

SYM-AM-20-049



PROCEEDINGS
OF THE
SEVENTEENTH ANNUAL
ACQUISITION RESEARCH SYMPOSIUM

**Acquisition Research:
Creating Synergy for Informed Change**

May 13–14, 2020

Published: April 8, 2020

Approved for public release; distribution is unlimited.

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

Disclaimer: The views represented in this report are those of the author and do not reflect the official policy position of the Navy, the Department of Defense, or the federal government.



ACQUISITION RESEARCH PROGRAM:
CREATING SYNERGY FOR INFORMED CHANGE

The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Defense Management at the Naval Postgraduate School.

To request defense acquisition research, to become a research sponsor, or to print additional copies of reports, please contact any of the staff listed on the Acquisition Research Program website (www.acquisitionresearch.net).



ACQUISITION RESEARCH PROGRAM:
CREATING SYNERGY FOR INFORMED CHANGE

Understanding the Incentives for Small Businesses to Participate in the Acquisition Process for R&D Intensive Products

Vivek Bhattacharya—is an Assistant Professor of economics at Northwestern University. He received a PhD in economics from Massachusetts Institute of Technology in 2017 and a BS in economics and physics from Duke University in 2012. His research focuses on industrial organization, with a primary focus on auctions and procurement and a secondary focus on financial markets. In prior work, he has studied structural models for research and development (R&D) contests, applying them to the Small Business Innovation Research program, in addition to designing contingent-payment auctions such as those for onshore oil drilling. He has a particular interest in analyzing defense procurement, both theoretically and empirically.

Abstract

This report studies the incentives that small businesses face when they participate in the procurement process for R&D-intensive products through the Department of Defense Small Business Innovation Research (SBIR) program. This program allows firms to compete over a set of phases to develop and then deliver research on a narrowly defined product. Given firms are selected over these phases for successively larger prizes, the SBIR program potentially provides strong internal incentives to succeed within each narrow topic. However, it may also provide strong external incentives, perhaps by preparing firms to compete successfully for non-SBIR contracts or by making firms seem attractive to potential acquirors. Using contract-level data, this report concludes that there are likely strong internal incentives within the SBIR program but finds less evidence for strong external incentives. Moreover, the timing of SBIR contracts relative to other contracts suggests that firms use SBIR and other contracts as substitutes rather than SBIR as a training ground to “graduate” to other contracts. Strong internal incentives suggest that the DoD could incentivize more firms to enter the procurement process by changing the structure of the SBIR program itself rather than changing the broader defense procurement ecosystem.

Introduction

The Department of Defense (DoD) has a stated interest in encouraging small businesses to enter the defense procurement ecosystem to broaden the defense industrial base. The benefits are clear for the acquisition of many standard products. A broader acquisition base can increase stability of the supply chain, increase peak capacity, and enhance competition—all of which can improve the speed with which goods are shipped to the warfighter while still controlling costs. The goal is somewhat different, although perhaps just as clear, when it comes to goods involving extensive research and development (R&D). Broadening the set of firms involved in defense R&D can help integrate new and creative approaches to important defense problems into the acquisition base, which is essential for national security.

The primary mechanism through which the DoD funds the R&D efforts of small businesses is the Small Business Innovation Research (SBIR) program. This program, which is discussed in more detail later in this paper, solicits research on fairly specific technologies directly related to an ongoing acquisition program for the DoD. It is structured as a multistage “contest” in which firms that are successful in early stages of the contest are eligible to compete for contracts in later stages of the contest—and potentially even compete for a large transfer or delivery contract. As such, the structure of the program in principle embeds strong *internal* incentives: within a narrowly defined topic, the firms who are competing by conducting R&D could be motivated by this final contract also related to this topic.



However, there is reason to believe that these may not be the only incentives that a firm faces and that *external* incentives are more important. Through the course of its participation in a specific SBIR topic, a firm may acquire knowledge that is useful for other projects—SBIR or otherwise. Even if it is unsuccessful in winning a large contract explicitly associated with the SBIR topic, participation could make it successful in winning contracts for related technologies. This narrowness of the DoD SBIR topics makes this an especially pertinent empirical question: it may be difficult to imagine there are externalities from participating in narrow contests, but the fact that there still is participation despite low success rates could suggest the opposite.

External incentives could come through the prospect of other contracts—SBIR or otherwise. One may hypothesize that, given the mandate of the SBIR program to encourage small businesses to get involved in federal R&D, the barrier to entry for SBIR programs is low, and successful firms graduate to other non-SBIR contracts. In this sense, part of the incentives for a firm to participate in SBIR would be to “prove themselves” in a testing ground. Similar incentives could come from acquisitions: if participation in SBIR leads to acquisitions, then part of the incentives could come from these potential acquisitions. In this sense, these external incentives would not necessarily be from the value-added of participation in R&D but rather from “signaling” to other procurers or potential acquirers.

Understanding these incentives is important in helping the DoD achieve its goal of encouraging small businesses to participate in the acquisition process. If the bulk of these incentives came from those internal to the topic, then we can think of the program as, to first order, a set of isolated “contests.” Encouraging more participation would involve an analysis of how to restructure the design of a contest itself. On the other hand, if the main reason firms participate in SBIR is for the external incentives—the prospect of other contracts or for signaling—then restructuring the SBIR program will only have limited use. In this case the DoD may consider policies that strengthen these external incentives, which may be as varied as broadening topics so that firms acquire a larger set of skills or can signal to a wider audience, or perhaps even policies as simple as more aggressive information disclosure about the performance of successful firms.

This report uses contract data from the Federal Procurement Data System, topic data from the Small Business Administration’s SBIR website, and mergers and acquisitions data from the Defense and Aerospace Competitive Intelligence system to evaluate these incentives. I find fairly robust evidence of internal incentives. However, there seems to be more limited evidence of external incentives, especially when making within-firm comparisons. More generally, there does not seem to be any evidence that the SBIR program is an entry-level program for firms, and firms participate simultaneously in SBIR and other contracts without “graduating” from the SBIR program. These results loosely suggest that policy reforms should focus on strengthening internal incentives or expanding the set of topics available.

This report will not investigate the broader but especially important question of whether the *focus* of the DoD SBIR program is effective at achieving the goal of the DoD. For instance, if the DoD is interested in broadening the set of innovative ideas proposed to its acquisition professionals, then the relatively narrow nature of the DoD SBIR topics may not be especially effective. I sidestep such issues but note that alternate programs, such as the Defense Innovation Unit (DIU), may address these challenges.

This paper discusses the institutions and data, provides evidence for the internal incentives embedded in the program by focusing on the Navy, provides some evidence of the limited external incentives, discusses the interpretation of these results and the limitations of the analysis, and then concludes with comments on future research.



Related Literature

Despite the importance of the SBIR program, academic work on it has been limited. Almost all work has focuses on the SBIR program outside the DoD. Lerner (2000) uses a matching estimator to show that SBIR awards enhance firm growth, and more so in areas with an active venture capital scene.¹ Howell (2017) shows similar positive effects of the SBIR program on growth but focuses on Department of Energy grants, which tend to be more general in nature. The contribution of that paper is to separate the “direct” effect of the SBIR program—that is, that it helps cash-constrained firms develop prototypes so that it can then get external funding to finance—from the “signaling” effect that the government simply gives firms a rubber stamp of quality. She finds evidence for the direct effect, although firms in her setting are relatively more cash-constrained than ones who participate in DoD SBIR. Her research design relies on accessing restricted data on scores; I am unable to replicate this analysis, but I share a goal of identifying the mechanism underlying the outcomes of the SBIR program. Lanahan and Feldman (2018) use exogenous variation in the size of SBIR grants (via state matches) and shows that these grants improve firm outcomes in some sectors. Relative to Lerner (2000) and Lanahan and Feldman (2018), I will study the incentives of SBIR participants rather than comparing them to nonparticipants. The internal and external incentives discussed above bear similarities with Howell (2017)’s classification but are not isomorphic.

There is much less work on the DoD SBIR program, despite its differences with the other programs. Wallsten (2000) uses the DoD SBIR program as a testing ground to investigate whether government R&D funding can crowd out private funding; using an instrumental variable strategy, he identifies almost one-for-one crowdout. While this observation brings up the important point that firms may have an incentive to participate in R&D even without the SBIR program, his analysis still takes for granted that the topics are still of interest to the DoD: thus, we cannot say that shutting down the SBIR program entirely will cause firms to fully substitute internal funding (even ignoring liquidity constraints). In prior work (Bhattacharya, 2018), I develop a game-theoretic model for firm behavior in the SBIR program; this paper presents results related to that paper (and refined due to funding from the grant for this report). However, that work assumes that all incentives are internal, and this report studies the plausibility of that assumption.

Institutions and Data

This section briefly discusses the structure of the SBIR program and discusses the various sources of data used in this analysis.

Institutions

The SBIR program is the largest federal program by which the government incentivizes small businesses to participate in R&D. Established in 1982, it requires every federal agency with at least \$100 million in extramural research funding to allocate approximately 3% of it to small businesses through this program.² This amounts to about \$3 billion in grants and

¹ However, not all work is necessarily as generous to the SBIR program: Lanahan et al. (2019) use a matched sample to suggest that the Lerner (2000) results have not withstood the test of time, and bureaucratic tape might hinder the growth of SBIR participants. To my knowledge, this result is unique in this relatively sparse literature, and there are of course standard concerns related to matching on observables. Yet, it is worth noting that it is not a foregone conclusion that the incentives provided by the SBIR program are necessarily positive.

² The percentages are changes on an approximately yearly basis, starting from 2.5% in 1997 to the current rate of 3.2% set in Fiscal Year 2017. The accounting underlying this calculation is complex, however, and agencies can report exemptions to extramural funding to effectively reduce the total percentage that must be budgeted to SBIR



contracts, an amount that does not include any follow-on contracts generated by the research in this program. The largest agency contributing to this amount is the DoD, which contributes over 40% of total funding in the SBIR Small Business Technology Transfer (STTR) program, even ignoring follow-on contracts.

The program is designed to have a multistage structure (SBA, 2017), which can loosely be thought of as going through the various stages of research, development, and commercialization. SBIR programs are organized into “topics,” which can be especially broad or narrow depending on the agency in charge, and each topic is grouped into three phases. Phase I is about feasibility—scientific and technical merit—of the proposed idea. It involves “quick and dirty” benchtop testing, simple experiments, and simulations. Given the nature of the work, funding tends to be low, and awards are on the order of \$100,000 over a period of six to 12 months.³ Phase II is for continued research and is a significantly more involved phase than Phase I, usually centered around features more directly related to the commercialization potential of the project. Awards range from \$750,000 to \$1,500,000 with a contract duration of up to six years, although the modal contract runs for about two years. There are further provisions, especially in recent years, to increase total funding to over \$2 million, partly through programs such as “Sequential Phase II” or the Commercialization Assistant Pilot Program. To the extent possible, I will aggregate these follow-on contracts to the Phase II contract, noting that while studying them separately is especially important for policy, it is not directly related to the research question at hand.

While some agencies do allow for open competition for Phase II contracts and grants, most do not, and competition for Phase II contracts within a topic is restricted to those who were awarded Phase I contracts. There is no explicit limit on the number of Phase I or Phase II contracts that can be awarded in a particular topic, but in the DoD the data indicate that approximately 40% of firms in Phase I make it to Phase II—a number that is in line with guidance provided in the DoD SBIR website.

Phases I and II are the “core” part of the SBIR program, and these are the phases that matter for meeting the congressional mandate. However, the stated goal of the SBIR program is not to simply marshal firms through multiple Phase I and Phase II contracts but rather to commercialize the products developed by the firms—what is called Phase III. While Phase III is not a uniformly institutionalized phase in the SBIR program, it refers to any research or production “that derives from, extends, or completes an effort made through SBIR/STTR-funded Phase I or II R/R&D but is funded by sources other than the SBIR/STTR Programs” (SBA, 2017). This could involve selling to private companies or government agencies. The DoD, and especially the Navy, labels follow-on contracts (which often involve delivery) as Phase III, but other agencies do not offer any contracts that are explicitly labeled Phase III.

This report focuses on the DoD SBIR program, which has two important distinctions from the programs in other agencies. The first is the definition of *small business*: while civilian programs tend to limit small businesses to those with 50 employees, the DoD has a more expansive definition of up to 500 employees. The second is more important for the question at hand: the civilian agencies tend to offer especially broad solicitations for topics, with the goal of including many distinct ideas that could lead to commercialization. On the other hand, the DoD largely solicits especially specific technologies that are almost always tied directly to an

programs. Even ignoring such exemptions, however, rough calculations suggest that most divisions of the DoD satisfy this constraint, and some (such as DARPA) even exceed it considerably. See SBA (2017).

³ In recent years, total funding in Phase I has grown to up to \$225,000, and there is variation within topic in funding for Phase I. However, in the time period I analyze, funding is even lower, and there is very little variation in Phase I funding. Most Phase I contracts are for \$70,000 to 80,000.



acquisition program, and Phase III DoD contracts can often delivery of these technologies (or transfer contracts). This distinction motivates the empirical exercise in this paper: one may imagine that specific solicitations limits the scope for incentives beyond the specific contest, as knowledge gained from the solicitation may not be transferable. On the other hand, given that knowledge is not transferable and Phase III contracts are not common, the fact that we see participation may be a sign that other incentives are important.

Finally, the STTR program has requirements that are distinct from those of SBIR, including mandated involvement of an academic institution. While I understand that this program may have different incentives embedded in it, I group it with SBIR in this report, mainly for the purposes of power.

Data Sources

I use a combination of three data sources to perform the analysis in this report. First, I use data for all federal contracts from the Federal Procurement Data System (FPDS). I access this data through www.usaspending.gov. This dataset includes information about each federal contract, subject to information disclosure restrictions.⁴ The dataset involves three sets of information:

- *Information about the agency letting the contract.* In particular, the dataset often includes details about the subagency in addition to the general agency letting the contract. In the DoD context, this would mean that I observe the specific service involved in the contract, but in contexts outside the DoD this information seems to be less uniform. Furthermore, the FPDS does incorporate flags for whether the program is let through SBIR or STTR, which provides a cross-check to data sources below.
- *Information about the firm.* I observe the name, location, and Data Universal Numbering System (DUNS) number of the firm who was awarded the contract. While sometimes the dataset provides other information (like number of employees at the time, whether the firm is minority-owned, etc.), but I do not incorporate such information into my analysis.
- *Information about funding.* The FPDS incorporates significant detail about contract amounts. It lists the initial contract amount, modifications to the contract (including the dollar value of such modifications), and often disbursement schedules (listed as the total contract amount disbursed at the time of a modification). In this sense, I have an estimate for initial and “final” contract amounts.

The unique identifiers that let me link across datasets (and across records within the datasets) are the contract number and the firm DUNS number. The dataset also includes additional information, such as the contract type (e.g., firm-fixed-price versus cost-plus) and competitive information such as the number of offers received. For my purposes, the variation in contract type is not relevant, and it is unclear whether number of offers received is coded uniformly across SBIR and non-SBIR contracts. As such, I do not incorporate such information in my analysis.

The second group of datasets I use are SBIR-specific datasets from www.sbir.gov and www.nabysbirsearch.com. These datasets contain all SBIR and STTR topics that were announced in the past, along with information about contracts that were awarded. This dataset

⁴ Classified contracts are of course not listed in the FPDS. Moreover, there is a disclosure delay in reporting to the FPDS, which is longer for DoD contracts than other agencies. However, given that the analysis in this paper involves historical contracts, I do not anticipate the disclosure delay to be relevant for the analysis conducted in this report.



includes the contract number, which allows me to link to the FPDS. The value-added of this secondary dataset is two-fold. First, it provides a cross-check on the contract amount provided in the FPDS. Second, it provides more information about the contracts than is available on FPDS, including contract descriptions, solicitations for the topics, and maps between contracts and topic numbers—so that we can track contracts across different phases of the same SBIR topic.⁵

The dataset from www.navysbirsearch.com is a secondary dataset that provides an important additional source of information that we use for the within-topic analysis later in this paper. The data from www.sbir.gov only includes information about Phase I and Phase II contracts, and the FPDS is inconsistent in labeling Phase III topics. The data from the Navy, on the other hand, explicitly lists Phase III topics. This is partly because the Navy SBIR program is more systematic about classifying contracts as such, so we should not be surprised the data is cleaner on this dimension. The benefit of this dataset, therefore, is that it allows for better analysis of within-topic incentives. Moreover, this dataset lists the acquisition program in charge of the topic, which is not uniformly listed in the FPDS.

The final dataset is on mergers and acquisitions and comes from the Defense and Aerospace Competitive Intelligence System (DACIS). DACIS is a commercial data provider that tracks deals in the defense and aerospace industry, collecting this data through press releases. As an additional service, they provide an interface to the FPDS. While I do not use their interface to the FPDS, the fact that they provide one means that they link their deals to the FPDS via the firm DUNS number. As such, firms in the SBIR dataset can be linked to mergers and acquisitions (M&A) through the DUNS number. Unlike the other sources of data in this project, however, data quality is a potential concern for DACIS's M&A database, and a natural concern is that there is incomplete coverage of mergers. In the results below, I report that only a small handful of firms involved in the SBIR program are involved in M&A, which is admittedly in line with this concern.⁶

Analysis of Within-Topic Incentives: Evidence from the Navy

In this section, I study incentives within a program by analyzing the relationship between funding, success, and competition in various phases.⁷ I focus my analysis on the Navy SBIR program from 2000 to 2012. The Navy has a clear classification of contracts into Phase III contracts, which provides information about transfer and delivery contracts that are still “internal” to the topic. I limit my analysis to older contracts so that they have a chance of entering Phase III if needed. By way of presenting these results, I also present summary statistics that provide quantitative information of the structure of the program to the uninitiated reader.

Before discussing results, I note some data cleaning steps that I take. If there are multiple contracts in a specific phase for the same topic awarded to the same firm, I aggregate

⁵ The FPDS also includes topic number in principle, but I have found this data to be inconsistently recorded. When topic numbers can be extracted from the FPDS, they tend to match the ones from www.sbir.gov, which provides a good cross-check on the data. However, topic numbers are often absent and sometimes buried in free-text fields that make them difficult to find.

⁶ Informal comparisons to external data sources such as Thompson Reuters's SDC Platinum show no obvious discrepancies between the two for large mergers. Moreover, discussions with the data provider provide confidence that acquisitions of small companies by large defense contractors are likely recorded well, as DACIS monitors press releases by the large contractors carefully. The concern may be that we are excluding “growth” strategies by small and medium-sized firms, who acquire similarly small firms to grow.

⁷ Much of the quantitative analysis in this section is presented in Bhattacharya (2018), but the grant that funded this report was used to refine the results of this analysis. Moreover, the discussion of the results is tailored to the question at hand.



them. Some contracts are given jointly to two firms, in which case I record that each firm won a separate contract. If a firm wins a Phase II contract without winning a Phase I contract, I add a Phase I contract to the dataset for that firm, noting that the Navy does not offer direct-to-Phase II contracts. Finally, I drop four contests with multiple Phase III contracts. These data cleaning decisions affect a very small number of contests, and at the end of this I am left with 2,875 contests.

Table 1 provides summary statistics of the distribution of the number of competitors in each phase within a topic. This provides the first set of qualitative evidence for the extent of internal incentives in the SBIR program.

Table 1: Distribution of the Number of Participants in Navy SBIR Contests from 2000 to 2012

	0	1	2	3	4	≥ 5
# Phase I Competitors		12.9%	41.8%	32.8%	8.9%	3.6%
# Phase II Competitors	16.9%	61.1%	19.0%	2.3%	0.6%	0.2%
# Phase III Competitors	91.3%	8.8%				

While contests are small, there is still a healthy amount of competition in Phase I: about 75% of all contests have two or three competitors, and about one-eighth of them have four or more. The other one-eighth only have one contestant. However, progress to Phase II is not guaranteed, and there is competition both with other contestants and with the “outside option,” as 17% of the contests do not even have a Phase II. Three-fourths of contests have only one firm entering Phase II. The situation is even more stark with Phase III: fewer than 10% of contests have a contract that the Navy labels as Phase III. Phase III (almost) always has one competitor; as noted above, Phase III with multiple competitors is especially rare and likely due to idiosyncrasies in the contest.

At first blush, these distributions may indicate *limits* to internal incentives. After all, if the prospect of a Phase III contract is so unlikely, how can this be the motivation for firms to participate in the SBIR program? Figure 1 provides some evidence against this concern. The top panels show the distribution of Phase II and Phase III contract amounts. As discussed above, Phase I contract amounts are almost always around \$70,000. Phase II contracts are on average about \$803,000, and very few are beyond \$2 million. On the other hand, Phase III contracts are especially large: the mean contract value is \$8.77 million, with a substantial right tail (part of which is truncated in the histogram), and even a sizeable mass at \$25 million. Thus, what is potentially the “internal” prize is rare, but it is substantial.

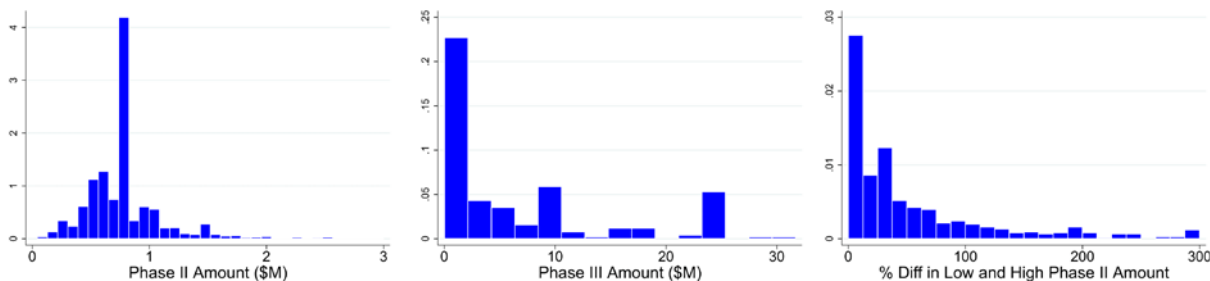


Figure 1: Contract amounts in Phases II and III.

The rightmost panel shows the distribution of the percent difference between the highest and lowest funded competitors for Phase II with multiple competitors.

A large Phase III award is suggestive of strong internal incentives, but yet stronger evidence would be that firms are actually acting to respond to the Phase III grant. If firms did not



seem motivated to win the Phase III award, then it would be suggestive of the fact that other external incentives are substantially more important. Since I do not observe all actions that a firm takes in service of winning the Phase III contract, my approach will be to use intermediate contract amounts as a (noisy) signal of firms' efforts. In particular, I will use the Navy's stated claim in its guidelines that Phase II allows for increased funding based on a project's transition potential. Thus, I interpret Phase II funding as indicative of the efforts of the firms—although it may be confounded with the inherent quality of the firm. Bhattacharya (2018) discusses the ramifications of this assumption formally in the context of a game-theoretic model.

With this assumption, a necessary condition for internal incentives to be important is for effort and outcomes to be related to each other. The empirical strategy will thus effectively be to regress Phase III outcomes on Phase II outcomes and test whether there is a positive correlation. Of course, a raw regression of these quantities would be riddled with endogeneity issues: to the extent that certain topics are both more valuable and more costly to conduct research on, this correlation would confound the relationship of interest.

Thus, we take two approaches. The first is to use cross-topic variation to study within-topic incentives. An important assumption underlying the validity of this approach is homogeneity across contests, so we will have to control for as much variation across contests as possible. To do so, I use another feature of the Navy dataset: the fact that the full text of the solicitations and the abstracts of the winning proposals are public. Using this text, I classify projects into fine topics generated automatically using a Latent Dirichlet Algorithm (Blei et al., 2003) implemented through MALLET.⁸ I also add in fixed effects for fiscal year as well as the systems command of the Navy that led the project, which is another feature of the Navy dataset that is not available in the full dataset. The second approach is to use within-topic variation: the rightmost panel in Figure 1 shows the percent difference in funding between the highest-funded contestant in Phase II and the lowest-funded contestant. This variation perfectly controls for heterogeneity in contests (since we are comparing within a contest), and we still see there is substantial variation in this dimension. If outcomes respond to this variation, this would be especially strong evidence of the potential for internal incentives—although interpretation merits caution since this is based on a selected subsample.

Figure 2 provides a first set of results. The left graph shows nonparametric (locally linear) regressions of a dummy for Phase III success (whether a competitor is awarded a Phase III award) on the Phase II award amount for that competitor. The blue line shows a clear positive relationship, suggesting that firms with more Phase II funding—the proxy for effort here—are more likely to win Phase III contracts. Of course, this does not control for cross-topic heterogeneity, so we add in controls into the analysis. The result, which is computed through the semiparametric estimator of Robinson (1988), is shown in the dashed red line. The qualitative pattern does not change, and it seems that controlling for contest heterogeneity strengthens the relationship between effort and outcomes.

⁸ This algorithm is a Bayesian hierarchical model that takes in documents and groups words into topics based on whether they appear in the same document. It then groups documents back into topics based on the collection of words in it. For instance, it automatically groups “optics,” “laser,” “fiber,” “infrared,” and “wavelength” together in a category that presumably is related to optics. In the results presented here, I restrict to 20 categories, but I have checked for robustness of the main results to up to 50 categories.



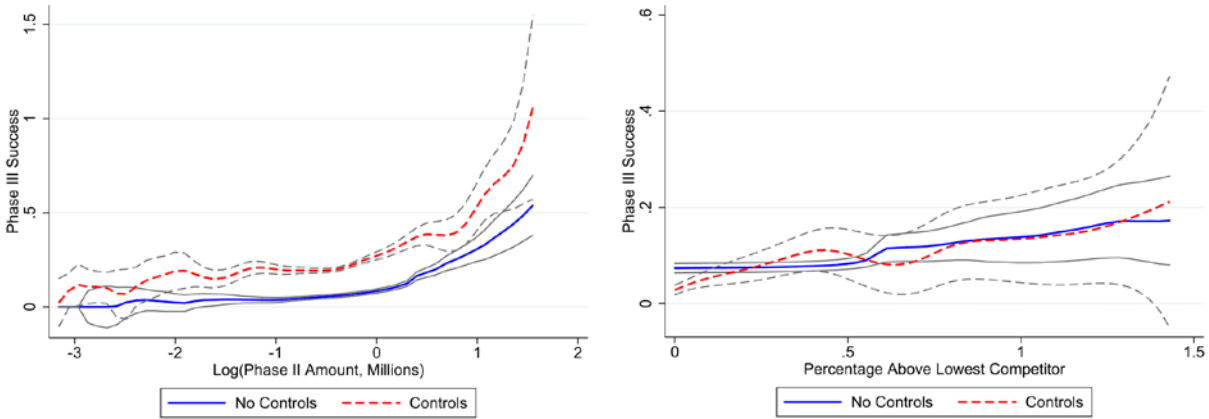


Figure 2: Probability of winning a Phase III contract as a function of Phase II contract amount (left) and a function of the percentage in funding above the lowest competitor (right).

Controls include the topic fixed effects generated from the LDA, fiscal year fixed effects, and systems command fixed effects. Gray lines indicate pointwise 95% confidence intervals.

The graph to the right controls for cross-topic variation perfectly, restricting to the set of contests with multiple Phase II competitors. We regress a dummy for Phase III success on the proportion above the lower competitor the Phase II funding; the lowest competitor would then have a horizontal value of 0. While the results are noisier and the 95% confidence interval cannot rule out a flat line, we see that the point estimates are noticeably increasing. Controlling for cross-contest heterogeneity semi-parametrically (dotted red line), we see that an effort equivalent to the lowest effort yields a success rate lower than 5%, while doubling effort (horizontal axis of 1) can increase it beyond 10%, and increasing effort by 150% can increase the probability of success to past 20%. Thus, both tests strongly suggest that there is a correlation between effort and outcomes, suggesting room for internal incentives.

We provide a set of regressions to further analyze this correlation between effort and outcomes, using cross-topic variation with controls. Table 2 provides this analysis.

Table 2: Regression of outcomes on measures of competition and effort.

	Phase I (1)	Phase II (2)	Phase I (3)	Phase II (4)	Phase II (5)	Phase III (6)
# Phase I Competitors	0.066 (0.009)	-0.018 (0.008)	-0.128 (0.008)	-0.023 (0.008)	0.016 (0.012)	0.234 (0.110)
# Phase II Competitors		0.076 (0.016)		0.028 (0.010)	-0.002 (0.016)	-0.429 (0.176)
Log(Avg Phase II Amount)		0.157 (0.018)				
Log(Phase II Amount)				0.250 (0.031)		0.330 (0.195)
R^2	0.083	0.128			0.133	0.422
N	2,773	2,292	2,773	2,292	2,292	151

All specifications control for topic, year, and systems command fixed effects. Columns (1) and (3) use a dummy for whether the contest enters Phase II and Columns (2) and (4) study whether the contest enters Phase III. Columns (3) and (4) use a parametric selection model. Columns (5) and (6) regress log Phase II and Phase III funding on the covariates. Column (6) restricts to Phase III above \$1 million to avoid especially small Phase III values that may be due to data errors. Standard errors are clustered at the topic level when appropriate.



Columns 1 and 2 report linear probability models of whether a contest moved from Phase I to Phase II or from Phase II to Phase III on the number of competitors in previous phases, effort as proxied by average funding amount, and the standard battery of controls. Column 1 shows that a larger number of Phase I competitors leads to a higher probability of success; by itself, this result is not especially informative of the correlation between effort and outcomes, as it could be from partially uncorrelated draws of success, but it is useful to know that this coefficient has a reasonable sign.⁹ Column 2 shows a positive relationship between the number of Phase II competitors and success in Phase II—which could again be due to more draws—and a negative relationship with the number of Phase I competitors. This relationship could be due to endogeneity in terms of project difficulty, or it could be indicative of detrimental competitive incentive effects (as possible in the model in Bhattacharya [2018]). However, it is interesting to note for the purposes of this report that there is a positive correlation between the average Phase II funding—a proxy for average “effort”—and success.

Columns 3 and 4 replicate this analysis at the individual level, replacing the dummy for whether the contest succeeds with a dummy for whether the individual succeeds in winning a contract for the next phase. The econometric difficulty is that whether an individual wins a contract is correlated with whether its competitors do, and in the extreme case there is selection. Thus, I run a model where we estimate the probability of an individual “success” (i.e., whether an individual would have been eligible for a contract) and say that the number of contracts I observe is a selected sample of the potential number of contracts. I estimate these models through maximum likelihood; I omit the likelihood here but note that it is a selected binomial. Column 3 shows that more competition leads to lower individual probabilities of success; given that this is even conditional on the selection, this is consistent with competitive effects in a standard model of contests, which provides auxiliary information that internal incentives are strong.¹⁰ Column 4 shows evidence of some competitive effects with the number of competitors, and it also verifies the observation in Figure 2 that individual-level funding is correlated with success.

Columns 5 and 6 go beyond binary measures of success and regress (log) Phase II and Phase III funding on the left-hand side on the same battery of covariates. We include these columns for completeness, but the of these point estimates are actually ambiguous with competitive effects. We can focus on the relationship between Phase II and Phase III funding; a 10% increase in Phase II funding is associated with a 3.3% increase in Phase III funding. To the extent that Phase III funding is an unambiguous measure of quality, this is the direction we would expect the correlation to go.¹¹

In summary, the results in this section largely suggest that (1) there is scope for internal incentives given the structure of the contests, and (2) correlations between (proxies for) effort and outcomes are strong—both using within-contest variation and cross-contest variation. (Of

⁹ Alternatively, one could imagine that for especially difficult contests, the Navy awards more Phase I grants, in which case we could expect a negative sign. The fact that this endogeneity concern does not seem to dominate is good news for the effectiveness of the controls.

¹⁰ If internal incentives were very weak, then variation in competition should not lead to any competitive effects, and we should expect a zero in Column 3. Of course, endogeneity due to unobserved heterogeneity across auctions could also generate this pattern, but the running identification assumption is that the controls are sufficiently rich.

¹¹ Unlike Phase II funding, there is reason to believe that lower Phase III funding may correspond to projects developed from higher effort. This is because Phase III often includes delivery contracts, and if these are cost-plus contracts and research leads to lower costs, the contract amount for Phase III could be lower but still lead to a higher margin for the competitor. Bhattacharya (2018) controls for this through a more intricate structural model, but the message from that paper is that this (potentially counterintuitive) possibility is not the empirically relevant one. Thus, we ignore this analysis for the purposes of this report.



course, it is worth reiterating that even though we use cross-contest variation in estimation, the goal is really to exploit this variation to understand within-contest incentives.) This seems to largely suggest that firms are responding to within-contest incentives, and these may be an important part of the reason why small businesses are participating in the SBIR program.

External Incentives

Even though we have reasonably convincing evidence for within-contest incentives, they need not be the entire picture. In fact, if we see convincing evidence that success in a particular SBIR contest leads to success in other contracts (SBIR or not), or if success in the SBIR program leads to acquisition, we may think that these alternate incentives dominate the internal ones documented above. In this section, I investigate three potential sources of external incentives, and I discuss the analysis methodology in each section rather than upfront. Note that I only provide a subset of the analysis conducted in each section to economize on space; instead of providing a uniform presentation of results, I err on the side of presenting a handful of different approaches, omitting analysis similar to other sections.

The data in this section uses all SBIR contracts from 2000 to 2017, using Phase III as marked in FPDS. This may lead to undercounting Phase III contracts, as discussed above.

Does SBIR Participation Improve Outcomes in Other SBIR Topics?

To study whether success in SBIR leads to future success, I first look for a correlation between past SBIR experience and future contracts. To do so, I run a regression at the firm-year level of the number of SBIR contracts from each service (plus DARPA, NASA, and Other) that a firm wins in a particular year on the cumulative total SBIR contracts won in all prior years. Changing number to total value or restricting to the nearer future does not qualitatively affect results. If SBIR success were to have no future effects, we would expect this regression to return a series of zeros. However, strong positive numbers—especially cross-service—may suggest that external incentives are substantial. Table 3 presents the results of this analysis. Each column corresponds to a regression of the number of SBIR contracts awarded for the specified agency on the cumulative number from all agencies.

Table 3: Regression of the number of SBIR contracts of each types won in a particular year on cumulative in all prior years, at the firm-year level. All specifications include a year fixed effect.

	Air Force	Army	DARPA	NASA	Navy	Other
Air Force	0.201 (0.001)	0.124 (0.001)	0.00002 (0.00001)	0.023 (0.001)	0.041 (0.001)	0.034 (0.0003)
Army	0.002 (0.0002)	0.009 (0.0002)	0.000 (0.000)	-0.001 (0.0002)	0.003 (0.0002)	0.002 (0.0001)
DARPA	-0.430 (0.046)	0.001 (0.045)	-0.0001 (0.001)	0.840 (0.047)	-1.582 (0.050)	-0.468 (0.022)
NASA	0.010 (0.001)	0.011 (0.001)	-0.00001 (0.00001)	0.467 (0.001)	-0.035 (0.001)	-0.001 (0.001)
Navy	0.032 (0.001)	0.093 (0.001)	0.00002 (0.00001)	-0.004 (0.001)	0.280 (0.001)	0.016 (0.0003)
Other	0.129 (0.002)	0.178 (0.002)	-0.0001 (0.00002)	0.049 (0.002)	0.045 (0.002)	0.261 (0.001)
Adjusted R^2	0.579	0.556	0.0001	0.501	0.614	0.455
N	312,569	312,569	312,569	312,569	312,569	312,569



A first observation is that the estimates coefficients are not zeros across the board, which suggests that—were it not for endogeneity concerns—there may be evidence for external incentives. For instance, interpreting the first coefficient in the first column would mean that one additional SBIR contract from the Air Force would increase the number of Air Force contracts won in a year by 0.2. This is a sizeable effect, although on the higher end of what we see in the table. The second observation is that not all coefficients are significant. With some exceptions, it seems that the coefficients on the diagonal are considerably larger than the off-diagonal ones. This is sensible, since it suggests that success in a particular type of SBIR contract is correlated with success in similar contracts, which is reasonable given the narrow nature of the topics.

However, a word of caution is warranted in interpreting these regressions. This analysis is done at the cross-firm level, so the estimates incorporate variation both within-firm over time and across firm. To isolate the variation within-firm—and to approximate the effect within-firm of winning an additional SBIR program—I add firm fixed effects to the above regressions. In the interest of space, I do not show the table with these results, but the qualitative results mirror those shown in sections below with firm fixed effects. Adding firm fixed effects tends to dampen the estimates by about two-thirds and can even change the sign of these estimates. This suggests that while there is a noticeable correlation between past success and future success (within the same agency), it is less likely that past success *causes* future success in different contests, and external incentives may be more muted within the SBIR program.

Does SBIR Participation Improve Outcomes in Non-SBIR Contracts?

A natural hypothesis is that even if follow-on success within SBIR is muted, the goal of SBIR could be to wean firms off SBIR and into other contracts. First, I replicate the same analysis but change the left-hand side of the regression to non-SBIR contracts. Here, I show results after aggregating across all SBIR contracts (but separating by phase); that is, I do not subdivide by agency, although results are qualitatively similar (but noisier) in such specifications. Table 4 shows the results of this analysis.

Table 4: Regression of the number of non-SBIR contracts won in a year on the number of past SBIR contracts won (overall)

	All Other Contracts			Other R&D Contracts		
	(1)	(2)	(3)	(4)	(5)	(6)
Past # SBIR Phase I	0.005 (0.02)	0.01 (0.02)	-0.01 (0.03)	0.01 (0.001)	0.01 (0.0003)	0.005 (0.0004)
Past # SBIR Phase II	0.03 (0.04)	0.03 (0.05)	0.10 (0.06)	0.03 (0.001)	0.03 (0.001)	-0.02 (0.001)
Past # SBIR Phase III	0.25 (0.001)	0.25 (0.001)	-0.95 (0.001)	0.02 (0.002)	0.03 (0.001)	-0.01 (0.001)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE			Y			Y
Only Small Firms		Y			Y	
Adjusted R^2	0.01	0.01	0.46	0.01	0.02	0.27
N	5555391	4431180	4431180	5459061	4347124	4347124

Column 1 shows a noisy effect that an increase in Phase I and Phase II SBIR contracts leads to a tiny increase in the number of other contracts won in a particular year. This remains true even if considering only small firms (with fewer than 50 employees), as show in Column 2. However, Phase III SBIR contracts are correlated with a sizable increase in the number of non-



SBIR contracts in a year. Given Phase III contracts tend to be rare, this raises the question of whether the variation we see is due to heterogeneity. To control for this, we add in firm fixed effects in Column 3. As alluded to previously, these fixed effects reverse the point estimate on the effect of Phase I SBIR contracts and (even more starkly) Phase III contracts. That is, while it is true that firms with a larger number of prior Phase III contracts are more likely to be awarded non-SBIR contracts in a particular year, the variation is *not* within-firm. In fact, within-firm, we see the opposite effect (which could be due to capacity constraints, or perhaps spurious). This fights against the interpretation that non-SBIR contracts provide external incentives.¹²

A concern may be that the firms involved in SBIR are, to first order, not even eligible for the typical FPDS contract (which may involve delivery). While given the left-hand side is in levels and contracts are additive, this should not affect results if *no* SBIR firm can earn a subset of FPDS contracts, the fact that some firms might could affect the weighting implicit in OLS, especially with fixed effects. Thus, we rerun the same set of regressions in Columns 1 to 3 but only use contracts marked as R&D as an outcome. Results are more precise, but point estimates do not change markedly—except for Phase III. This provides further evidence that perhaps the Phase III effect from Columns 1 to 3 is picking up a dimension of firm heterogeneity that is not related to incentives per se.

A different way of looking at the question of external non-SBIR incentives would be to ask whether SBIR is a “testing ground” for other contracts. If so, it may provide a different source of evidence that external incentives are important. As a metric of this, for each SBIR contract in the data, we compute

$$\frac{(\text{total non-SBIR contracts by that firm}) - (\text{cumulative non-SBIR contracts up to that point})}{(\text{total non-SBIR contracts by that firm})}$$

If all SBIR contracts occur before non-SBIR contracts, then this metric should be 1 for all SBIR contracts (since cumulative non-SBIR contracts will be 0). If all non-SBIR contracts happen before SBIR contracts, this metric should be 0. We then average across all SBIR contracts a firm has and ignore the firms that do not have non-SBIR contracts. Table 5 shows summary statistics of this metric by groups of firms. These groups correspond to quantiles of the number of SBIR contracts a firm has won over the time frame.

Table 5: Share of non-SBIR contracts that happen after SBIR contracts

SBIR Quantile (1)	Mean # SBIR (2)	All FPDS Contracts			Only R&D Contracts		
		Mean # FPDS (3)	Mean % SBIR (4)	% SBIR Before (5)	Mean # FPDS (6)	Mean % SBIR (7)	% SBIR Before (8)
1	1.0	36.0	62.2	57.2	2.8	76.6	54.7
2	1.2	29.5	60.4	57.8	2.9	76.4	57.1
3	2.3	18.4	61.6	59.4	4.0	76.1	57.5
4	4.6	34.9	58.1	56.0	8.2	71.3	54.1
5	31.5	61.0	60.3	56.2	44.8	70.9	54.1

We see that across quantiles, about 60% of contracts are SBIR contracts, suggesting that firms have a substantial number of non-SBIR contracts. Column (5) shows, however, that

¹² Admittedly, the increased point estimate on Phase II is counter to this observation, but this direction is unusual among all regressions I have tried, and it is not robust to other specifications of the variables.



the average of the metric is about 55% to 60% regardless of the quantile. This is suggestive that firms do not “graduate” from SBIR to other types of contracts but rather win SBIR and other contracts simultaneously. Columns 6 to 8 repeat the analysis but only restrict to FPDS contracts that are marked as R&D. This increases the share of SBIR contracts to about three-fourths but does not otherwise alter their average “timing.”

These results suggest that there does not seem to be a substantial within-firm correlation between success in SBIR and success outside SBIR—although there is a substantial cross-firm one. Moreover, the timing of the contracts does not suggest that SBIR is being used as a testing ground at the start of the life cycle of a small business; rather, firms seem to participate in SBIR and other contracts simultaneously.

Mergers and Acquisitions

Another potential source of external incentives is the possibility of acquisition. To study this, I downloaded all M&A data from DACIS from 2004 to 2018 and matched with the SBIR and FPDS datasets using firm DUNS numbers. I restricted the analysis to firms who have won at least one SBIR Phase I contract. The first observation is that acquisitions are relatively rare: fewer than 0.5% of firms who have ever won a Phase I SBIR contract have been acquired. However, they are targeted: firms who have been acquired account for about 6% of all contracts (among the set of contracts won by this set of firms).

An interpretation of these results is that, much like firm heterogeneity is an important issue in the previous subsections, mergers are simply picking up firm heterogeneity. The more direct question is whether success in SBIR directly leads to acquisitions. To study this question, I run a linear probability model of a dummy for whether a firm is acquired in a particular year on the total dollar value SBIR contracts won in the “recent” past. The results in this paper proxy the recent past by the past two years, but results are qualitatively robust to these decisions. Results of this analysis are presented in Table 6. Each observation is a firm-year pair, with years after a firm is acquired dropped from the analysis.

Table 6: Linear probability model of whether a firm is acquired in a year on SBIR contracts won in the past two years. Coefficients are multiplied by 10,000.

	(1)	(2)
Value of Past SBIR Phase I	0.001 (0.001)	-0.01 (0.002)
Value of Past SBIR Phase II	0.001 (0.0004)	-0.01 (0.001)
Value of Past SBIR Phase III	0.0002 (0.0001)	0.0001 (0.0001)
Year FE	Y	Y
Firm FE		Y
Adjusted R^2	0.0001	0.04
N	5,546,947	5,546,947

Column 1 shows results of the linear probability model with year fixed effects to control for variation across different years in macroeconomic environments that may lead to differential M&A activity. While the point estimates all suggest that past SBIR contracts lead to a higher likelihood of acquisition, they are mostly noisy—except for the Phase III estimate. Ignoring this noise, the interpretation of this estimate would be that a \$1 million Phase II contract would increase the probability of being acquired by 0.01, and a \$10 million Phase III contract would



increase the probability of being acquired by 0.02 (which is statistically significant). These are somewhat sizeable numbers given the low baseline probability of acquisitions. At face value, this would suggest that there is some correlation between success in SBIR and acquisitions.

Of course, another interpretation of this regression is that it is picking up heterogeneity across firms. To control for this heterogeneity, I add in firm fixed effects in Column 2. The interpretation of this regression is that if firm “quality” remains constant, then the year-to-year variation is due to the success in SBIR, which could potentially capture a signaling story. Interestingly, I find *negative* point estimates (that are statistically significant) on the number of Phase I and Phase II contracts, and a more muted effect of Phase III. The point estimates are rather large in magnitude as well—and perhaps implausibly so. One interpretation may be that involvement in SBIR leads to bureaucratic red tape that larger firms do not want to deal with, or perhaps there are difficulties in acquiring a firm with an ongoing SBIR contract due to the size restriction on such contracts. I hesitate to speculate too much along these dimensions, but the robust conclusion seems to be that the fixed effects regression suggests that firm heterogeneity is playing a sizeable role in Column 1.

Given the summary statistics at the start of this section, I speculate that the effects may be driven by a handful of especially successful (and thus especially high-quality) firms, whose influence gets dampened when incorporating firm fixed effects. However, nonlinear specifications that try at addressing this heterogeneity are especially noisy and thus omitted.

Discussion, Limitations, and Conclusion

This report uses contract-level data to analyze the incentives that a small business faces when it chooses to participate in R&D through the DoD SBIR program. The strategy has been to look for outcomes that are correlated with success in the SBIR program—within a specific SBIR topic but also more broadly beyond the topic and even beyond the SBIR program. If correlations, controlling as best as possible for potential endogeneity issues, are strong with a specific output, that is suggestive evidence that this output may be incentivizing firms participating in SBIR. The main message from this report is that internal incentives seem to be strong: there is strong correlation within a topic between “success” in one round and “success” in future rounds, using both cross-topic variation and (more limited but more convincing) within-topic variation. However, there is more muted evidence for external incentives: while correlations are noticeable cross-firm, controlling for firm fixed effects tends to either dampen or often eliminate these correlations. Moreover, the timing of non-SBIR contracts is not supportive of the idea that external incentives are important: firms seem to engage in SBIR and non-SBIR contracts simultaneously and treat them as substitutes.

As with most empirical analysis, the main limitation of this study is heterogeneity across firms. Adding limited firm-level variables in the cross-firm analysis does not change the message appreciably, and these variables of course get absorbed by fixed effects. Without more detailed data on the performance of firms in these contracts, it is difficult to come up with more credible controls for heterogeneity. One possibility that is SBIR-specific is to use data on technical scores that are used to award contracts. These scores can be used to make comparisons between firms that just barely are awarded contracts and those that just barely lose out. Moreover, more detailed information about contracts (SBIR or FPDS) can allow us to construct backlog measures that can deal with issues like capacity constraints that may be driving strongly negative within-firm results for Phase III contracts. Both these avenues would be difficult to accomplish with public data (without especially crude measures of backlog).

Another comment is that it may still be true that for a certain subset of firms, external incentives are important. To the extent that heterogeneity is substantial (and variance in



summary statistics distributions suggests that it may be), there may be a small set of firms who have high inherent quality and are looking for a field to showcase this quality. This mechanism would be similar to Howell's (2017) proposed mechanism for how the SBIR program operates in the Department of Energy. However, it is difficult to investigate this mechanism here because of power issues and the lack of data on scores.

Finally, data on "Phase III" commercialization directly related to a topic but to sources outside the federal government is limited. The SBIR program offices do collect this data, and it would allow for richer analysis. Of course, the bias induced by assuming non-DoD commercialization of topics is zero would be to underestimate internal incentives, which would strengthen the message of this report.

Nevertheless, taking the interpretation of the results of this report at face value, the fact that internal incentives seem to be dominant suggests that if the DoD wants to use the SBIR program to incentivize more firms to participate, focusing on the structure of the SBIR program itself would go a long way. Bhattacharya (2018) studies some methods to do this—such as changing competition, information sharing, or the sharing of the surplus promised to firms. A message of this report is that the results of that analysis may be applicable even in the face of external incentives. In general, given that external incentives are often outside the direct control of the DoD, it may be heartening for policy-makers to know that the tools they do have at hand may still be effective.

Acknowledgements

This project has been funded by a grant from the Acquisition Research Program at the Naval Postgraduate School. Part of the analysis included in this write-up are modifications of calculations started under a project funded by the National Science Foundation under the Graduate Research Fellowship Program under Grant Number 1122374. I would like to thank John Williams and G. Nagesh Rao at the Small Business Administration for helpful conversations and Robert Smith at the Office of Naval Research for discussions about data sources. Many of the computations in the current version of the draft were made possible by excellent research assistance from Aleksandra Paluszynska and especially Tai Lam. All errors are my own.

References

- Bhattacharya, V. (2018). *An empirical model R&D procurement contests: An analysis of the DoD SBIR program* [Manuscript submitted for publication, Northwestern University].
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3(4–5), 993–1022.
- Howell, S. T. (2017). Financing innovation: Evidence from R&D grants. *American Economic Review*, 107(4), 1136–64. Retrieved from <https://doi.org/10.1257/aer.2>
- Lanahan, L., & Feldman, M. P. (2018). Approximating exogenous variation in R&D: Evidence from the Kentucky and North Carolina SBIR state match programs. *Review of Economics and Statistics*, 100(4), 740–752. Retrieved from https://doi.org/10.1162/rest_a_00681.0150808
- Lanahan, L., Joshi, A. M., & Johnson, E. (2019). *The economic returns from federal R&D investment in small business: Evidence from the SBIR/STTR program, 2000–2015* [Unpublished manuscript, University of Oregon].



- Lerner, J. (2000). The government as venture capitalist: The long-run impact of the SBIR program. *Journal of Private Equity*, 3(2), 55–78. Retrieved from <https://doi.org/10.3905/jpe.2000.319960>
- Robinson, P. M. (1988). Root-N-consistent semiparametric regression. *Econometrica*, 56(4), 931–954. Retrieved from <https://doi.org/10.2307/1912705>
- Small Business Administration (SBA). (2017). *Small Business Innovation Research annual report: Fiscal year 2017*. Retrieved from <https://www.sbir.gov/sites/default/files/SBIR%20FY2017%20ANNUAL%20REPORT.pdf>
- Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: The case of the Small Business Innovation Research program. *RAND Journal of Economics*, 31(1), 82–100. Retrieved from <https://doi.org/10.2307/2601030>





ACQUISITION RESEARCH PROGRAM
GRADUATE SCHOOL OF DEFENSE MANAGEMENT
NAVAL POSTGRADUATE SCHOOL
555 DYER ROAD, INGERSOLL HALL
MONTEREY, CA 93943

WWW.ACQUISITIONRESEARCH.NET