimates in Table 13 show Phase II firms growing by 27 fewer employees (p-value = 0.001) and \$6.07M less in annual sales (p-value 0.012) than matched control firms (again with standard errors not accounting for first-stage propensity score estimation).

Similar to Specification 4, Specification 5 examines the findings in Specification 3 by removing the geography variable. Phase II participants in Specification 5 experience similarly poor performance, with declines of \$1.83M and 14.4 employees (p-values 0.000) in the precise-match difference-in-difference model (Table 11, columns 7 and 8; Figure 12). Propensity score matching produces an ATT of -269% in employment growth and -320% in sales growth with strong statistical significance (p-value 0.000) and the propensity-score-matched difference-in-

difference model produces even stronger evidence of underperformance (Table 13, columns 7 and 8).

Unlike Phase-I-only firms, performance of this treatment group relative to the control (\$1.83M and 14.4 employee mean decline; see Table 11) was greater than that of the geographically-matched sample in Specification 3 (\$1.09M and 7 employee mean decline), with stronger levels of statistical significance. As we saw in Specification 1, regional agglomeration effects may account for this bias upward in absolute value. Firm performance relative to neighboring firms is more similar, while performance differences relative to a national baseline are magnified. I speculate that the absence of this effect for Phase-I-only firms may reflect a failure to integrate with the local community of similar firms.

The finding in Specification 3 provides support for the hypothesis that SBIR/STTR participants excel not at innovation, but at remaining small and collecting subsidies while their peers grow. The Specification 3 result is also interesting in comparison to Specification 2. Both groups participated in the program, but firms with longer periods of participation and higher levels of funding experienced levels of poor performance similar to those that failed early on. It is apparent from this result that failure in the SBIR/STTR program (i.e., non-progression to Phase II) is not the operative indicator of broader market failure.

D. Alternative Models: Ordinary and Weighted Least Squares

Ordinary and weighted least squares estimates of treatment effects presented in Table 14 similarly suggest that SBIR/STTR participants grow more slowly than their peers. Using the propensity scores estimated in Table 5, I again compare the matched treatment and control groups used above in an ordinary least squares model that includes the treatment dummy as an independent variable. I also use the number of firms calculated to be matches to weight each

observation in the model. Positive Specification 1 results reported above are absent in this model, while in Specifications 2 and 3 participating firms are again shown to grow significantly slower than their peers.

Section V: Conclusion

Competing schools of thought on the effects of government subsidies on private R&D efforts come to different conclusions. One school emphasizes the externality problems associated with private innovation. Non-appropriable, non-rival ideas spill over to the broader marketplace, producing large social benefits that can only be partially captured by individual investors. Agency conflict in venture capital markets excludes small, dynamic innovators from competition for private-sector financing. This line of reasoning arrives at the conclusion that government subsidies are necessary to correct market failures and maximize innovation and growth of the national economy. The alternative literature asks not whether market failures exist, but whether government agents are able to correct them. Proponents of this school suggest that bureaucrats administering subsidy programs do not have the strong incentives faced by private investors to select high-quality projects and carry them through to commercialization. Applicants for the subsidies are incentivized not to innovate and grow, but to negotiate the process to win government contracts and to remain small and thus eligible for funding.

The conclusion of this investigation is that support for the former position seems to rely on outlying case studies and on evidence provided by individuals motivated to paint the program in a positive light. Using more objective methods and sources of data, recipients of SBIR/STTR funding are found to dramatically underperform relative to their peers. In the most telling model presented here (Specification 3), program participants that progressed successfully through the

program experienced growth in annual sales more than \$1.09M , or more than 200%, lower than that experienced by similar firms who did not receive subsidies. Their employment growth over the six-year period examined was lower by approximately 7 employees, or again more than 200% (see Table 11 and Table 12). These results are stronger under alternative specifications of the model (Table 13).

Careful consideration of the evidence presented leads to the conclusion that the results may be worse than the numbers seem to suggest. The model aggregates funding over the full period of the study, meaning that awards received in 2012 are treated the same as those received in 2007. This is unlikely to be the case. Effects of participation on employment and sales growth take time to manifest. While we likely see the full effect for 2007 participants, 2012 participants would continue to feel an impact beyond the end of the observation period.

A subsidy program that distributes funds collected through taxation creates deadweight losses that can be avoided through private funding mechanisms. Optimal public subsidy programs therefore target marginal firms not funded by the private sector. We can combine this intuition with empirical evidence on the dynamics of small business in the U.S. economy. Small businesses generate substantial employment growth as they emerge, but few survive beyond five or ten years. The net contribution to growth of the small business sector is far smaller than its gross contribution. The sector relies on a few star performers to make up the difference.

Where on the continuum of net project returns is the marginal firm that just misses out on obtaining private venture capital funding (Figure 2)? This is the firm that should be targeted by subsidy programs such as SBIR/STTR. Intel and Apple may have obtained government startup subsidies in their early years but it is unlikely that Gordon Moore or Steve Jobs would have given up in the absence of public support. That they received subsidies may represent a failure

rather than a success of program administrators. Which firms should SBIR/STTR administrators target? Where is the marginal firm? Given the long tail of the distribution of small business performance, and the fact that private venture capital investments usually fail, the marginal unfunded firm may be one that would be ultimately unsuccessful in making a positive social contribution.

I leave determination of the placement of this critical margin for future research, but its importance reveals a deeper theoretical problem for the SBIR/STTR program than the empirical evidence presented here. The empirical evidence suggests that subsidizing R&D for small businesses is a challenge given the misalignment of incentives and the administrative challenge of picking winners. The theoretical evidence suggests that effective subsidy programs may be, in fact, impossible. If the marginal firm in the competition for private investment does not produce positive social benefits, then even an optimal subsidy program will target firms with a negative net impact on the economic performance of the U.S. economy. If a gap does exist between the margin of social benefit and the margin of private funding, it will be difficult for program administrators to target this gap if outcomes are consistently at odds with stated objectives.

Tables and Figures

**Figure 1: Total SBIR/STTR Awards
(2012 dollars)**

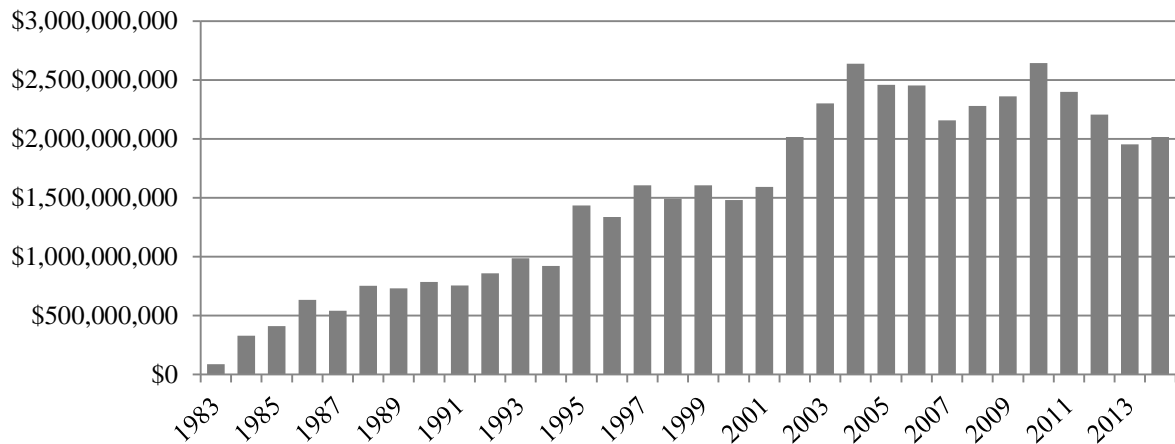


Figure 1: Total annual SBIR/STTR funding since program inception, as measured by Phase I and Phase II awards reported at www.SBIR.gov for fiscal years 1983 through 2014.

**Table 1: Number of SBIR/STTR Awards by Year, FY2000-2014
(random selection of recipient firms)**

Firm Name	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Total
Julia Group, The													1	1		2
Fulcrum Corp.		2		2	1											5
Laser Sensing Co.													2			2
Paragon Space Development Corp.			1		3	4	1	2	3	2	4	5	2	4	5	36
Zircon Computing LLC													1			1
Ekos Corporation	2	2														4
Nia Solutions Corporation					1											1
Advanced Cell Diagnostics, Inc.							1		1		1		1		1	5
Cornerstone Research Group, Inc.	3	3	5	13	8	12	13	10	13	12	15	13	8	3	10	141
Sims Brothers Incorporated											1	1				2
Hawthorne Mushrooms Inc.				1					1							2
Martek Bioscience Corporation	1	1														2
BI Healthcare, Inc.				1		2										3
Energy Quest Technologies Inc.											1		2		1	4
Scencezar Corp.	1	4														5
Ventana Research												1				1
Isotron Corporation				1	3	1	2		1							8

Table 1: Total number of separate Phase I and Phase II awards received by a random sample of SBIR/STTR program participants in fiscal years 2000 through 2014.

Figure 2: Target for Optimal R&D Subsidies

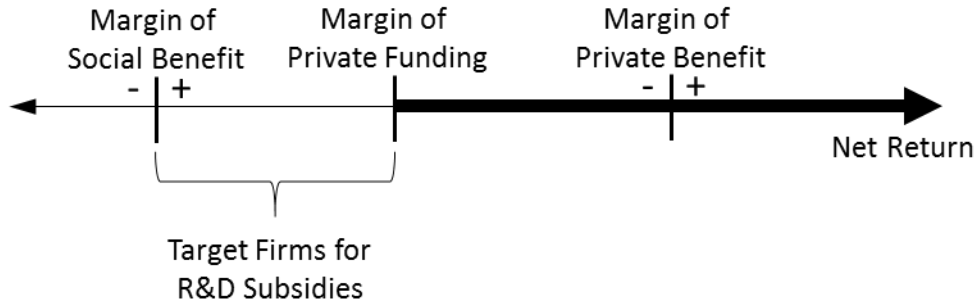


Figure 2: This figure illustrates the target range for projects funded by government R&D subsidies. The figure assumes that private agents require a larger net return to be willing to invest in a project than is socially optimal. It also assumes that many funded projects do not produce a positive private rate of return. If the margin of private funding falls to the left of the margin of social benefit, then no optimal policy exists for publicly subsidizing R&D projects.

Figure 3: Total SBIR/STTR Funding by Agency (2012 Dollars)

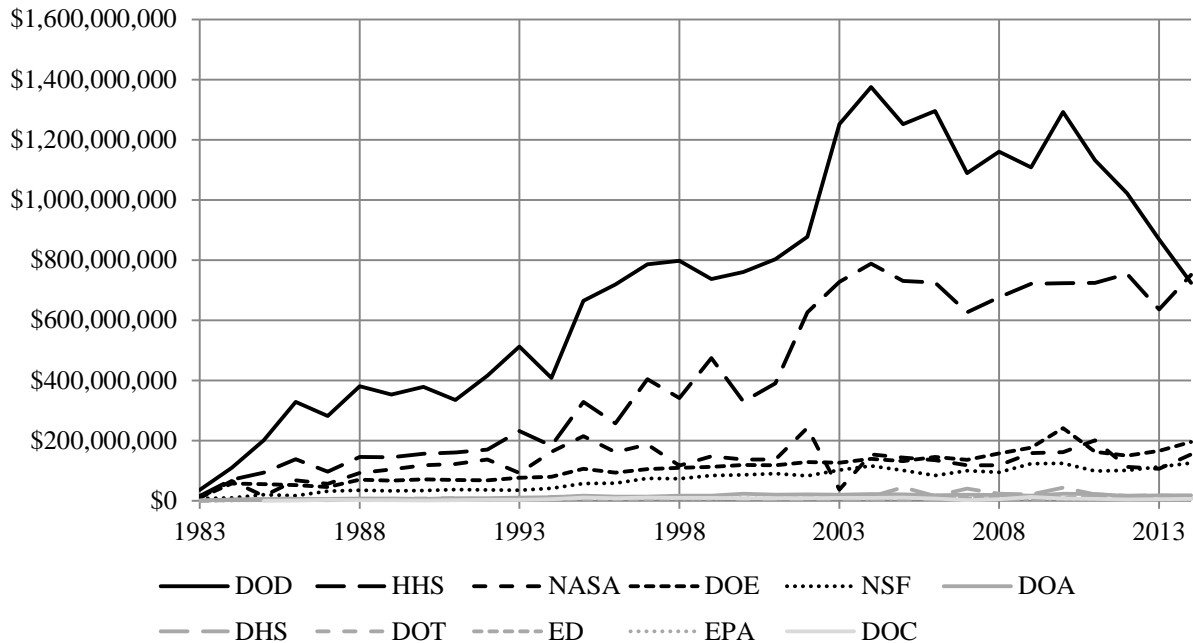


Figure 3: Total SBIR/STTR Phase I and Phase II funding by administering agency in fiscal years 1983 through 2014.

**Figure 4: Average SBIR/STTR Phase I Awards for Select Agencies
(2012 dollars)**

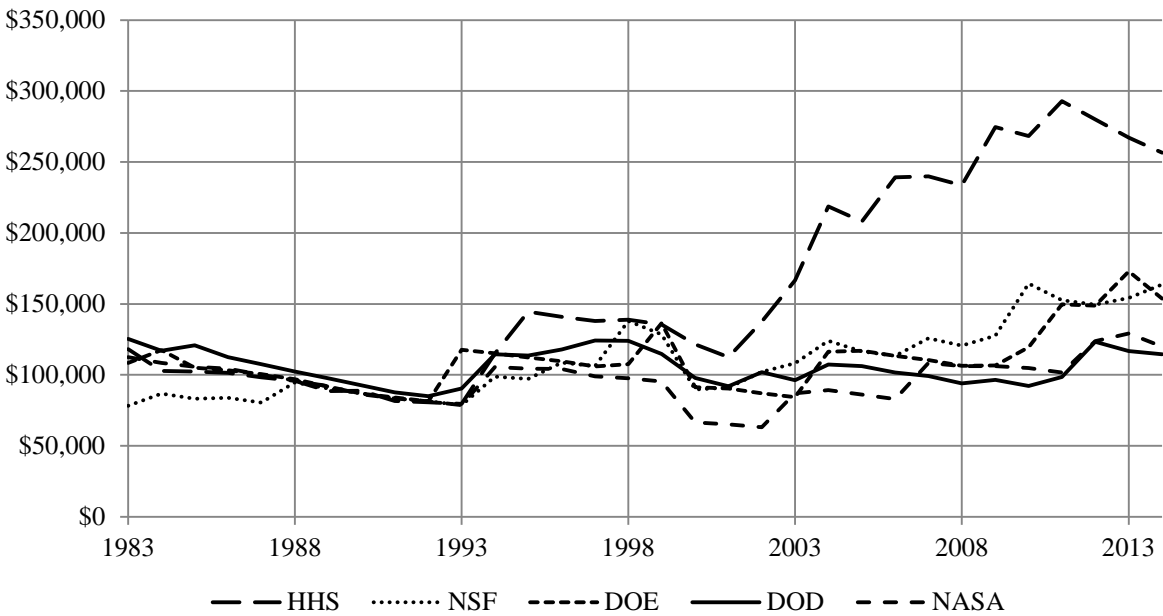


Figure 4: Average size of SBIR/STTR Phase I awards by agency in fiscal years 1983 to 2014.

**Figure 5: Average SBIR/STTR Phase II Awards for Select Agencies
(2012 dollars)**

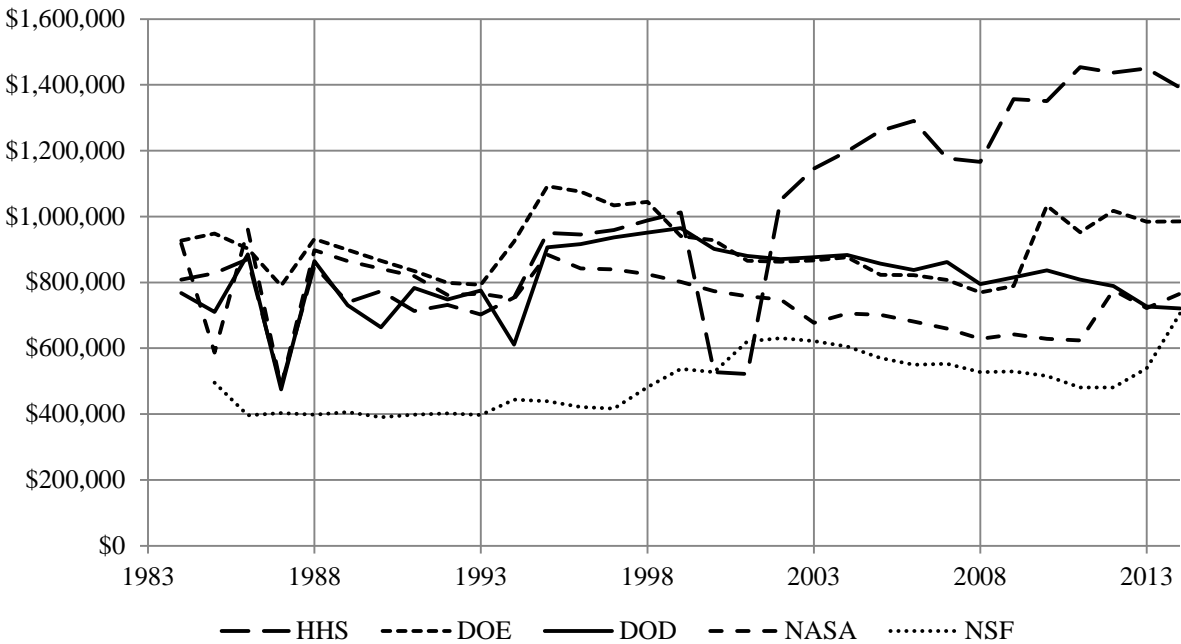


Figure 5: Average size of SBIR/STTR Phase II awards by agency in fiscal years 1983 to 2014.

**Figure 6: Total SBIR/STTR Funding by State (Top 5)
(2012 dollars)**

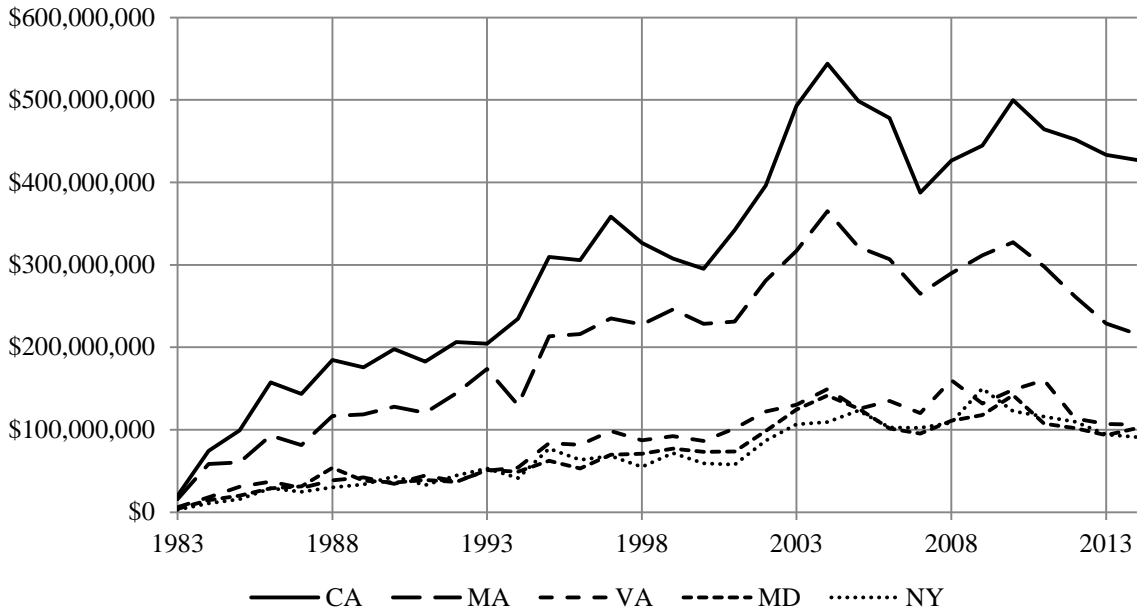


Figure 6: Total SBIR/STTR Phase I and Phase II funding by state of recipient firm in fiscal years 1983 through 2014.

**Figure 7: Total SBIR/STTR Funding by CBSA
(2012 dollars)**

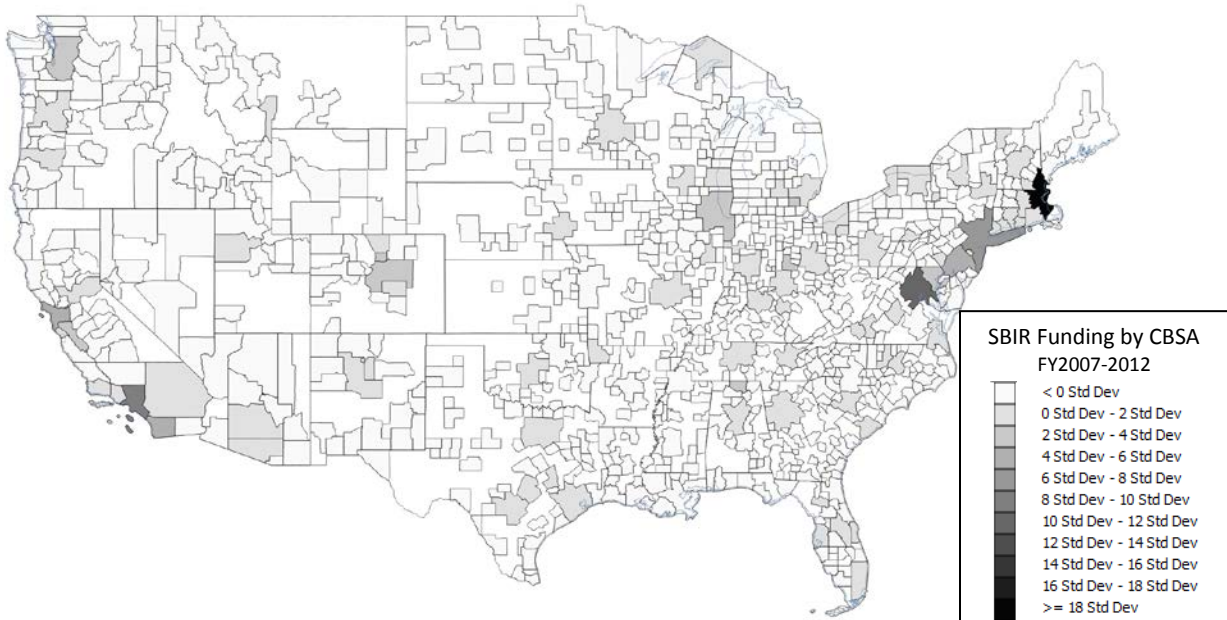


Figure 7: Total SBIR/STTR Phase I and Phase II funding by CBSA in fiscal years 2007 through 2012. Includes only SBIR recipients matched to NETS database firms. Top 5 CBSAs by funding are (respectively) Boston, MA; Washington, DC; Los Angeles, CA; New York, NY; and San Diego, CA.

Table 2: Treatment and Control Group Summary Statistics: Specification 1

	Mean	Std. Dev.	Min	Max	Obs
	Treatment Group				
Employees	3.60	5.63	0	100	1,555
Annual Sales	\$370,188	\$644,302	\$0	\$7,269,780	
Phase I Awards	\$479,751	\$678,345	\$0	\$6,856,135	
Phase II Awards	\$1,739,419	\$1,951,572	\$57,963	\$26,200,000	
	Control Group				
Employees	3.21	5.65	0	90	1,543
Annual Sales	\$329,511	\$645,319	\$0	\$7,375,086	
Phase I Awards	\$250,825	\$319,073	\$32,327	\$4,806,344	
Phase II Awards	\$0	\$0	\$0	\$0	

Table 2: Treatment and control group summary statistics for Specification 1. The treatment group contains firms awarded positive Phase I and Phase II SBIR/STTR awards between fiscal years 2007 and 2012. The control group contains firms that were awarded Phase I contracts but did not progress to Phase II. Treatment firms are matched to control firms by 8-digit SIC, employment level and annual sales.

Table 3: Aggregate Summary Statistics

	Mean	Std. Dev.	Min	Max	Obs
	Recipients of Phase I Funding Only				
Employees, 2007	8.07	25.5	0	475	3,138
Annual Sales, 2007	\$1,159,361	\$5,281,840	0	\$192,000,000	
Firm Age in 2012 (years)	9.84	10.2	1	117	
Phase I Awards	\$245,038	\$303,941	\$22,702	\$4,806,344	
	Recipients of Phase II Funding				
Employees, 2007	12.4	25.8	0	330	3,656
Annual Sales, 2007	\$2,028,673	\$13,100,000	0	\$679,000,000	
Firm Age in 2012 (years)	13.4	10.0	1	124	
Phase I and II Awards	\$3,064,484	\$6,123,499	\$106,637	\$150,000,000	
	Non-SBIR/STTR Firms With Active Federal R&D Contract Vehicles				
Employees, 2007	115	683	0	34,000	35,172
Annual Sales, 2007	\$17,100,000	\$161,000,000	0	\$23.5B	
Firm Age in 2012 (years)	23.3	25.9	1	376	
Federal R&D Funding	\$10,600,000	\$230,000,000	0	\$19.9B	

Table 3: Summary statistics for the overall populations of SBIR/STTR recipient and non-recipient firms. The top portion of the table contains firms that were awarded Phase I contracts between fiscal years 2007 and 2012 but did not progress to Phase II. The center portion contains firms awarded positive Phase II SBIR/STTR awards. The bottom contains non-SBIR/STTR participants who had active R&D contract vehicles with the federal government between 2007 and 2012.

Table 4: Treatment and Control Group Summary Statistics: Specification 2

	Mean	Std. Dev.	Min	Max	Obs
	Treatment Group				
Employees	2.32	6.71	0	110	885
Annual Sales	\$221,497	\$627,497	\$0	\$11,000,000	
Phase I Awards	\$244,037	\$279,581	\$32,327	\$3,977,982	
Phase II Awards	\$0	\$0	\$0	\$0	
	Control Group				
Employees	2.32	6.37	0	106	1,017
Annual Sales	\$214,170	\$600,650	\$0	\$11,500,000	
Phase I Awards	\$0	\$0	\$0	\$0	
Phase II Awards	\$0	\$0	\$0	\$0	

Table 4: Treatment and control group summary statistics for Specification 2. The treatment group contains firms awarded positive Phase I SBIR/STTR awards, but no Phase II awards, between fiscal years 2007 and 2012. The control group contains non-SBIR/STTR firms who were awarded other government R&D contracts. Treatment firms are matched to control firms by 8-digit SIC, CBSA, annual sales (within \$500,000) and employment level (within 10 employees).

Table 5: Probit Regression for Estimation of Propensity Scores

	Specification 2	Specification 4	Specification 3	Specification 5
Treatment Group:	Phase I only		Phase I and Phase II	
Control Group:	Non-SBIR R&D funding		Non-SBIR R&D funding	
Dependent Variable:	Treatment	Treatment	Treatment	Treatment
	(1)	(2)	(3)	(4)
<i>Number of firms of matching SIC & CBSA</i>	-0.00155*** (0.000131)		-0.000434*** (0.0000841)	
<i>Number of firms of matching SIC</i>		0.0000564** (0.0000235)		0.000019 (0.0000248)
<i>Employment, 2007</i>	-0.00515*** (0.000666)	-0.00513*** (0.000673)	-0.00329*** (0.000349)	-0.0105*** (0.000755)
<i>Log Annual Sales, 2007</i>	-0.0336*** (0.00254)	-0.0343*** (0.00254)	-1.12e-09 (1.49e-09)	0.00489* (0.00283)
<i>Firm Age in 2012</i>	-0.0148*** (0.00151)	-0.0139*** (0.00152)	-0.0131*** (0.00071)	-0.0105*** (0.00124)
<i>Log Federal Funding</i>	0.161*** (0.00277)	0.154*** (0.00263)	-8.8e-11*** (2.97e-11)	0.352*** (0.00623)
<i>Constant</i>	-2.32*** (0.0296)	-2.32*** (0.0287)	-0.983*** (0.0146)	-5.27*** (0.076)
Observations	38,310	38,310	38,828	38,828
Pseudo R-squared	0.2450	0.2374	0.0512	0.4118

Notes: *** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level
(Robust standard errors)

Table 5: Results for probit regressions used to estimate propensity scores for treatment/control group matching. The probit model estimates the probability that a given firm receives SBIR/STTR funding given the levels of the included control variables.

Table 6: Treatment and Control Group Summary Statistics: Specification 3

	Mean	Std. Dev.	Min	Max	Obs
	Treatment Group				
Employees	4.36	7.35	0	80	828
Annual Sales	\$454,356	\$898,914	\$0	\$9,462,606	
Phase I Awards	\$462,057	\$683,967	\$0	\$5,780,221	
Phase II Awards	\$1,826,980	\$2,298,800	\$126,550	\$23,200,000	
	Control Group				
Employees	4.01	7.40	0	80	963
Annual Sales	\$418,065	\$875,518	\$0	\$9,126,717	
Phase I Awards	\$0	\$0	\$0	\$0	
Phase II Awards	\$0	\$0	\$0	\$0	

Table 6: Treatment and control group summary statistics for Specification 3. The treatment group contains firms awarded positive Phase I and Phase II SBIR/STTR awards between fiscal years 2007 and 2012. The control group contains non-SBIR/STTR firms who were awarded other government R&D contracts. Treatment firms are matched to control firms by 8-digit SIC, CBSA, annual sales (within \$500,000) and employment level (within 10 employees).

Table 7: Treatment and Control Group Summary Statistics: Specification 4

	Mean	Std. Dev.	Min	Max	Obs
	Treatment Group				
Employees	3.50	9.73	0	220	1,955
Annual Sales	\$374,589	\$1,134,010	\$0	\$23,200,000	
Phase I Awards	\$234,489	\$275,802	\$22,702	\$4,131,702	
Phase II Awards	\$0	\$0	\$0	\$0	
	Control Group				
Employees	3.43	9.20	0	223	2,448
Annual Sales	\$365,169	\$1,069,146	\$0	\$23,500,000	
Phase I Awards	\$0	\$0	\$0	\$0	
Phase II Awards	\$0	\$0	\$0	\$0	

Table 7: Treatment and control group summary statistics for Specification 4. The treatment group contains firms awarded positive Phase I SBIR/STTR awards, but no Phase II awards, between fiscal years 2007 and 2012. The control group contains non-SBIR/STTR firms who were awarded other government R&D contracts. Treatment firms are matched to control firms by 8-digit SIC, annual sales (within \$500,000) and employment (within 10 employees). Firms are not matched by CBSA as in Table 4.

Table 8: Treatment and Control Group Summary Statistics: Specification 5

	Mean	Std. Dev.	Min	Max	Obs
Treatment Group					
Employees	6.48	13.4	0	300	1,933
Annual Sales	\$734,779	\$1,829,492	\$0	\$40,800,000	
Phase I Awards	\$536,938	\$1,145,657	\$0	\$24,900,000	
Phase II Awards	\$2,059,290	\$3,644,023	\$57,963	\$81,100,000	
Control Group					
Employees	6.16	14.0	0	300	2,390
Annual Sales	\$697,427	\$1,811,722	\$0	\$41,000,000	
Phase I Awards	\$0	\$0	\$0	\$0	
Phase II Awards	\$0	\$0	\$0	\$0	

Table 8: Treatment and control group summary statistics for Specification 5. The treatment group contains firms awarded positive Phase I and Phase II SBIR/STTR awards between fiscal years 2007 and 2012. The control group contains non-SBIR/STTR firms who were awarded other government R&D contracts. Treatment firms are matched to control firms by 8-digit SIC, annual sales (within \$500,000) and employment level (within 10 employees). Firms are not matched by CBSA as in Table 6.

Table 9: t-Tests for Equality of Means in Treatment and Candidate Control Groups

		Obs.	Mean	Std. Err.	H _A : Diff. < 0	H _A : Diff. ≠ 0	H _A : Diff. > 0
Specification 1							
Emp. Chg.	Control: Phase I	3,138	0.714	0.0606	0.775	0.450	0.225
	Treatment: Phase II	3,656	0.660	0.0389			
	Combined	6,794	0.685	0.0350			
Sales Chg.	Control: Phase I	3,138	1.25	0.421	0.535	0.930	0.465
	Treatment: Phase II	3,656	1.20	0.206			
	Combined	6,794	1.22	0.224			
Specification 2							
Emp. Chg.	Control: Non-SBIR	35,172	1.34	0.155	0.999	0.0002	0.0001
	Treatment: Phase I	3,138	0.714	0.0606			
	Combined	38,310	1.29	0.142			
Sales Chg.	Control: Non-SBIR	35,172	2.52	0.506	0.973	0.0536	0.0268
	Treatment: Phase I	3,138	1.25	0.421			
	Combined	38,310	2.41	0.466			
Specification 3							
Emp. Chg.	Control: Non-SBIR	35,172	1.34	0.155	1.00	0.000	0.000
	Treatment: Phase II	3,656	0.660	0.0389			
	Combined	38,828	1.28	0.140			
Sales Chg.	Control: Non-SBIR	35,172	2.52	0.506	0.992	0.0163	0.00820
	Treatment: Phase II	3,656	1.20	0.206			
	Combined	38,828	2.39	0.459			

Table 9: t-tests for equality of means across treatment and control candidate populations. Variables of interest are the change in employment and sales between 2007 and 2012, computed as $(\text{Value}_{2012} - \text{Value}_{2007}) / \text{Value}_{2007}$. Treatment and control group variances are not assumed equal.

Table 10: Difference-in-Difference Results for Precise-Match Samples, Specification 1

		Specification 1					
Treatment Group:		Phase I and Phase II					
Control Group:		Phase I only					
Matching Variables:		SIC, employment, sales		SIC, CBSA, employment, sales		SIC, Phase I awards, employment, sales	
Dependent Variable:		Sales	Empl.	Sales	Empl.	Sales	Empl.
		(1)	(2)	(3)	(4)	(5)	(6)
<i>Treatment * Period</i>		83600***	0.377	-13000	-0.209	-2710	-0.495
		(28000)	(0.27)	(77300)	(0.643)	(88200)	(0.74)
<i>Treatment</i>		40700***	0.39***	35900***	0.472***	142000***	1.27***
<i>(Treat = 1, Control = 0)</i>		(4900)	(0.0456)	(10300)	(0.0664)	(25700)	(0.267)
<i>Period</i>		155000***	2.19***	226000***	2.73***	220000**	2.83***
<i>(After = 1, Before = 0)</i>		(36500)	(0.218)	(81200)	(0.575)	(86700)	(0.669)
<i>Constant</i>		330000***	3.21***	197000***	2.12***	168000***	1.77***
		(31100)	(0.282)	(20700)	(0.215)	(22600)	(0.216)
Observations		6,196	6,196	2,584	2,584	3,478	3,478
R-squared		0.0130	0.0264	0.0155	0.0352	0.0191	0.0354

Notes: *** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level
(Robust standard errors clustered by NAICS)

Table 10: Results for Specification 1. The models are of the functional form $y_{i\tau} = \alpha + \beta t_i + \gamma a_\tau + \delta t_i a_\tau + \varepsilon_{i\tau}$, where $y_{i\tau}$ is the level of sales or employment for firm i in period τ , t_i is a dummy variable indicating treatment status of firm i , a_τ is a dummy variable indicating either 2007 or 2012 values of the dependent variable, and $\varepsilon_{i\tau}$ is an error term that is assumed orthogonal. The variable of interest is δ , which is the coefficient on the interaction term between t_i and a_τ . The values in the shaded row of the table above represent estimated values of the difference-in-difference estimator:

$$\hat{\delta} = (\bar{y}_{(treat)(after)} - \bar{y}_{(treat)(before)}) - (\bar{y}_{(control)(after)} - \bar{y}_{(control)(before)}).$$

Table 11: Difference-in-Difference Results for Precise-Match Samples, Specifications 2 - 5

	Specification 2		Specification 3		Specification 4		Specification 5	
Treatment Group:	Phase I only		Phase I and Phase II		Phase I only		Phase I and Phase II	
Control Group:	Non-SBIR R&D funding		Non-SBIR R&D funding		Non-SBIR R&D funding		Non-SBIR R&D funding	
Matching Variables:	SIC, CBSA, employment, sales				SIC, employment, sales			
Dependent Variable:	Sales	Empl.	Sales	Empl.	Sales	Empl.	Sales	Empl.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Treatment * Period</i>	-1880000***	-11.7***	-1090000**	-7.07*	-1950000***	-10.6**	-1830000***	-14.4***
	(655000)	(4.06)	(541000)	(3.79)	(669000)	(4.2)	(433000)	(3.98)
<i>Treatment</i>	7330	-0.00318	36300***	0.356***	9420	0.065	37400**	0.318**
(<i>Treat = 1, Control = 0</i>)	(6740)	(0.0468)	(9470)	(0.0778)	(8140)	(0.0673)	(16700)	(0.124)
<i>Period</i>	2210000***	15.1***	1370000**	10.2***	2170000***	13.3***	2070000***	17.2***
(<i>After = 1, Before = 0</i>)	(663000)	(3.9)	(527000)	(3.76)	(674000)	(4.21)	(447000)	(4.07)
<i>Constant</i>	214000***	2.32***	418000***	4.01***	365000***	3.43***	697000***	6.16***
	(39200)	(0.39)	(65900)	(0.486)	(49000)	(0.418)	(82200)	(0.702)
Observations	3,804	3,804	3,582	3,582	8,806	8,806	8,646	8,646
R-squared	0.0048	0.0072	0.0047	0.0049	0.0050	0.0066	0.0055	0.0043

Notes: *** Significant at the 1 percent level
 ** Significant at the 5 percent level
 * Significant at the 10 percent level
 (Robust standard errors clustered by NAICS)

Table 11: Results for Specifications 2-5. The models are of the functional form $y_{i\tau} = \alpha + \beta t_i + \gamma a_\tau + \delta t_i a_\tau + \varepsilon_{i\tau}$, where $y_{i\tau}$ is the level of sales or employment for firm i in period τ , t_i is a dummy variable indicating treatment status of firm i , a_τ is a dummy variable indicating either 2007 or 2012 values of the dependent variable, and $\varepsilon_{i\tau}$ is an error term that is assumed orthogonal. The variable of interest is δ , which is the coefficient on the interaction term between t_i and a_τ . The values in the shaded row of the table above represent estimated values of the difference-in-difference estimator:

$$\hat{\delta} = (\bar{y}_{(treat)(after)} - \bar{y}_{(treat)(before)}) - (\bar{y}_{(control)(after)} - \bar{y}_{(control)(before)}).$$

Figure 8: Specification 1 Treatment and Control Groups

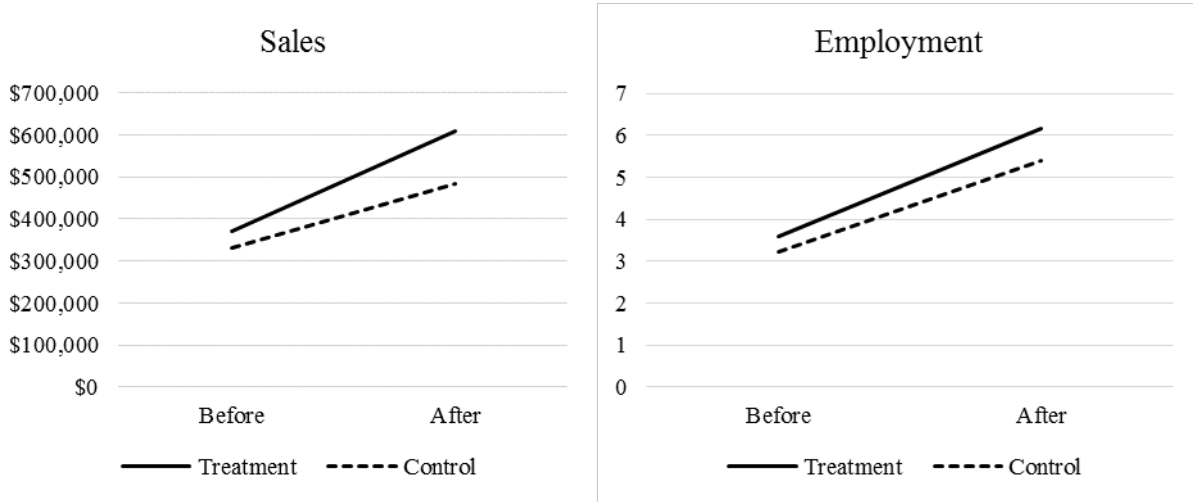


Figure 8: This chart provides visual representations of the difference-in-difference model specified in columns (1) and (2) of Table 10. The treatment group is composed of firms awarded Phase I and Phase II contracts. Control group firms participated in the program but did not progress beyond Phase I. Groups are matched on industry, 2007 employment and 2007 sales. The solid line represents the change in sales or employment of the treatment group between 2007 and 2012. The dashed line represents the change in sales or employment of the control group.

Figure 9: Specification 2 Treatment and Control Groups

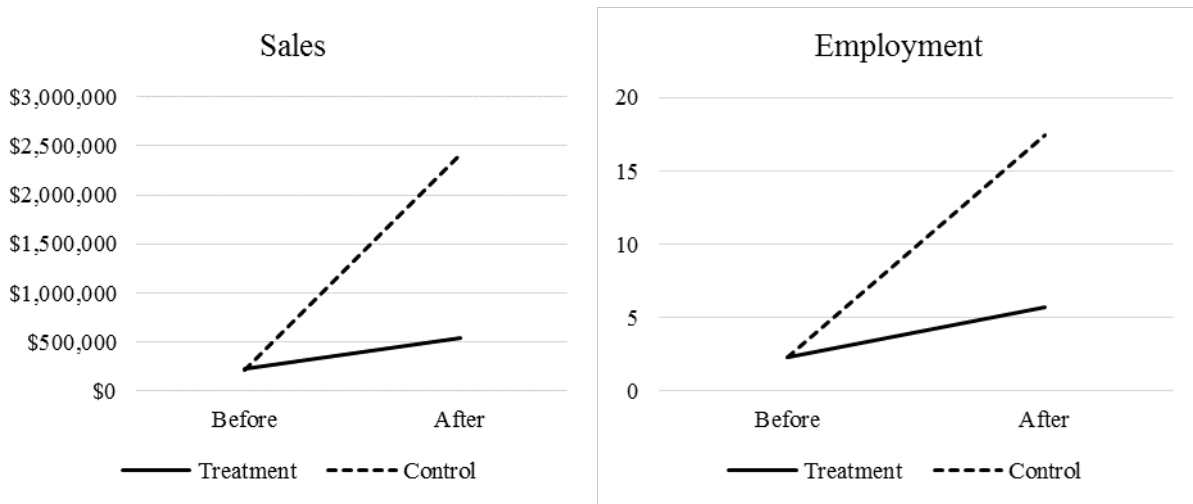


Figure 9: This chart provides visual representations of the difference-in-difference model specified in columns (1) and (2) of Table 11. The treatment group is composed of firms awarded Phase I contracts only. Control group firms did not participate in the program, but did receive other government R&D contracts during the period. Groups are matched on industry, CBSA, sales and employment. The solid line represents the change in sales or employment of the treatment group between 2007 and 2012. The dashed line represents the change in sales or employment of the control group.

Table 12: PS Matching Estimates of Average Treatment Effect on the Treated

		Coef.	AI Robust Std. Error	z	P > z	Obs.
Spec. 2	Employment	-3.83	2.74	-1.40	0.162	38,310
	Annual Sales	-3.12	2.41	-1.29	0.196	38,310
Spec. 3	Employment	-2.17	0.713	-3.04	0.002	38,828
	Annual Sales	-2.50	0.763	-3.27	0.001	38,828
Spec. 4	Employment	-3.38	1.54	-2.20	0.028	38,310
	Annual Sales	-2.98	1.42	-2.11	0.035	38,310
Spec. 5	Employment	-2.69	0.705	-3.81	0.000	38,828
	Annual Sales	-3.20	0.821	-3.89	0.000	38,828

Table 12: Estimates of the average treatment effect on the treated (ATT) in the propensity score matching models in Table 5. Reported values are differential growth in employment and annual sales computed as $(\text{Value}_{2012} - \text{Value}_{2007}) / \text{Value}_{2007}$. Estimates use Abadie and Imbens (2012) robust standard errors.

Table 13: Difference-in-Difference Estimates with Propensity Score Matching

	Specification 2		Specification 3		Specification 4		Specification 5	
Treatment Group:	Phase I only		Phase I and Phase II		Phase I only		Phase I and Phase II	
Control Group:	Non-SBIR R&D funding		Non-SBIR R&D funding		Non-SBIR R&D funding		Non-SBIR R&D funding	
PS Match Variables:	CBSA/SIC matches, employment, log sales, age, funding		CBSA/SIC matches, employment, log sales, age, funding		SIC matches, employment, log sales, age, funding		SIC matches, employment, log sales, age, funding	
Dependent Variable:	Sales	Empl.	Sales	Empl.	Sales	Empl.	Sales	Empl.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Treatment * Period</i>	-2370000***	-13.7***	-6070000**	-27.5***	-4090000**	-21***	-6340000***	-33.4***
	(753000)	(3.49)	(2420000)	(8.12)	(1910000)	(6.34)	(2440000)	(8.48)
<i>Treatment</i>	-594000***	-2.02**	-273000	-1.94**	-487000***	-1.48*	-867000***	-3.46***
(<i>Treat = 1, Control = 0</i>)	(206000)	(0.802)	(419000)	(0.96)	(186000)	(0.811)	(278000)	(0.997)
<i>Period</i>	2470000***	16.1***	5880000**	29.9***	4180000**	23.5***	6520000***	36***
(<i>After = 1, Before = 0</i>)	(732000)	(3.37)	(2380000)	(8.06)	(1900000)	(6.28)	(2420000)	(8.42)
<i>Constant</i>	2040000***	12***	3100000***	18***	1920000***	11.3***	3330000***	19.5***
	(167000)	(0.557)	-273000	(0.641)	(143000)	(0.577)	(203000)	(0.708)
Observations	9,592	9,592	8,228	8,228	9,686	9,686	8,308	8,308
R-squared	0.0047	0.0073	0.0024	0.0051	0.0018	0.0044	0.0031	0.0071

Notes: *** Significant at the 1 percent level
 ** Significant at the 5 percent level
 * Significant at the 10 percent level
 (Robust standard errors)

Table 13: Difference-in-difference estimates using all treated observations and control groups derived using propensity score matching from the probit model in Table 5.

Figure 10: Specification 3 Treatment and Control Groups

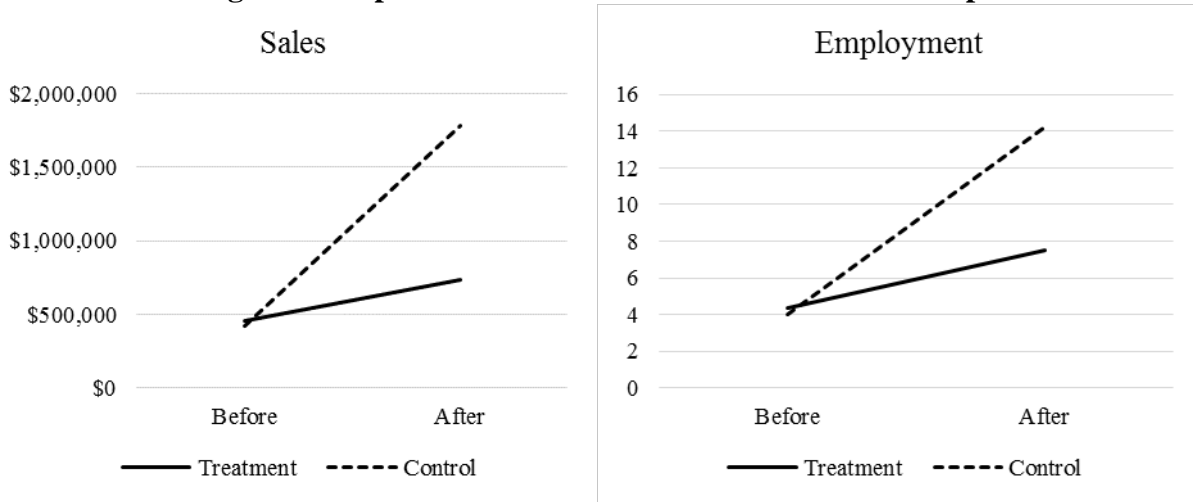


Figure 10: This chart provides visual representations of the difference-in-difference model specified in columns (3) and (4) of Table 11. The treatment group is composed of firms awarded Phase I and Phase II contracts. Control group firms did not participate in the program, but did receive other government R&D contracts during the period. Groups are matched on industry, CBSA, sales and employment. The solid line represents the change in sales or employment of the treatment group between 2007 and 2012. The dashed line represents the change in sales or employment of the control group.

Figure 11: Specification 4 Treatment and Control Groups

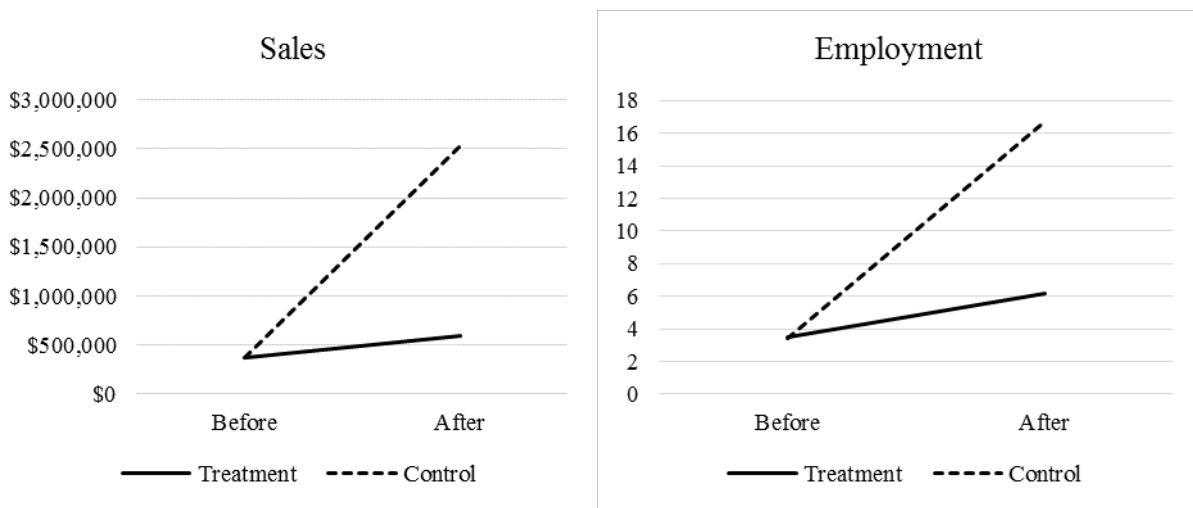


Figure 11: This chart provides visual representations of the difference-in-difference model specified in columns (5) and (6) of Table 11. The treatment group is composed of firms awarded Phase I contracts only. Control group firms did not participate in the program, but did receive other government R&D contracts during the period. Groups are matched on industry, sales and employment, but not CBSA. The solid line represents the change in sales or employment of the treatment group between 2007 and 2012. The dashed line represents the change in sales or employment of the control group.

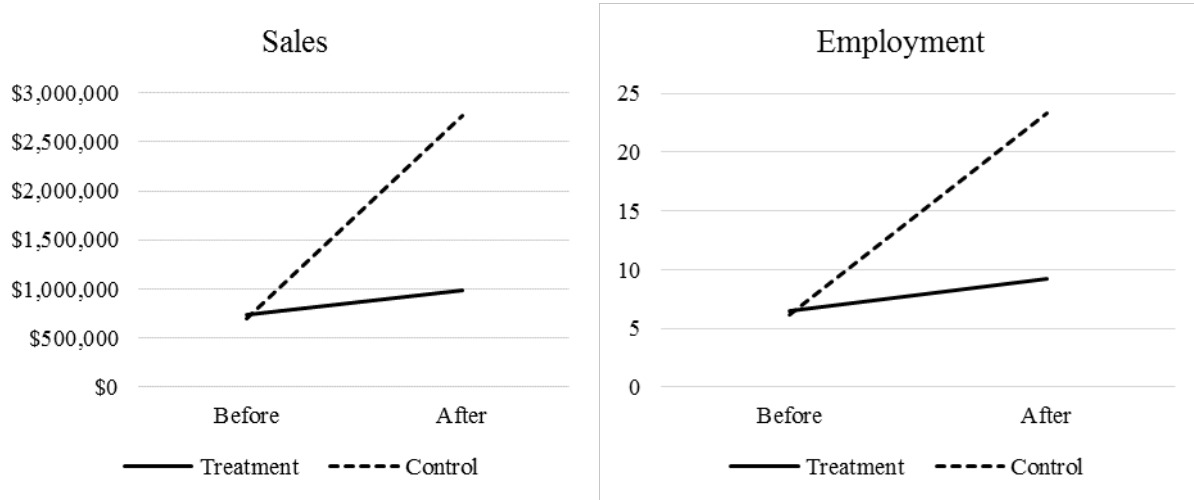
Figure 12: Specification 5 Treatment and Control Groups

Figure 12: This chart provides visual representations of the difference-in-difference model specified in columns (7) and (8) of Table 11. The treatment group is composed of firms awarded Phase I and Phase II contracts. Control group firms did not participate in the program, but did receive other government R&D contracts during the period. Groups are matched on industry, sales and employment, but not CBSA. The solid line represents the change in sales or employment of the treatment group between 2007 and 2012. The dashed line represents the change in sales or employment of the control group.

Table 14: Ordinary and Weighted Least Squares Estimates

	Specification 1: OLS		Specification 2: OLS		Specification 2: WLS		Specification 3: OLS		Specification 3: WLS	
Treatment Group:	Phase I and Phase II		Phase I only				Phase I and Phase II			
Control Group:	Phase I only		Non-SBIR R&D funding				Non-SBIR R&D funding			
Dependent Variable:	Sales Chg.	Empl. Chg.	Sales Chg.	Empl. Chg.	Sales Chg.	Empl. Chg.	Sales Chg.	Empl. Chg.	Sales Chg.	Empl. Chg.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment Indicator	-0.385	-0.173*	-2.32***	-1.44***	-1.47***	-1.4**	-1.95***	-1.65***	-3.12***	-2.37***
	(0.406)	(0.09)	(0.86)	(0.297)	(0.417)	(0.656)	(0.728)	(0.338)	(0.767)	(0.658)
<i>Number of firms of matching SIC & CBSA Employment, 2007</i>	0.00205	0.000676***	0.00409***	0.00214***	0.000984***	0.000661***	0.00424***	0.00216	-0.000555***	-0.00018
	(0.00184)	(0.000233)	(0.000877)	(0.000599)	(0.000363)	(0.000244)	(0.000808)	(0.00174)	(0.000209)	(0.000415)
<i>Log Annual Sales, 2007</i>	-0.00566***	-0.00341***	0.00326	-0.000328***	-0.000714	-0.000355	0.00328	-0.000322***	-0.00424***	-0.00421***
	(0.00203)	(0.000818)	(0.00233)	(0.000116)	(0.000634)	(0.000489)	(0.00233)	(0.000124)	(0.00061)	(0.000371)
<i>Firm Age in 2012</i>	-0.0535**	-0.0178**	-0.319	-0.0323*	-0.0449**	0.00191	-0.336	-0.0321	-0.0432	-0.00741
	(0.0211)	(0.00812)	(0.211)	(0.0186)	(0.0205)	(0.0369)	(0.218)	(0.0203)	(0.034)	(0.0144)
<i>Log Federal Funding</i>	-0.0000473	-0.0209***	0.065	-0.00461	-0.01***	-0.00632**	0.0651	-0.0048	-0.00357	-0.000972
	(0.0235)	(0.00362)	(0.077)	(0.00827)	(0.00272)	(0.00269)	(0.0771)	(0.00826)	(0.00394)	(0.00381)
<i>Constant</i>	0.233**	0.11***	0.179	0.124***	0.0628	0.283	0.182	0.127***	0.317	0.344**
	(0.0995)	(0.0389)	(0.143)	(0.0423)	(0.0838)	(0.2)	(0.143)	(0.0386)	(0.227)	(0.16)
<i>Constant</i>	-1.16	-0.261	3.08**	0.897***	2.11**	-1.51	3.26**	0.843**	0.115	-1.73
	(1.38)	(0.48)	(1.46)	(0.296)	(1.04)	(2.19)	(1.49)	(0.352)	(3.14)	(1.88)
Observations	6,736	6,736	36,191	36,191	38,056	38,056	36,703	38,828	38,674	38,828
R-squared	0.0006	0.0149	0.0012	0.0008	0.0048	0.0070	0.0012	0.0009	0.0121	0.0103

Notes: *** Significant at the 1 percent level
 ** Significant at the 5 percent level
 * Significant at the 10 percent level
 (Robust standard errors clustered by CBSA)

Table 14: Least squares models estimate $y_i = \alpha + \beta t_i + \gamma X + \varepsilon_i$ where y_i represents either the percent growth in employment or sales for firm i calculated as $(\text{Value}_{2012} - \text{Value}_{2007}) / \text{Value}_{2007}$. t_i indicates SBIR/STTR participation with β the coefficient of interest. Control variables are included in the matrix X . Error is captured in ε_i . WLS frequency weights are the number of matching firms based on propensity scores calculated in Table 5.

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