Opening up Military Innovation:

Causal Effects of Reforms to U.S. Defense Research*

Sabrina T. Howell, Jason Rathje, John Van Reenen and Jun Wong†

October 2, 2024

Abstract

For governments procuring innovation, one choice is whether to specify desired products (a "Conventional" approach) or allow firms to suggest ideas (an "Open" approach). Using a U.S. Air Force R&D grant program, where Open and Conventional competitions were held simultaneously, we find that Open awards increase both commercial innovation and technology adoption by the military. In contrast, Conventional awards have no positive effects on new technology, but do create more program lock-in. We present evidence that openness matters independently from inducing differential selection, for example of less well-established firms. These results suggest benefits from open approaches to innovation procurement.

JEL: O31, O32, O38, H56, H57
Keywords: Innovation, defense, R&D, procurement

*We thank Chris Benson, David O'Brien, Susan Celis, Charles Chimento, Gregory Coleman, Allen Franke, Steve Lauver, Charles Perla, David Shahady, Molly Walsh, Will Roper and many others at the U.S. Air Force who have helped make this research possible. We also thank Jon Asker and four anonymous referees for extensive comments as well as Pierre Azoulay, Liat Belinson, Adam Jaffe, Saul Lach, Josh Lerner, Danielle Li, Ramana Nanda, Trang Nguyen, Jacquelyn Pless, Claudia Steinwender, Noam Yuchtman, Tom Wollman and seminar participants at the AEA, Bocconi, Erasmus, European Commission, INSEAD, LSE, MIT, Northwestern, Nova, NYU, Rotterdam, Stockholm, Tsinghua, U.S. Census Bureau, USI Lugano, Utah, WEFI and WFA. Howell served as an unpaid Special Government Employee of the U.S. Department of Defense to perform this research, and would like to thank the Kauffman Foundation for financial support. Van Reenen would like to thank the ESRC for financial support through POID. The views expressed herein are those of the authors and do not necessarily reflect the views of the United States Air Force.

†Howell: NYU Stern & NBER (sabrina.howell@nyu.edu). Rathje: U.S. Air Force (jason.rathje@gmail.com). Van Reenen: LSE, MIT & NBER (j.vanreenen@lse.ac.uk). Wong: University of Chicago (junwong@uchicago.edu).

All material funding of any scale is derived via the requirements process; there are people in the military who take in reports, they write requirements, and then a program is formulated around those requirements. I'm reminded of the old saying from Henry Ford: "If I asked people what they wanted they would say faster horses," vs. the entrepreneur who says, "Let me figure out what the best solution to your problem is."

– Doug Beck, Director of the Defense Innovation Unit[1]

1 Introduction

Amid concern about declining productivity growth, the role of innovation policy has become ever more important (Decker et al. 2016, Syverson 2017, Goolsbee and Jones 2022). Although the economics literature has paid much attention to the government's role as a major funder of R&D, there is much less study of how the public sector should *design* innovation procurement. A key decision is whether to take a centralized approach where the desired innovation is tightly specified or to take a more open, decentralized approach where applicants are given leeway to suggest solutions. There are trade-offs. The open approach may result in too many suggestions that are not useful to the funder, whereas the centralized approach may work poorly if there is uncertainty about what opportunities exist and may result in insularity if a small group of firms specializes in the specified projects.

We study these trade-offs in the context of a reform that took place in the Small Business Innovation Research (SBIR) program at the U.S. Air Force. The "Conventional" approach to this small business R&D grant program has been to hold competitions with highly specific topics such as "Affordable, Durable, Electrically Conductive Coating or Material Solution for Silver Paint Replacement on Advanced Aircraft." After 2018, the Air Force also included an "Open" competition which ran alongside the Conventional model, where firms could propose developing any technology that they thought the Air Force might need.

Open was launched in response to a growing concern that amid consolidation in the traditional defense industrial base, American military innovation was in decline. We document that this concern appears to be empirically justified. The Open reform represents one important part of a broader strategy shift that has taken place since 2015, in which the Department of

[1] Quoted March, 2024 (a16z Podcast, 2024).

Defense's (DoD) innovation strategy now centers squarely around encouraging younger and smaller firms to enter the defense industrial base.

The Air Force's Open reform has proved not to be idiosyncratic; instead, it has become an exemplar for similar programs across and beyond the DoD. By the end of 2022, among the 11 agencies that participate in SBIR, seven had Open topics, and at those agencies the Open topics composed on average 40% of all awards between 2019 and 2021, totalling $4.1 billion in Open topic awards. The Air Force is pursuing an 80%-20% budgetary split between Open and Conventional (OSD, 2021). In 2022, Congress legislated that every part of the DoD must conduct Open SBIR solicitations. Outside the SBIR, governments around the world, including in the EU, UK, and other U.S. agencies such as DARPA, the NIH, and DoE, have sourced innovative ideas from firms via open solicitations.[2]

To evaluate the Air Force's Open program relative to the Conventional one, we use rich administrative data between 2003 and 2019 on applications and evaluation scores to assess the causal impact of winning an award on performance outcomes through early 2023. The data include 21,365 proposals from 6,701 unique firms. We focus on outcomes identified as the goals of DoD's SBIR program historically, and that also form the agenda of the recent legislation mandating Open topics. First, to measure the transition of commercial technology into the DoD, we consider the firm's subsequent non-SBIR DoD contracts. Second, to measure expansion of the small business nontraditional industrial base and commercialization derived from DoD investment, we use venture capital investment (VC) and patenting (both counts and quality). This reflects DoD's increasing interest in pursuing "dual-use" technologies that are employed in both the defense and private sectors.

We identify the causal effects of winning with a sharp regression discontinuity design (RDD) that compares winning and losing applicants around a cutoff for the award, estimating effects for Open and Conventional in the same model in order to assess statistical differences between the two. We focus on a sample of 2,283 firms that applied during the 2017-19 period when Open and Conventional were run simultaneously and that had not previously won an SBIR award, which provides a more homogeneous sample.[3] Although the programs are not identical, comparing them offers a first step towards assessing the impacts of bottom-up innovation pro-

[2]For example, the largest EU small business innovation funding program, the Horizon SME Instrument, started using open topics in 2018 (EU, 2020). Other examples include the U.K.'s Defense and Security Accelerator Open Call for Innovation, the U.S. Department of Energy's ARPA-E (ARPA-E 2020), and the National Institutes of Health, which funds both "investigator-initiated competitions," similar to Open, as well as more specific "requests for applications," similar to Conventional (Myers 2020).

[3]We show that our results are robust to using all applicants and competitions as far back as 2003.

curement. Our research design exploits the facts that (a) the review and selection process was the same across the Open and Conventional programs; and (b) the RDD can be implemented using the rank that determines the award decision as a running variable. This ranking is constructed by the forced ordering of independent scores from three evaluators. The cutoff is independent of the evaluation process, making the manipulation of any firm around the cutoff extremely unlikely.[4]

Our main result is that winning an Open award significantly increases the measures of dual-use commercialization. In our baseline model, we show that winning an Open award increases the chances of the military adopting the new technology via non-SBIR DoD contracts by 11.4 pp (percentage points), 69% of the sample mean. It increases the probability of subsequent VC investment by 12 pp (178% of the mean). Finally, it increases the chance of having a patent by 8.9 pp and a high-originality patent by 7 pp (79% and 194% of their respective means).

By contrast, winning a Conventional award has no positive effects on any of these outcomes. Furthermore, there were no causal impacts of winning a Conventional award before the Open program was introduced, so it is not the case that Conventional projects require a longer time horizon or were crowded out by Open ones. Where Conventional does have an effect is on the chances of winning a future SBIR award of operation, while there is no effect on this outcome in the Open program, at least in its first six years. This is considered an undesirable feature of the Conventional program from a policymaker perspective, as it creates lock-in and insularity.

An example of a new entrant to the defense industrial base which came out of the Open program is Anduril, a VC-backed startup founded in 2017 that builds software and hardware for high-tech military applications. Anduril's first contract with the U.S. government was an Air Force Open SBIR award in 2019. It went on to obtain at least $756 million in contracts from the Navy, Special Operations Command, and the Air Force through 2023. In 2024, Anduril was among five firms competing to develop collaborative combat aircraft, a"large-build" drone aircraft program at the Air Force worth $6 billon (Easley, 2024; Cameron, 2024). Anduril was selected as one of two companies to go forward with manufacturing, beating out the traditional prime defense contractors such as Boeing and Lockheed Martin (AF, 2024).

We find that the Open program reached new types of firms like Anduril, which was one policymaker objective. Compared to firms applying to Conventional topics, Open topic appli-

[4]We document a smooth density around the cutoff and continuity in baseline covariates. One downside of RDD is that the results are necessarily local. However, in our case, because the results are generally similar when we use the whole sample or a narrow bandwidth, and with or without rank controls, they seem likely to apply more broadly.

cants are younger, less likely to have previous defense contracts, and more likely to be located in high-tech entrepreneurial hubs like Silicon Valley. Although reaching new firms was one aim of the reform, it raises the question of whether Open was more successful due to this kind of selection. This would limit the implications of our results, because in many settings it is infeasible to alter applicant composition. In practice, we do not find that Open's differential impact depends on firm lifecycle factors. Specifically, our results are not driven by the subsamples of younger or smaller firms.

In addition, we use three complementary research designs to show that the positive effects of openness go beyond inducing a different composition of applicant firms. First, we control for lifecycle covariates and narrow technology classes. Second, we characterize the degree of specificity for each topic using a machine learning algorithm to classify application abstract texts. We show that when a Conventional topic is less specific—and thus closer to the Open program's approach—winning an award in that topic *does* increase patent-based innovation measures. Third, we find positive effects of Open even among the firms that previously applied to the Conventional program. All three designs balance the characteristics of applicant firms in different ways, but all three imply that the success of openness is in part due to the way it incentivizes greater innovation from broadly the same pool of firms.

Why does Open work so well? Belenzon and Cioaca (2021) offer a useful starting point for thinking about this. They point out that government R&D contracts implicitly promise potential future public demand. DoD SBIR awards are R&D contracts with such an implicit potential for subsequent downstream procurement, unlike the R&D grants studied in Howell (2017) and elsewhere. Belenzon and Cioaca (2021) show that R&D contracts crowd-in private R&D investment due to the potential for noncompetitive downstream procurement. Our evidence indicates that the Open program allows firms to bring new technologies to the defense market that are potentially useful to DoD but, crucially, about which DoD was not previously aware (or was unaware of how they could be useful). This leads them to invest more in innovation, measured both with patents and VC. Startups with a successful Open Phase 1 can bring evidence to VCs that large defense customers are interested in their commercially-driven development efforts, which appears to improve their odds of raising funds. In other words, the Open program seems to work in part because it provides firms with an avenue to identify technological opportunities about which the government is not yet fully aware but that can represent an entry point to much larger public sector contracts. The dual-use nature of the Open technologies, where firms are encouraged to re-purpose something they are working on for private markets for the defense market, is central to this mechanism.

The U.S. DoD is the largest single investor in R&D in the world and comprises about 60% of total U.S. federal government R&D (CRS 2018). DoD has historically been an important financier and early customer for technology, both transformational and incremental (Mowery and Rosenberg 1991, Mazzucato and Semieniuk 2017, Gross and Sampat 2020). Its investments often have dual-use properties, generating opportunities for large private sector spillovers. Contrary to popular belief, small firms make up a substantial part of DoD procurement in general, and R&D in particular. This is often disguised by the large amount of defense sub-contacting. Small firms constitute about a third of all DoD R&D dollars spent. Even within "large build" programs such as Lockheed Martin's F35, about a quarter of contract value goes to smaller firms (see Appendix B for more details).

Our paper joins a small literature on economic dimensions of defense R&D. Defense is unique because the buyer is a monopsonistic government agency providing a public good. This implies a narrow market, but one with potentially high risk tolerance and—particularly in the U.S.—immense buying power in the event of success. The defense setting enables us to study the government as a customer rather than a regulator or financier. While there is extensive literature on the latter two roles (e.g. Jaffe and Palmer 1997, Bloom et al. 2002, Denes et al. 2020), the former is quantitatively important in the U.S. and even more so in many other countries. The literature has also used military spending as an exogenous shock to demand (Ramey 2011, Barro and Redlick 2011, Nakamura and Steinsson 2014), has studied the the crowd-in effects of defense R&D on private R&D (Lichtenberg 1984; 1988; 1995, Middleton et al. 2006, Draca 2013, Moretti et al. 2020), and finally has studied competition in procurement, including Bhattacharya (2021) on the Navy's SBIR program.

Our primary contribution is to offer the first study of top-down vs. bottom-up mechanisms for innovation procurement. We show that decentralization and openness are relevant for public R&D procurement. This joins work on how to motivate or procure innovation, such as Manso (2011), Azoulay et al. (2011), Nanda et al. (2014), Halac et al. (2017), Krieger et al. (2018) and Che et al. (2021). It is related to the large empirical literature on innovation subsidies, which includes Goolsbee (1998), Atkeson and Burstein (2019), Bloom et al. (2019), Pless (2019), Rathje and Katila (2020), and Akcigit et al. (2021). Work specifically on direct R&D grants or contracts includes Lach (2002), Jacob and Lefgren (2011), and Azoulay et al. (2019), with the SBIR program receiving particular attention (Lerner, 1999; Wallsten, 2000; Howell, 2017; Lanahan and Feldman, 2018). Santoleri et al. (2022) assess the impact of European R&D grants and find strong positive effects on investment and patenting, which they show are driven by a funding mechanism rather than certification.

Open innovation connects to a literature about corporate innovation, the boundary of the firm, and decentralization of decisions between principals and agents (Mowery, 1983; Cohen et al., 1990; Aghion and Tirole, 1997; Gibbons et al., 2013). Settings where decentralization likely has greater benefits have more uncertainty, are closer to the innovation frontier, and face more information asymmetry (Bloom et al., 2010; Howell, 2024). R&D is an example of this, especially in the frontier sectors relevant for defense. Chesbrough (2003) introduced the idea of "open innovation" in the sense that large corporations were increasingly losing ideas to startups but also acquiring ideas from them. Closely related to open innovation procurement is the crowdsourcing of ideas or solutions to problems, which has pursued by institutions ranging from Apple to LEGO to NASA (Tushman et al., 2012; Lakhani et al., 2013).[5]

One theme of this literature is that open innovation is better suited to tasks that are more modular and in more widespread use (also see Baldwin and Von Hippel (2011)). Chesbrough (2003) argues that faster product development cycles, foreign competition, and more mobile skilled workers pave the way for a more open innovation system. These insights have parallels in the defense context, where the frontier of military technology has shifted to some degree from integrated, highly capital intensive and defense-specific platforms—such as nuclear submarines or fighter jets—to technologies with strong civilian innovation ecosystems, lower barriers to entry, and more modular architectures. For example, in discussing the new replacement for the Bradley tank, an infantry fighting vehicle, Army Lt. Gen Ross Coffman noted that:

> "A big difference will be its so-called open-systems architecture, in which it is built in a modular way so that its software and hardware, from guns to engines, are easy to swap out and so upgrade" (MacDonald and Sivorka, 2024).

Open innovation may have been successful in the Air Force SBIR program in part because the organization increasingly needed technologies that are more widely used. Indeed, we document larger relative effects of Open among firms in non-defense sectors. Establishing general conditions for Open procurement to be successful is a fruitful avenue for future research.

The remainder of the paper is organized as follows. In Section 2 we provide institutional context for the reform we study. In Sections 3 and 4 we describe the data and empirical

[5] There is also a large literature on open source innovation, which is distinct as it involves many people working for free on a common project (Lakhani and Von Hippel, 2004; Lerner and Schankerman, 2013).

strategy, respectively. The main results comparing the effects of the Open and Conventional programs are in Section 5. We explore mechanisms for the larger effect of the Open program in Section 6. Finally, supplementary and robustness tests are in Section 7.

2 Defense R&D Institutions and SBIR Reforms

Defense Policy Context. The addition of an Open program to the Air Force SBIR was motivated by concerns among policymakers about declining innovativeness among prime defense contractors as well as the SBIR program's failure to generate useful technologies for military and commercial purposes. As we could find no existing quantitative studies showing that, in fact, defense innovation has declined, we describe the economic context for U.S. military R&D and document innovation trends in Appendix A. The results of this exercise reveal a dramatic consolidation among prime contractors in recent decades, accompanied by a decline in innovation quality relative to the private sector (Figures A.1 and A.3 panel A). This has occurred despite a substantial increase in prime contractors' profits and assets (Figure A.5 panels C and D).

The prime contractors we study in Appendix A account for 30-40% of total defense contract value across our sample period from 1976 to 2019. Outside of this subset, small firms have long played a meaningful role in defense procurement. We document this in Appendix B.1. We show that about a third of all DoD R&D dollars goes to smaller firms. The challenge that DoD has identified is not that there are no small firms in the defense industrial base, but rather that there has been a failure to bring in new firms with frontier technologies. These stylized facts set the stage for the reform we study.

In response to these issues, a strategy shift has occurred over the past two decades in the DoD, with a notable acceleration starting in 2015. Since 2015, DoD's principal and explicit innovation strategy has been to encourage new small businesses to enter the defense industrial base (Kotila et al., 2022). This shift, which we describe in more detail in Appendix B.2, represents an effort to go beyond the historical focus on small businesses towards a new focus on innovative startups. For example, Secretary of Defense Ash Carter explained that:

> *"To invest in the most promising emerging technologies, the department needs the creativity and innovation that comes from startups and small businesses. This is particularly important, because startups are the leading edge of commercial inno-*

vation" (Pellerin, 2015).

The vehicles for the policy change are a series of new Defense Innovation Organizations (DIOs), of which AFWERX is one.[6] They aim to reduce barriers between defense field missions and commercially focused companies that are not traditionally defense contractors. Among these DIOs, more than 90% of innovation contracts are to small businesses.[7]

SBIR Context and Challenges. Congress first authorized the SBIR program in 1982 to strengthen the U.S. high technology sector and support small firms. Today, the SBIR is among the world's largest and most influential small business R&D grant programs, spending $3.11 billion across 11 Federal agencies in 2018. Of this, the DoD accounted for $1.32 billion, and the Air Force had the largest program among the military services. It is worth noting that there are no classified (i.e. "secret") SBIR projects. In being applied and not classified, SBIR is representative of the vast majority of defense R&D. SBIR applicant firms are typically small and high-tech, a firm type that is crucial to job creation and innovation, especially those that receive VC backing.[8]

SBIR has two Phases. An initial, small Phase 1 award funds proof-of-concept work, after which a firm may apply for a larger Phase 2 award to support later stage demonstration.[9] SBIR at DoD funds applied R&D, as opposed to basic research. The SBIR is one of the only ways that new firms enter the defense industrial base. Importantly for our study, the only way for SBIR-funded technologies to be used within the DoD is via a subsequent non-SBIR contract. The idea is that small contracts in the SBIR program can feed into the broader defense industrial base when an SBIR awardee becomes a major contractor, as in the case of Progeny or Qualcomm, or is acquired by a prime contractor (SBIR.gov 2011). Policymakers have expressed concern about lock-in at the SBIR program, with repeat contracts awarded to firms (so-called "SBIR mills") that are interested neither in commercializing innovation nor

[6] The first was the Defense Innovation Unit (DIU) within the Office of the Secretary of Defense, established in 2015. In the subsequent years, DoD added the Army Applications Lab, Naval X, AFWERX, SOFWERX (part of the Special Operations Command), DEFENSEWERX, the National Security Innovation Network (NSIN), the Army Venture Capital Initiative, and others.

[7] In part this is by construction since they primarily use SBIR to make direct awards. The figures are based on the Federal Procurement Data System and conversations with DoD officials. These agencies' spending cannot be distinguished in the public contracts data.

[8] See Kortum and Lerner (2000), Foster et al. (2008), Haltiwanger et al. (2013), Arora et al. (2018), and Howell et al. (2020).

[9] The Small Business Technology Transfer (STTR) program is an add-on to the SBIR program and requires small businesses to collaborate with a research institution in the initial research phases. Our main findings do not differ across SBIR and STTR, so we refer to them jointly as "SBIR."

in seeking scale in the defense market (Edwards, 2020). Since SBIR-funded technology has no particular application without a subsequent contract, DoD wishes for SBIR to serve as a stepping stone rather than a destination for contractors.

The concern about SBIR mills may be related to the decline in relative innovation that we observe among winners in the Conventional SBIR program (Figure A.3 Panel B), paralleling the decline among the prime contractors. Since firms must be small to participate, concentration is not a primary concern in the SBIR. However, Figure A.2 panel A uses the Herfindahl-Hirschman Index (HHI) to show that the DoD SBIR program has become more concentrated over time, with more firms winning many awards in a single year.

This declining innovation and increasing lock-in at DoD may help to explain the difference between our findings in the Conventional program and the strong positive effects of Department of Energy (DoE) SBIR grants in Howell (2017). We show that the DoE SBIR program has a much higher share of awardees who have not won in the past three years relative to DoD; for example, in 2019, roughly 50% for DoE compared to 25% for DoD (Figure A.2 Panel B). The greater lock-in at DoD might reflect the large size of DoD's SBIR program and the many similar types of R&D procurement contracts that DoD offers, which can be sustainably lucrative to a small research firm. In Section 8 below, we also note that DoE topics are relatively more open than those in the Conventional program we study.

SBIR Process at the Air Force. The Conventional and Open programs that we study have a common administrative process. First, the Air Force issues a public solicitation for applications. The solicitation describes one or more "topics," each of which represents a discrete competition. Once applications are received, the evaluation process has three steps. In the first step, ineligible applicants are disqualified. In the second step, multiple government evaluators with expertise in the topic area independently evaluate the application. Evaluators produce scores on three criteria: Technology, Team, and Commercialization.[10] The commercialization sub-score reflects the potential to sell any derived product or service within and outside the government. Firms' proposed cost is not a factor in the evaluation if the cost is below the

[10] The official description for the Conventional program of these criteria is: "(1) Technical Merit – The soundness, technical merit, and innovation of the proposed approach and its incremental progress toward topic or subtopic solution. (2) Qualifications of the Principal Investigator (and Team) – The qualifications of the proposed principal/key investigators, supporting staff, and consultants. Qualifications include not only the ability to perform the research and development but also the ability to commercialize the results. (3) Potential for Commercial Application– The potential for commercial (Government or private sector) application and the benefits expected to accrue from this commercialization."

maximum amount identified in the solicitation; that is, firms are not more likely to win if they submit a lower amount. This is different from an auction where firms compete on cost, which is used elsewhere in DoD procurement.

The three sub-scores are summed, and the winners are those whose overall scores are above a threshold determined by the amount of funding available. We will return to this point in the empirical design in Section 4, but this process implies that treatment (award) is exogenous to the running variable (score). While the overall score threshold is sometimes known to the evaluator in advance, no single evaluator can manipulate a firm's position around the cutoff because each evaluator independently scores the proposal. In the final step, a contracting officer awards the contract and administers the award. This step does not disqualify applicants based on technical merit but does occasionally disqualify applicants for a business reason, such as a cost that is found to be ineligible, or if the proposal is found unrelated to R&D. After the awards are made, the winner identities are immediately public. The non-winner identities that we use in this study are never public, and the scores are never released beyond the evaluation team (i.e., no firms observe their own scores). After removing disqualified awardees, we obtain data for a sharp regression discontinuity design within each topic.

Overall, the Open and Conventional programs have the same review process, metrics, and selection mechanism. Indeed, sometimes the evaluators are the same Air Force Science and Technology personnel. This makes them well-suited for a comparative evaluation.

SBIR Reforms: Open vs. Conventional. Conventional topics solicit highly specific technologies. One example is: "Develop Capability to Measure the Health of High Impedance Resistive Materials." In contrast, Open topic solicitations contain no direction regarding the technology that the applicant may propose.[11] With an reference to seeking "unknown unknowns" in the solicitation, Open topics are designed to let the private sector do the work of identifying military applications for its technology. The firm's objective is to demonstrate the feasibility of developing a product or service with an Air Force partner interested in potentially procuring the firm's technology. The Phase 1 deliverable is a white paper or report describing the outcomes of research. The idea behind Open is that if its approach is successful in this context, it might be applied to the larger acquisition programs with the hope of garnering interest in the defense market among the large tech firms. In Appendix C, we provide further

[11] The SBIR reforms have taken place within a new organization called Air Force Ventures. This is the business division of AFWERX, an office that seeks to foster innovation within the Air Force. Conventional topics are sourced primarily from the Air Force Research Laboratory (AFRL).

details about the Open reform as well as additional examples of Conventional topics.

Open topics were first deployed in May 2018. In these and each subsequent year, there have been three solicitations, each of which has many Conventional topics but only one Open topic. All Open topics are the same; there are multiple topics because they are issued at different points in time (i.e., in different solicitations). That is, there are three Open topics a year with the same rubric. An applicant's pool of competitors in an Open topic depends on when it applies because scoring and ranking are within-topic. This creates a different distributional structure in Open topics, as there are many more applicants but also far more winners. The difference in topic structure should not bias the results towards favoring a stronger effect in Open because we estimate the effect of winning within each program, and the cutoff point for winning is lower in the score distribution for Open. We also show that the effects of the program do not depend on the number or fraction of winners in any given competition.

The award amount for Phase 1 Open topics is about $50,000, while it is $150,000 for Conventional. This should bias towards finding more positive effects in the Conventional program. The Open program also has a shorter time frame, at 3 vs. 9 months. The Phase 2 awards of $300,000 to $2 million are intended to last 12-24 months and fund a prototype (we focus on Phase 1; further details and analysis of Phase 2 is in Appendix F.1). In the later Open topics, the Air Force sought to encourage Phase 1 winners to access outside funding from private or government sources with a matching provision in Phase 2. We evaluate the impact of match availability separately from openness in Appendix F.2.

Importance of the Open Program. The Air Force Open program represents a key initial implementation of the broader policy pivot discussed above towards soliciting frontier innovation from start-ups. Over time, this first Open program at DoD was replicated across the department, at other U.S. government agencies, and beyond. The scope of Open topic proliferation across U.S. agencies between 2019 and 2021 is summarized in Table E.1. For example, 100% of NSF SBIR awards are made via Open topics. The overall share across all agencies increased from 36% in 2019 to 46% in 2021 (GAO, 2023).

The perceived success of the Air Force Open program led Congress to legislate in 2022 that every part of the DOD must conduct Open SBIR solicitations, with the Air Force version as the model.[12] Congress (2022) requires that each DoD component with an SBIR program have

[12]The assertion that the AFWERX Open program was the model is based on conversations with U.S. Senate Committee on Small Business and Entrepreneurship staff, including Samantha Scoca.

at least one Open topic per fiscal year, with the following four goals:

1. Increase the transition of commercial technology to DoD,
2. Expand the small business nontraditional industrial base,
3. Increase commercialization derived from DOD investments, and
4. Expand the ability for qualifying small business concerns to propose technology solutions to meet DoD needs.

These Congressional policy aims correspond well with DoD's stated goals and the outcome measures we use in our study.

3 Data and Summary Statistics

This section summarizes our data sources, sample construction, and outcome variables. They are described in detail in Appendix D. We begin with a dataset of applications and awards to the Air Force SBIR program between 2003 and 2019. We observe complete evaluation data between 2017 and 2019, and further evaluation data for Conventional topics in 2003-2007, 2015, and part of 2016 (the remaining years' data were inadvertently destroyed in 2016). We restrict the sample to the three years of 2017-2019 and to firms who have not won a previous SBIR award, so that the relevant economic environment and defense procurement factors are similar across the sample. As mentioned above, we focus on Phase 1. In this main analysis sample, we observe proposals from 2,283 unique firms.

We collect outcome data through at least 37 months after the last award (through January 2023), providing sufficient time to observe effects. For all outcomes, we employ binary indicators. The first outcome is technology adoption as measured by non-SBIR DoD contracts, which we gather from the Federal Procurement Data System (FPDS). These represent success in the sense that the research has led to a practical application for the military. The technology in the subsequent, non-SBIR contract need not be the same as the one that was the subject of the SBIR contract.[13] What links them is the firm, not the technology. Since a key policy goal

[13]We cannot easily link these non-SBIR contracts to particular SBIR awards because summaries of the contracts' contents are not available. However, we can manually identify a number of examples. One from the Open program is the firm Aevum, which designs drone-launched rockets in a former textile mill. After winning a $50,000 Open Phase 1 award in July 2019, Aevum was awarded a $4.9 million Air Force launch contract in September 2019. An example in the Conventional program is Ascendant Engineering Solutions. After winning a $149,000 Conventional Phase 1 award in September 2016 to work on gimbals, Ascendant Engineering Solutions was awarded a $7.5 million Air Force contract for its tactical gimbals in February

was to bring new, innovative firms into the defense industrial base, the most important unit of observation is the firm. Also, it is important to emphasize that there are no means for SBIR technologies to "plug in" to the R&D apparatus or ultimately to impact operations without a subsequent non-SBIR contract. Simply performing R&D and developing a prototype *per se* within the confines of the SBIR program are not useful for the military unless these activities lead to a non-SBIR contract. Therefore, this outcome is equivalent to technological adoption, something that is often hard to observe in empirical studies.

The second outcome is VC investment. The Air Force leadership views commercial innovation as evidence of initial success, based on the idea that a strong U.S. industrial base will ultimately enable strong defense, especially if its research has early-stage ties to DoD (Williams 2020). From an economic perspective, VC is a useful proxy for high-growth innovation potential (Lerner and Nanda 2020). Although VC-backed startups make up only 0.11% of new firms, over 44% of public company R&D is performed by formerly VC-backed startups (Puri and Zarutskie 2012, Gornall and Strebulaev 2015). We obtain VC deals mainly from Pitchbook but also from from CB Insights, SDC VentureXpert, and Crunchbase.

The third outcome, patents, capture innovation with intent to commercialize. Patents are especially useful for us because they are not subject to the same concern that VCs focus only on young firms. Innovative firms wishing to protect new intellectual property generally consider patenting, and patent-holding firms account for the lion's share of private R&D spending (Mezzanotti and Simcoe, 2023). We categorize patents as pre- or post-award depending on their application date. A post-award patent is one applied for after the SBIR award date that was ultimately granted by the USPTO.[14] We also calculate patent citations and originality (Jaffe and Trajtenberg 2002). A patent's originality score is low if it cites previous patents in a narrow set of technologies, and high if it cites previous patents in a wide range of fields.[15] We split around the median originality and citation measures to construct indicators for high originality and high citations.

The final outcome is all-agency SBIR awards (the results are similar using Air Force or all-DoD SBIR awards). We obtain these from the Small Business Administration. We examine whether winning one SBIR award causally increases the probability of winning more than one

2018. (A gimbal is a pivoting support that permits an object to rotate on a single axis.)

[14] Patenting involves some amount of disclosure, but all SBIR awardee technology abstracts are publicly available, and no projects are classified. Therefore, secrecy orders on patent applications are unlikely to affect our results.

[15] Originality for patent i is defined as $1 - \sum_j c_{ij}^2$, where c_{ij} is the percentage of citations that patent i makes that belong to patent class j.

future SBIR awards, to assess lock-in to the SBIR program.

We make use of the text in proposal abstracts to assign proposals to technology clusters. Employing a machine learning algorithm called "k-means clustering" (Forgy 1965, Bonhomme and Manresa 2015), we classify each abstract based on its word embedding.[16] Applications are clustered into groups based on the similarity of the vectors (i.e. minimizing the total within-cluster variance using their vector representation). We use a 25-cluster model to classify proposals into granular technology classes. The top words in each cluster are listed in Table E.14.[17] Further details on this method are in Appendix D.3.

Table 1 contains descriptive statistics on applicant and competition characteristics for Open and Conventional in the main analysis sample.[18] Open applicant firms are younger than Conventional ones (nine vs. twelve years old on average), although not significantly so. They are also smaller (18 vs. 23 employees), although this difference is only significant at the 10% level. Open applicants are more likely to be in on of the three VC hubs of San Francisco Bay, greater Boston, and New York City.[19] They are less likely to be in a county where there is an Air Force base or to be owned by a women or minority, but are more likely to be owned by an immigrant.

Looking at pre-award values in Table 1, Open applicants are more likely to have previous VC financing, (9.7% vs. 2.3%) and to have patented (15.2% relative to 11.7%). However, Open and Conventional applicants have similar originality and citations, with no statistical differences across the originality and citation outcomes. No firm has previous SBIR awards in this analysis sample, because as noted we drop previous winners to generate a more homogeneous (we relax this condition in extensions reported below).

Overall, the Open program seems to have attracted new types of firms into defense R&D procurement, just as DoD policymakers wanted. In Section 6, we show that selection does *not* explain our results and that there is an additional causal role for openness.

Table 1 also contains competition characteristics. As explained above, Open topics have

[16]The process essentially converts the text into vectors of numbers. Each application is represented by a vector whose elements reflect the words used in the application.

[17]We also use a two-cluster model in a robustness test, which yields a clear dichotomy between software- and hardware-based technologies. The word clouds of keywords for are in Figure E.2.

[18]This comparison using continuous outcome variables is in Table E.3. Table E.2 describes counts of topics, firms, and proposals for all programs.

[19]To describe their geographic diversity, we map the location of applicants in Figure E.8, with larger bubbles indicating more firms, and overlay the locations with VC activity. Some of the locations with high applicant density are defense spending hubs such as Washington DC and Ohio, where the AFRL is located. The same set of maps for awardees is in Figure E.9 and documents similar patterns.

many more applicants and winners. While the number of applicants and share of winners is different in Open, this stems from the fact that Open represents a single topic per solicitation rather than the many specific topics in each solicitation for Conventional. The review process is the same for Open and Conventional and we show below that the effect of winning does not depend on the number of applicants or fraction of winners.

4 Empirical Design

We employ a regression discontinuity design (RDD) to assess the effect of winning in a Conventional or Open topic. The RDD approximates the ideal experiment of randomly allocating awards among applicants. The intuition is either a discontinuity at the cutoff (Hahn et al. 2001) or local randomization around the cutoff (Lee 2008). It is relevant in settings where treatment assignment is based on an applicant's location around a cutoff in a rating variable. Our setting permits a sharp RDD because the running variable perfectly predicts award in all topics in both Open and Conventional. This is shown for four representative topics in Figure 1; the probability of treatment jumps from zero to one at a cutoff.

A valid sharp RDD has four conditions (Lee and Lemieux 2010, Gelman and Imbens 2018). First, the rating variable must be established before treatment is assigned (i.e., treatment cannot cause the rating variable). This is the case in our setting, as evaluators score before the award decision is made. Also, as mentioned above, the cutoff (i.e., threshold for winning) is completely independent of the evaluation process and reflects budgets for the current SBIR cycle. Second, treatment assignment must be based solely on the combination of the rating variable and the cutoff. This is true for all the topics and, as mentioned above, is illustrated in Figure 1. As the scores and the cutoff vary across topics, we normalize scores into a rank around the cutoff, such that a rank of 1 is the lowest-scoring winner, and a rank of -1 is the highest-scoring loser.

The third condition for a valid RDD is that the cutoff must be independent of the rating variable. That is, the rating variable cannot be manipulated around the cutoff to ensure certain applicants receive treatment. The most important test for manipulation, common to all RDD settings, is to observe whether there is bunching around the cutoff. In Figure 2, we graph the density of the rating variable around the cutoff within each program. There is no bunching, consistent with no manipulation. The formal test also yields no evidence of manipulation, consistent with the figures (the p-value of the manipulation test is over 0.6 in both groups). The second test is to assess the continuity of observable baseline covariates around the cutoff. Figures E.3-E.6 show 11 baseline covariates, including all the outcome variables, observed at the time of application. There are no discontinuities around the cutoff in any of the variables, consistent with an absence of manipulation. In Table E.7 we formally confirm that there are no significant differences around the cutoff among the baseline covariates.

There may be concern that evaluators could manipulate sub-scores based on an ex-ante preference for which firms should win, potentially leading to scores that are not randomized around the cutoff. An intended benefit of three independent evaluators for three sub-scores is that this sort of manipulation is difficult. An individual evaluator cannot, in general, systematically sway applicants' award status. To confirm this, we examine sub-score variation within the topic. If the three sub-scores are usually correlated so that there is little variation in sub-scores around the cutoff, it might be easier for an evaluator to nudge applicants below or above the threshold. By contrast, if sub-scores exhibit substantial variation, such that often a winning firm has at least one sub-score that is lower than a loser sub-score, and vice versa, it will point to little scope for manipulation. Figure E.7 shows substantial variation in sub-scores around the cutoff. The red bars to the right side of zero show that many unsuccessful applicants (losers) have a sub-score that exceeds the lowest sub-score among winners. Similarly, the blue bars to the left side of zero show that many winners have sub-scores that are lower than the highest loser sub-score. Altogether, 81% of applicants have at least one sub-score that is a "crossover." This should make manipulation very unlikely. It is also worth noting that the evaluators are Air Force government officials (military officers and civilians), and manipulation would constitute a serious violation of acquisition rules.

The last condition for a valid RDD is to control for the rating variable in a well-specified functional form. Our primary model includes all ranks with linear controls for rank on either side of the cutoff. We use a triangular kernel to weight observations far from the cutoff less than those close to the cutoff, following DiNardo and Tobias (2001). Specifically, we use the formula $\text{Kernel}_{iT} = 1 - \frac{|\text{Rank}_{iT}|}{\max_j |\text{Rank}_{iT}| + (0.01)}$ for application i in topic T.[20] This kernel weighting approach weakens the parallel trends assumption for awardees and non-awardees.

Our main estimation model is as follows:

[20] We add .01 so that the observations with the maximum absolute rank do not end up with a weight of zero (which would cause them to drop out of the regression).

$$
\begin{aligned}
Y_i = {} & \alpha + \beta_1 \text{Award}_{iT} + \beta_2 \text{Award}_{iT} \cdot \text{Open}_T && (1)\\
& + \gamma_1 \left[\text{Rank}_{iT} \mid \text{Rank}_{iT} > 0\right] + \gamma_2 \left[\text{Rank}_{iT} \mid \text{Rank}_{iT} > 0\right] \cdot \text{Open}_T \\
& + \gamma_3 \left[\text{Rank}_{iT} \mid \text{Rank}_{iT} < 0\right] + \gamma_4 \left[\text{Rank}_{iT} \mid \text{Rank}_{iT} < 0\right] \cdot \text{Open}_T + \delta \text{Score}_{iT} + \mathbf{X}_i' \theta + \alpha_T + \varepsilon_{iT}.
\end{aligned}
$$

Here, the dependent variable Y_i is a post-award decision outcome such as DoD technology adoption. We use ever-after outcomes, though the results are similar when restricting the outcome variable to 12 or 24 months after the award decision. Award_{iT} is an indicator for winning an award in topic T (we do not consider the award amount because it is co-linear with winning). Score_{iT} is the continuous score received by the applicant. This model includes data from both Open and Conventional topics. Open_T is an indicator that takes a value of 1 if the topic is Open, and zero if Conventional. The coefficients of interest are β_1 which gives the effect of winning in the Conventional program and and β_2 which indicates whether the impact of the Open program is statistically significantly different from the Conventional program.

We interact Rank_{iT} with Open_T on each side of the cutoff in case Rank_{iT} may represent something different in the two types of competitions. The fixed effects for the topic (α_T) are necessary for the RDD assumptions to hold, since rank and thus randomization conditional on rank is defined within each topic. These fixed effects also control for the independent effect of program type and the date of award. In some models, we include two sets of firm-level controls $\mathbf{X}_i'$. The first set are "Lifecycle" controls composed of the number of employees and firm age at time of the application. The second set is a vector of 25 narrow technology fixed effects based on natural language processing of application abstracts (described above). In robustness checks we include a variety of additional controls.

Our primary models exclude applications after a firm's first win, so that firms do not appear more than once. But we also report results using all proposals, which dramatically increases the sample but yields similar results. We show several further models in robustness tests, including a narrow bandwidth around the cutoff. We cluster the errors, ε_{iT} by topic (and also by firm in the extended models where firms can appear more than once). We also conduct randomization inference tests following Cattaneo et al. (2015).

5 Effects of the Open and Conventional Programs

This section describes the effects of winning Open and Conventional competitions on contracting, investment, and innovation outcomes. We focus on binary indicators for success in each domain for three reasons: (a) the outcome is zero for many firms; (b) the extensive margin is more economically meaningful (for example, in the case of non-SBIR DoD contracts, we are interested in entry into the defense industrial base and technology adoption); and (c) binary outcomes makes the results easily interpretable and comparable. In Panel A of Table 2 we report estimates of Equation 1 with no additional firm-level controls.

One goal of the SBIR reforms is to enable more firms to transition technologies out of the SBIR program to operational programs of record. We therefore consider in column 1 the effect of winning an award on an indicator for subsequent technology adoption in the form of non-SBIR DoD contracts. In our baseline specification in panel A, winning a Conventional award has an insignificant effect of negative 8.6 pp, suggesting that if anything, Conventional SBIR awards crowd out other DoD contracts. In contrast, winning an Open award has an effect that is significantly higher by 20 pp, implying an effect of Open of about 11.4 pp (= 0.200 - 0.086), which is 69% of the overall sample mean.[21] The confidence interval for this point estimate is large, implying that we should have some caution in interpreting the magnitude. However, we document below that the result is robust to a large variety of alternative specifications, in which both the significance at the .05 level and the general magnitude are maintained. Moreover, the linear effect of Open of 11.4 pp is significant at the 5% level (p-value 0.019). Therefore, we are confident that the effect of Open is well above the effect for Conventional.

VC investment represents high-growth innovation potential and leads to spillovers, in addition to being a goal of the program. In column 2, we examine the effect of winning an award on receiving any VC after the award decision.[22] While winning a conventional award has no effect, winning an Open award has an effect that is just over 12 pp larger, which is more than the sample mean of 9.2%. This effect is also significantly different from the Conventional effect at the 5% level.

We next turn to two patent-based outcomes as alternative measures of commercially-oriented innovation. The first row of column 3 indicates a negative (and weakly statistically significant) effect of winning a Conventional award on any subsequent patenting. To the degree

[21] Here and subsequently, the mean of the dependent variable is reported at the bottom of each panel.
[22] In unreported models, we find similar results using the level and log amount of VC funding.

these firms are mostly focused on getting the next SBIR award, there is less reason to invest in patents, which measure the intent to commercialize an invention. In contrast, winning an Open award has a significantly larger effect than winning a Conventional award, suggesting an Open effect of 8.9 pp which is 79% of the mean. The second patent outcome is originality. Winning an Open award has a strong positive effect on producing an above-median originality patent (defined among all the applicants in our sample) of 7 pp (194% of the mean), while winning Conventional has no effect (column 4).[23] These effects of Open on patenting are significantly different from the Conventional effects at the 1% level.

Last, we consider the chances of subsequent SBIR contracts. The RDD helps us to overcome the difficulty of separating state dependence (the causal impact of the lagged dependent variable) from unobserved heterogeneity (e.g., if the best firms keep winning SBIR contracts). The effect on this outcome is rather different than the previous columns. Column 5 of Table 2 shows that when we add the two coefficients, there is no effect of winning an Open award on obtaining future SBIR contracts. In contrast, there is a positive effect of winning Conventional awards on getting another SBIR award in the future, at roughly three times the mean. This effect is only weakly significant, so it should be interpreted with caution, but it suggests a "lock-in" effect of the Conventional competitions, but not the Open ones.

We next report graphically the effects by rank around the cutoff within each program. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers.[24] For our measure of technological adoption (DoD non-SBIR contracts), the visual results are in Figure 3. There is a clear level shift upwards to the right of the cutoff in Open (Panel A) but not in Conventional (Panel B). Figure 4 shows similarly shows that subsequent VC investment rises just to the right of the cutoff for Open. By contrast, we see no relationship for Conventional topics in Panel B. For the patenting metrics, we again see a similar pattern in Figures 5 and 6, where there are positive effects for Open but none for Conventional. Finally, Figure 7 shows the impact on future Air Force SBIR awards, which has a positive and significant effect for Conventional wins, but nothing for Open.

In sum, the visual effects by rank confirm the results in Table 2, showing a discontinuity

[23] We do not use citations as an outcome for the 2017-19 analysis sample, since there is little time after the awards for citations to accrue. Below we do document citation effects when we have a longer time series from 2003 onwards in Table 5.

[24] The estimating model is the same as Equation 1 but restricted to a single program (and thus without the interaction coefficients), with separate coefficients for each rank, (with ranks below -4 and above +4 collapsed into a single indicator) and without the additional **X** controls.

around the cutoff. They further point to external validity beyond the region immediately around the cutoff, since the results are fairly flat in rank on either side.

6 Does Selection Explain the Larger Effects of Open?

Our conclusions from Section 5 are clear. Winning an Open award increases the chances of supplying the DoD with future technologies, obtaining subsequent VC funding, and successfully increasing the number and originality of patenting. In contrast, the only effect of winning a Conventional SBIR contract is to increase the firm's chances of winning *another* SBIR contract in the future. Note that the causal effects are separate from different base rates. For example, even though Conventional applicants have higher base rates of patenting and DoD contracting across both winners and losers, the absence of a causal effect means firms would have these higher rates even if they had not won a Conventional award. Since we are using first-time winners only, it is not the case that the overall program is important for these firms and there is some average effect of having many SBIR awards that we fail to capture with the RDD. This is important for whether the program produces new, useful innovations.

We now explore whether the success of Open is due to the composition of applicants or whether Open is more effective even for observationally identical firms. This matters for policy, both within the specific program we study and for considering the implications of our findings in other settings. For example, if certain effects require particular types of firms to select in, the policymaker might consider encouraging those firms to apply without changing the nature of the program. We examine the role of selection using three methods. The first focuses on the role of firm characteristics in our main sample. The second subdivides the Conventional program into more and less "open" topics. The third examines firms that applied to both programs and thus are by definition not selecting into only one or the other.

6.1 Selection on Firm Characteristics

Does the effect of winning an Open award depend on applicant composition? We focus on two dimensions. The first is whether the results rely on firms that are less well-established and at an earlier stage in their lifecycle selecting into Open. The second is whether firms working on different technologies explains the differentially higher effect of Open. In our first test of this hypothesis, we repeat the analysis in Table 2 Panel A but add controls to assess whether the different causal effects in Open could reflect correlations with certain firm or technology characteristics. The first set of controls are firm age and firm size (the number of employees) as of the application. The second set comprises 25 narrow technology fixed effects.

The results, in Panel B of Table 2, are very similar to those in Panel A, which is reassuring for the validity of our empirical design, since firm-level controls should not affect causal RDD estimates. In Panel C we continue to employ the controls but use all application data, creating a larger sample in which firms may appear more than once and from any year since 2003 (instead of 2017-19 only). We find results that are slightly smaller in magnitude, but more precisely estimated. The implied effect of Open is very similar across Panels A-C except for in column 5, where using all proposals in Panel C we observe a smaller positive effect of Conventional on winning future SBIR contracts. In Appendix Table E.11, we show that the results remain similar using alternative quadratic or dummy controls for age and employment.

If the more positive effect of Open reflects attracting younger or less well-established firms, then the effects should be larger within this group. We assess this possibility by splitting the sample around median employment as a proxy for size, and median age as a proxy for lifecycle position (these values are five employees and four years, respectively). We then re-estimate our main model (Equation 1) within these subsamples. The results are in Table 3. They indicate somewhat differential effects within different groups, and these vary across the outcomes. However, it is notable that contrary to the lifecycle hypothesis, it is not young or small firms that explain our main results in Table 2. For example, the effects on technological adoption (DoD contracts) and high-originality patents are found within the sample of *older* firms (columns 2 and 8). While these two results are highly significant, many coefficients are imprecise in these sample splits.

We further disaggregate the results in Appendix Figures E.12 and E.13. Here, we split the sample into narrower bins identified by the y-axis label. Each marker represents the coefficient on $\text{Award}_{iT} \cdot \text{Open}_T$ from a single regression estimated within the identified sample. While we lose precision (which is to be expected), they tell us exactly which groups are driving which result. The results are consistent with Table 3, and are contrary to the hypothesis that the large effects of Open reflect a sample of younger firms.

Finally, in Appendix F.3, we follow Altonji et al. (2005) and Oster (2019) to make inferences about the maximum possible bias due to selection on unobservables, exploiting variation in selection on observables. Using the most conservative assumptions in the literature, we find that accounting for selection on unobservables could maximally attenuate the difference in treatment effect of winning an Open vs. Conventional award on future DoD and VC contracts by about 50%, while it would increase this effect for any future patents, high-originality patents, and SBIR contracts. We also show that selection on unobservables would have to be at least twice as important as selection on observables to reduce our main results to zero for DoD contracts and VC, and would have to move in the *opposite* direction of observables by many factors to drive the effects for patents, high-originality patents, and SBIR contracts to zero. Overall, this offers strong support for our conclusion that selection into applying to Open does not fully explain its larger effects. Also, it is important to note that this is a worst-case scenario bounding exercise and does not imply that our main findings are necessarily biased.

6.2 More "Open" topics in the Conventional Program.

Some Conventional topics are more specific than others in identifying the technology that DoD wishes to procure. If openness is important, there should be larger positive effects of winning a Conventional award when the topic is more technology-neutral, encouraging a broader range of ideas. To develop a measure of topic specificity, we employ the machine learning algorithm for proposal abstract text introduced in Section 3. After summarizing the text as a vector of word embeddings, we measure the topic's specificity based on the distribution of its applications. Specifically, we calculate the cosine similarity between the two vectors representing the proposal and the average (the centroid) for the topic. The nonspecificity index is the standard deviation of these similarity scores. If a topic has a higher standard deviation of cosine similarity, there is more diversity in the content of proposals, and thus the topic is more "open" and less specific. To validate this approach, we measure the non-specificity of Open topics and find that they are three times less specific than Conventional (0.65 vs. 0.21 in Table 1). Nevertheless, there is considerable heterogeneity in the degree of specificity within the pool of Conventional topics, and we exploit this in the following design.

We first check that observables are balanced across more and less specific topics in the Conventional program in Table 4. We split at the 66^{th} percentile, but results are similar for other thresholds. The baseline characteristics and pre-award outcomes are very similar across all 13 company characteristics and pre-award outcomes. There are 13.4 proposals on average in the less specific topics, compared to 12.4 in the more specific topics. Since this difference is significant, we ensure below that it does not confound our analysis by controlling for the interaction between winning and the number of proposals.

Table 5 restricts the sample to Conventional topics and employs all data from 2003 onwards. We interact the indicator for winning an award with an indicator for being in a non-specific topic. All columns include topic fixed effects, which absorb the specificity indicator. The strongest results are for the patent-based innovation measures. Columns 3-5 of Panel A show that number and quality (measured by originality in column 4 and citations in column 5) of future patenting is significantly higher for winners of non-specific topics. In Panel B, we find roughly similar results after including the controls for firm age and size, the 25 narrow technology fixed effects, and an interaction between number of proposals in the topic and award.[25] We also observe a significantly *negative* effect of winning a specific Conventional award on patent measures. This is important because patent output has been a central argument in favor of retaining the Conventional SBIR structure (Glover, 2021). The results in Table 5 suggest that the more specific Conventional awards in fact deter patenting.

Regarding the other outcomes, column 1 of Table 5 shows that winners of non-specific Conventional topics more likely to have their technologies adopted by the DoD (although this is only weakly significant in Panel A). Column 2 looks at VC, and although the Open interaction is positive, it is insignificant. Since only potentially high-growth, young startups are at hazard of receiving VC, this outcome appears to rely more on applicant selection. We do not find any significant differences for future SBIR contracts in the last column.

In sum, the positive effects of the interaction between non-specificity and winning an award indicates that more "open-style" Conventional topics yield a relatively larger positive effect of winning on innovation within the Conventional sample. This suggests that the Conventional program is more impactful when it takes a more open approach, consistent with openness being important independently from selection or other characteristics of the Open reform program.

6.3 Firms that Applied to Both Programs.

We now examine the effect among firms that apply to both programs, whose unobservable characteristics are tightly matched by construction. Specifically, we restrict the sample to those firms which had previously applied to Conventional and then applied to Open. We assess the effect of the Open award within this narrow sample of 507 unique firms. These firms are described in Table E.4. In comparison to Table 1, we observe that their characteristics lie

[25] All results are qualitatively similar if we instead interact with the continuous measure of the non-specificity index. We also find similar results when we control for the interaction between winning and other topic characteristics such as topic competitiveness (winners per applicant).

in between Open and Conventional for some variables such as being in a VC hub city or having previously raised VC. However, they are also more established and larger, and are more likely to have previous DoD contracts and patents. These

The results are reported in Table 6, with the no-controls model in Panel A and the full-controls model in Panel B. We observe positive effects on all four performance outcomes, with especially strong effects on non-SBIR DoD contracts and high-originality patents (columns 1 and 4). These two effects are, in the models with all controls, 15.1 percentage points and 10.7 percentage points, respectively, which are comparable to the magnitudes in the main model counterpart from Table 2, though smaller as a percentage of the means. The effect on VC (column 2) is positive, but becomes insignificant once controls are added in Panel B. This again may reflect the fact that firms which are at hazard of raising VC may not select into Conventional. As with all Open winners, there is no lock-in effect on future SBIR awards (column 5).[26] In sum, Table 6 offers compelling evidence against the hypothesis that the effects of Open are solely an artifact of entry by new types of firms.

Summary. This section has used three alternative strategies to show that selection is unlikely to explain Open's success. In other words, if the Conventional program were just to restrict itself to firms with "startup-like" characteristics and not move to less specific calls for proposals, it would be unlikely to have the same large positive effects as Open.

7 Supplementary Tests

We have implemented a battery of robustness tests on our results, and summarize a few of the more important ones in this section. In each of the panels of Table 7 and for each of the outcome variables, the first column shows the effect without controls while the second column reports effects with the lifecycle and technology area controls.

Additional Controls. In Panel A we add a vector of additional control variables to our baseline specification of Panels A and B Table 2. We include all the pre-award outcome variables; that is, any previous non-SBIR DoD contracts, VC, patents, and high-originality patents. We also include two indicators for whether the firm is located in a VC hub city or

[26] Consistent with the positive causal effect only for Open, we observe near-zero and insignificant effects of winning in Conventional within this population (Table E.5, and the same results for both groups in a pooled specification, though the results become somewhat less precise (Table E.6).

in a county with an Air Force base. Last, we add an indicator for whether the product is software vs. hardware. Consistent with a valid RDD, the coefficients are very similar to the main results and remain significant.

Local Effect. We next exploit the intuition of randomization around the cutoff and restrict the sample to the ranks immediately on either side of the cutoff, in which case no control for rank is needed. Specifically, in Panel B of Table 7 we use two ranks (to keep the sample size reasonably large) above and below the threshold ($\pm 1, \pm 2$). The results remain robust. This narrow bandwidth test also helps us understand the degree to which the results apply only in the region around the cutoff. Because the key results are similar when we use the whole sample or a narrow bandwidth, and are similar with and without rank controls, we believe they seem likely to apply more broadly.

Randomization Inference. To ensure that the small number of observations do not bias the RDD, we follow the randomization inference test of Cattaneo et al. (2015). The authors propose a framework that permits exact finite-sample inference conducted on a small sample in a narrow window around the cutoff within an RDD. We implement the test within a narrow bandwidth of $|\text{Rank}| \leq 2$ around the cutoff. We report the results in Table 7 Panel B, where the row "randomization inference p-value" shows the p-values of the interaction term ($\mathbb{1}(\text{Award}) \times \mathbb{1}(\text{Open})$) from the randomization inference approach. The significance levels are very similar to our baseline approach of clustering by topic. This provides some reassurance that the small N and the nature of the outcome variables do not bias our standard errors.

Conventional Effects in the pre-Open period. The zero effects for Conventional in the 2017-19 period might reflect the Open program crowding out good Conventional projects. However, crowding out does not seem to play a role because we find no effect of Conventional when we restrict to earlier periods when Open did not exist. Panel C of Table 7 uses the 2003-16 period and shows no positive significant effects except for subsequent SBIR as above.

Conventional Firms who did not Subsequently Apply to Open. In Table 6, we showed that conditioning on firms who applied to both Open and Conventional (and so are homogeneous by definition), we found the same pattern of results as we did in the baseline results. Panel D of Table 7 presents the complement, looking at the outcomes for firms who applied for Conventional, but did not apply for Open. As expected, there are no positive effects of winning in Conventional except on subsequent SBIR awards, as in the baseline results.

Intensive Margin Outcomes. Our primary outcome variables are binary. We also examined whether the results are robust to using intensive margin outcomes. The results are in Appendix Table E.9. We use the total dollar amounts of non-SBIR DoD contracts and VC investment (columns 1-3), the number of patents and highly original patents (column 4), and the total dollar amount of SBIR contracts (column 5). All outcomes are logged. The effects are similar to the main results, with no significant effects of winning in Conventional (in the first row), but strongly positive and significant effects of winning in Open (in the second row).

Acquisition as an outcome. To examine whether winning an award affects exit via acquisition, we obtained data from Pitchbook, Crunchbase, SDC Mergers and Acquisitions, and CB Insights through January 10, 2023. We match firms to these datasets using the same procedure described in Appendix D. Appendix Table E.10 shows the results. The effect of Open relative to Conventional on the chance of getting acquired is positive and large in magnitude relative to the mean, but it is insignificant. The effect on the acquisition amount is also large and positive, and significant at the 5% level with the full controls model. It suggests a roughly 20% increase in the acquisition amount. There is no effect of Conventional programs on getting acquired (the coefficients for Conventional topics are small and negative).

Matching. As explained in Section 2, an additional reform in the Open topics was to offer matching in Phase 2. Phase 2 applicants could request additional funds to match private or government money that they secured during the Phase 1 period. Several features of the program's implementation facilitate evaluation, for example, that matching was not available for the earlier Open topics. We discuss these factors and evaluate the role of matching in Appendix F.2. The main finding is that while matching does increase the probability of VC, winning an Open competition significantly increases VC even *without* the possibility of matching. Hence, we conclude that something over and above matching in the structure of Open made it more successful than Conventional.

Quality. There may be concern that quality, as measured by the evaluator ranks, differs systematically across the two types of competitions. For example, it is possible that non-marginal conventional winners were much better than the non-marginal Open winners. To test this, we interact winning with being in the right-tail of the rank distribution, defined as the top 15% of winner scores within topic. In addition to addressing selection on the quality distribution, this test offers a robustness test of our main results and supports our argument that our findings are not strictly limited to the region around the cutoff. The results, reported in Appendix Table E.8, show that there are no significantly different effects in the right tail. We observe similar results using thresholds other than 15%.

Competition We next ask whether the differential effect of Open reflects tougher competition due to a larger number of applicants (or weaker competition due to a higher number of winners). We interact our RDD treatment indicators with the topic's number of applicants (or number of winners) being above median (or above the 75^{th} or 90^{th} percentile). The interactions are always small and insignificant. In other words, the effects are not because of a larger number of applicants.

Further Specification Tests We conduct a number of additional unreported exercises. We find that the effect of Open does not differ significantly by year, and that the results are similar to the main model controlling for rank quadratically, omitting the kernel weighting, using alternative vectors of controls for baseline characteristics, or using no controls at all. We also find similar results scaling both the awards as well as the contracts or VC deals by dollar amounts. The results are even stronger in favor of Open because the Open awards are smaller. In a related test making use of one Open round in which the size of the award was increased to $75,000 from $50,000, we assess whether the effects differ by award amount. We do not find economically meaningful or statistically significant differences.

8 Implications for Innovation Procurement

In this section, we first discuss the main results and describe some key extensions. Then we explain how our findings could be relevant for innovation procurement reform.

8.1 Mechanisms and Extensions of Main Results

Our analysis indicates that winning an Open award has strong, positive effects on the key measures that DoD believes represent success: technology adoption (non-SBIR DoD contracting), private investment (VC), and commercial innovation intent (patenting). These outcomes also overlap with how technology innovation is often measured in the academic literature. This suggests that overall the Open program has been successful. In contrast, there are no measurable effects of the Conventional program, except on repeat SBIR contracts. In this subsection, we discuss mechanisms for each outcome.

Our evidence on non-SBIR DoD contracts indicates that the Open program enables successful applicants to prove that their technology is useful for the military and then leverage that work to access additional funding and contracts. This result is different from certification in that it requires work to prove—even via a White Paper—that the technology can be useful to the military. About half of the subsequent non-SBIR DoD contracts for winners in our data are from services besides the Air Force. In unreported analysis, we find roughly similar effects of Open vis-a-vis Conventional in both Air Force and non-Air Force contracts. Since all services view any DoD contract as a successful transition of an SBIR firm into the defense pipeline, it is important to consider contracts beyond the sponsoring service when evaluating the overall success of an award.[27]

Open's large impact could be specific to the defense sector, and may depend on a huge demand pull (i.e., downstream procurement). However, there are theoretical arguments that open innovation is better suited to innovation whose use is more widespread (e.g. see King and Lakhani (2013)). Open innovation may have been successful in the Air Force SBIR program because the organization increasingly needed technologies that are more widely used. This predicts that while the defense sector might especially benefit from an Open approach, the effects of Open should if anything be larger for firms with technologies that have civilian applications. We explore this by restricting the sample to firms that are not identified by Pitchbook as being in the Aerospace and Defense sector.[28] The results, in Appendix Table E.13, indicate a larger effect of Open here relative to our full sample model. For example, the coefficient for DoD contracts (column 1) is 16.4 pp, compared to 9.4 pp in the full sample. This suggests that in fact our results are not specific to defense-focused firms, and points to

[27] For example, the Navy's SBIR webpage states that "The Navy's SBIR/STTR Programs are primarily mission oriented, providing companies the opportunity to become part of the national technology base that can feed both the military and private sectors of the nation. To that end, the Navy incorporates into its Phase 2 component, the emphasis on the small business' need to market its technology to both military and private sectors." See https://www.navysbir.com/, accessed February 22, 2024.

[28] We observe Pitchbook industries for 49% of the sample. Within this subset, 40% are identified as Aerospace and Defense. To have a large enough sample, we replicate Table 2, Panel C (all proposals) but restrict to non-Aerospace and Defense firms.

external validity of our results.

A different question also related to the channel for our results is: Why would small contracts have such a large effect? The idea behind the DoD SBIR program is that small initial contracts to explore possible solutions and scope out demand can feed into the broader defense industrial base. The Phase 1 SBIRs are an entry point to much larger contracts in the future. A goal of the Open Phase 1 program is to find a large customer in the Air Force. Startups with a successful Open Phase 1 can bring evidence of large defense customers to VCs, which appears to improve their odds of raising funds.

Within SBIR, the expectation of a Phase 2 award, which averages about $830,000, may also help to explain the effect. Firms and their investors may be more willing to invest after a Phase 1 if they anticipate a reasonable chance of substantially more non-dilutive cash. Note that we find no effects of winning a Phase 2 award (Appendix F.1). However, Phase 2 could important for VC through a dynamic channel; that is, its implications for the Phase 1 treatment effect. This may help explain why the Phase 1 award can be so impactful.

The patenting results suggest that winning an Open award pushes firms to develop and protect their technologies for, presumably, dual-use objectives. To see whether the patenting effect reflects simply more effort to apply for protection vs. more innovation, we looked at the number of applications. In unreported analysis, we find no effects, suggesting that the positive effect on granted patents does not simply reflect different levels of effort to apply for patents. We also examined patent citations, which reflect patent quality. We do not find significant effects of Open on citations, which likely reflects insufficient time for them to accrue. However, for the 2003-19 period for Conventional, there is sufficient time. Although there was no overall positive effects of winning a Conventional award on citations in Table 5, this reflects a negative effect of highly specified awards and a positive effect of the non-specific Conventional topics (i.e. those closer in character to to Open). Howell (2017), did find a large effect of DoE SBIR grants on patent citations. Above, we documented greater firm lock-in at DoD than at DoE. The greater focus on the defense market among DoD SBIR winners could reduce incentives to patent in the Conventional program or reduce limitations on patenting among non-winners of a topic. The Open program, by reaching firms that are already oriented towards the civilian market, appears to have a more positive effect on patenting.

We observe greater lock-in for the Conventional program, which the DoD authorities wish to avoid, since the purpose of SBIR is to provide an R&D staging ground for firms to enter operational and R&D contracts within mission-oriented programs. The Open program may have avoided locked-in contractors only because it is new. To assess this, we use 2020 application data, which we do not use in the main analysis in order to have enough time to observe all outcomes. If Open awards will also suffer from lock-in, we expect to see some evidence of it in the third year. Appendix Figure E.10 contains a histogram of the number of Open and Conventional applicants in categories defined by the number of Air Force SBIR awards in the past three years, with Open applicants from 2020 and Conventional applicants from 2019.[29] Conventional applicants are far more likely to have many Air Force SBIR awards in the past three years. Nearly 100% of 2020 Open applicants are entirely new to the program, while only about 60% of Conventional applicants have no SBIR award in the previous three years. Conversely, there is a long tail of Conventional applicants with many Air Force SBIR awards in the previous three years. In sum, whether through reputation, dedicated staff, or some other channel, the traditional SBIR contract gives birth to recurring SBIR-winners. By contrast, Open topics have avoided this lock-in effect.

8.2 Implications for Innovation Procurement Reform

At a high level, our results suggest that there are benefits to moving towards more open and less tightly specified public procurement of innovation. The Open program at the U.S. Air Force that we study is an example of a radical reform. There are more incremental means. For example, the government could use more Requests For Information in advance of Requests For Procurement. This might improve the information flow. As a second example, the Air Force could bring in other parts of the DoD in making evaluation decisions to internalize some of the spillovers that we find (although this might increase administrative burden). We have shown that the benefits of technology adoption spill over to other parts of the DoD from the Air Force (as well as to the private sector), even though it is the Air Force who solely make the decisions over project funding.

There are policy implications that emerge from the contrast between our average null results for the Conventional program and the positive effects of U.S. Department of Energy (DoE) SBIR grants in Howell (2017). Specifically, there are two possible reasons for the difference that are relevant to innovation procurement design. First, the DoE SBIR program's topics appear to be substantially broader than the Air Force's Conventional topics, as they typically invite

[29] We do not observe Conventional application data in 2020, and this approach also aligns the sample with that of our main analysis (2017-19, where 2017 only contains Conventional applicants).

proposals for technologies that serve a whole energy subsector rather than request that firms build a highly specific device or piece of software. For example, DoE topics from 2022 include "Solar Hardware and Software Technologies: Affordability, Reliability, Performance, and Manufacturing", "Advanced Subsurface Energy Technologies" (i.e. geothermal), and "Rare Earth Elements and Critical Minerals" (i.e., making advanced metal alloys for a wide range of uses, such as in batteries and catalysts). In other words, DoE's SBIR program seems to compare more closely to the non-specific Conventional topics where we do find positive effects. Second, Howell (2017) finds that the positive effects of DoE's SBIR program are driven by new entrants. We observe that the DoD's SBIR program has more repeat awardees than the DoE program (Figure A.2 Panel B). This likely relates to DoD's massive procurement capability and much larger SBIR program, which allow firms to focus solely on the defense market.

The success of Open relates to the broad question of how to procure defense innovation. The main mechanisms are government contracting with private organizations, design competitions, and in-house R&D at government laboratories. In recent decades, the U.S. has emphasized the first channel, but before World War II and in certain parts of the defense establishment such as SBIR, the second channel of design competitions has been important (Mansfield 1971, Jacobsen 2015). In a traditional competition, the government identifies a need for a certain product, and firms must privately invest in initial R&D to compete for a prize. Competitions can enable more government flexibility and encourage contractor risk-taking (Lichtenberg 1984). However, a downside is that the technology must be specified ex-ante, while in direct contracting it can be more ambiguous and evolve over time. The Open program mitigates the downside of ex-ante specification by allowing firms to present their own ideas while evaluating them according to the same metrics. This potentially offers a new template for other competitive R&D procurement efforts in the public sector.

Che et al. (2021) theoretically compare cash prizes and follow-on contracts to motivate innovation, with intuition similar to Belenzon and Cioaca (2021). Che et al. (2021) argue that in the absence of perfect information, contract rights are the optimal mechanism, and furthermore that bundled approaches in which the innovating firm receives the follow-on contract are ideal for unsolicited proposals, akin to our Open setting. The authors point specifically to DoD SBIR as an important setting in which follow-on contracting is used to incentivize innovation.

9 Conclusion

This paper offers to our knowledge the first study comparing top-down (i.e. highly specified) and bottom-up (i.e. open) mechanisms for innovation procurement. We focus on the U.S. Air Force's Open topics, which introduced a bottom-up, open innovation dimension to its SBIR program, departing from the conventionally tightly specified SBIR topics. Our context is important because the U.S. DoD funds more R&D than any other single entity in the world. U.S. defense R&D is often regarded as an exemplar of how to stimulate innovation through mission-driven research, but—as we show—the luster has faded in recent decades, with the prime contractors becoming less innovative than the rest of the U.S. economy on several dimensions. Although though the SBIR program differs from mainline procurement, we document parallel problems of declining innovation and lock-in of repeat contractors.

These challenges motivated the Open program at the Air Force. We show that the Open program succeeded in its objectives. Our primary outcomes are proxies for military benefits of technology adoption (winning future non-SBIR DoD contracts) and civilian innovation benefits (VC investment and patenting). Using a regression discontinuity design, we find that winning an Open topic award has positive effects on these outcomes, whereas winning a Conventional topic award does not. By contrast, winning a Conventional award increases the chances of a subsequent SBIR contract, creating a lock-in effect for incumbents. Open's success was *not* simply due to attracting a different composition of firms. Using three designs, we find that openness matters. The Open program seems to enable firms to bring new, useful technologies to the defense market that the DoD had not realized it needed. This leads them to invest more in innovation, with the potential for large downstream procurement contracts.

Skeptics of the innovation benefits of military R&D have noted that while there is a surfeit of anecdotes, there is a dearth of rigorous evaluations of U.S. defense R&D programs. This paper helps to address the lacunae by causally evaluating the Air Force SBIR program, with a focus on the Open reform. It is relevant not only to DoD but to the many public sector agencies in the U.S. and abroad that are deploying open solicitations. Beyond the public sector, private sector companies are also increasingly using open innovation, especially in R&D-intensive industries (Chesbrough 2003, de Villemeur and Versaevel 2019). For example, Unilever's Open Innovation platform, launched in 2010, invites the public to submit ideas for potential adoption by the company in broad product areas. Successful submitters may be offered a commercial contract for their solution, and today more than 60% of Unilever's research projects involve external collaboration.[30] Another example is LEGO Ideas, which has led to 30 LEGO model kits based on externally submitted ideas (Richardson et al., 2020). An important avenue for future work is whether causal evaluations of other open R&D programs reveal similar patterns to those found here.

[30]See https://www.unileverusa.com/brands/innovation/open-innovation/, accessed April 24, 2024.

References

a16z Podcast, "From Silicon Valley to the Pentagon: The Future of Defense Innovation," Technical Report, Andreessen Horowitz Podcast, available at https://podcasts.apple.com/us/podcast/a16z-podcast/id842818711?i=1000648386972 2024.

AF, "Air Force exercises two Collaborative Combat Aircraft option awards," Technical Report, Secretary of the Air Force Public Affairs 2024.

Aghion, Philippe and Jean Tirole, "Formal and real authority in organizations," *Journal of political economy*, 1997, *105* (1), 1–29.

Akcigit, Ufuk, Douglas Hanley, and Nicolas Serrano-Velarde, "Back to basics: Basic research spillovers, innovation policy, and growth," *The Review of Economic Studies*, 2021, *88* (1), 1–43.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber, "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools," *Journal of political economy*, 2005, *113* (1), 151–184.

Arora, Ashish, Sharon Belenzon, and Andrea Patacconi, "The decline of science in corporate R&D," *Strategic Management Journal*, 2018, *39* (1), 3–32.

ARPA-E, "Small Business Research Program: Most Agencies Allow Applicants to Define Needs and Propose Solutions," Technical Report, U.S. Advanced Research Projects Agency-Energy 2020.

Atkeson, Andrew and Ariel Burstein, "Aggregate implications of innovation policy," *Journal of Political Economy*, 2019, *127* (6), 2625–2683.

Azoulay, Pierre, Joshua S Graff Zivin, and Gustavo Manso, "Incentives and creativity: evidence from the academic life sciences," *The RAND Journal of Economics*, 2011, *42* (3), 527–554.

_ , Joshua Zivin, Danielle Li, and Bhaven Sampat, "Public R&D Investment and Private Sector Patenting: Evidence from NIH Funding Rules," *Review of Economic Studies*, 2019.

Babina, Tania, Alex Xi He, Sabrina Howell, Elisabeth Perlman, and Joseph Staudt, "Does Funding Source Matter for University R&D? The Effect of Government vs. Industry Grants," *The Quarterly Journal of Economics, forthcoming*, 2020.

Baldwin, Carliss and Eric Von Hippel, "Modeling a paradigm shift: From producer innovation to user and open collaborative innovation," *Organization science*, 2011, *22* (6), 1399–1417.

Barro, Robert and Charles J. Redlick, "Macroeconomic Effects from Government Purchases and Taxes," *Quarterly Journal of Economics*, 2011.

Belenzon, Sharon and Larisa C Cioaca, "Guaranteed markets and corporate scientific research," Technical Report, National Bureau of Economic Research 2021.

_ and Mark Schankerman, "Spreading the word: Geography, policy, and knowledge spillovers," *Review of Economics and Statistics*, 2013, *95* (3), 884–903.

Bhattacharya, Vivek, "An empirical model of R&D procurement contests: An analysis of the DOD SBIR program," *Econometrica*, 2021, *89* (5), 2189–2224.

Bloom, Nicholas, John Van Reenen, and Heidi Williams, "A toolkit of policies to promote innovation," *Journal of Economic Perspectives*, 2019, *33* (3), 163–84.

__ , Raffaella Sadun, and John Van Reenen, "Recent advances in the empirics of organizational economics," *Annu. Rev. Econ.*, 2010, *2* (1), 105–137.

Bloom, Nick, Rachel Griffith, and John Van Reenen, "Do R&D tax credits work? Evidence from a panel of countries 1979-1997," *Journal of Public Economics*, 2002.

Bonhomme, Stephane and Elena Manresa, "Grouped Patterns of Heterogeneity in Panel Data," *Econometrica*, 2015, *83* (3), 1147–1184.

Bresler, Amanda and Alex Bresler, "Analyzing the Composition of the Department of Defense Small Business Industrial Base," Technical Report, Excerpt from the Proceedings of the Nineteenth Annual Acquisition Research Symposium 2022.

Cameron, Doug, "The Pentagon's Plan for More Ambitious, Affordable Jet Fighters: AI Pilots," Technical Report, The Wall Street Journal, March 3 2024.

Carril, Rodrigo and Mark Duggan, "The impact of industry consolidation on government procurement: Evidence from Department of Defense contracting," *Journal of Public Economics*, 2020, *184*, 104141.

Cattaneo, Matias D, Brigham R Frandsen, and Rocio Titiunik, "Randomization inference in the regression discontinuity design: An application to party advantages in the US Senate," *Journal of Causal Inference*, 2015, *3* (1), 1–24.

Che, Yeon-Koo, Elisabetta Iossa, and Patrick Rey, "Prizes versus contracts as incentives for innovation," *The Review of Economic Studies*, 2021, *88* (5), 2149–2178.

Chesbrough, Henry William, "Open innovation: The new imperative for creating and profiting from technology," *Harvard Business School Publishing Company*, 2003.

Cohen, Wesley M, Daniel A Levinthal et al., "Absorptive capacity: A new perspective on learning and innovation," *Administrative science quarterly*, 1990, *35* (1), 128–152.

Congress, "SBIR and STTR Extension Act of 2022," *U.S. Congress Public Law*, 2022.

Cox, Amy G, Nancy Y Moore, and Clifford A Grammich, "Identifying and eliminating barriers faced by nontraditional Department of Defense suppliers," Technical Report, RAND National Defense Research Institute 2014.

CRS, "Government Expenditures on Defense related R&D by the US and other OECD Countries," Technical Report, Congressional Research Service, https://fas.org/sgp/crs/natsec/R45441.pdf 2018.

de Villemeur, Etienne Billette and Bruno Versaevel, "One lab, two firms, many possibilities: On R&D outsourcing in the biopharmaceutical industry," *Journal of health economics*, 2019, *65*, 260–283.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, "Declining business dynamism: What we know and the way forward," *American Economic Review*, 2016, *106* (5), 203–07.

Denes, Matthew, Sabrina Howell, Filippo Mezzanotti, Xinxin Wang, and Ting Xu, "Investor Tax Credits and Entrepreneurship: Evidence from US States," *The Journal of Finance, forthcoming*, 2020.

Dial, Jay and Kevin J Murphy, "Incentives, downsizing, and value creation at General Dynamics," *Journal of Financial Economics*, 1995, *37* (3), 261–314.

DiNardo, John and Justin L Tobias, "Nonparametric density and regression estimation," *Journal of Economic Perspectives*, 2001, *15* (4), 11–28.

Draca, Mirko, "Reagan's innovation dividend? Technological impacts of the 1980s US defense build-up," *CAGE Working Paper Series No. 168*, 2013.

Easley, Mikayla, "At least 2 vendors will move into next phase of Air Force's CCA drone program," *DefenseScoop*, 2024.

Edwards, Colin, "SSTI analysis reveals SBIR mills take outsized portion of the programs awards," Technical Report, SSTI 2020.

EU, "The SME Instrument in action: an effective and innovative programme facing challenges," Technical Report, European Court of Auditors 2020.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "Place-based drivers of mortality: Evidence from migration," *American Economic Review*, 2021, *111* (8), 2697–2735.

Flamm, Kenneth, *Creating the computer: government, industry, and high technology*, Brookings Institution Press, 1988.

Forgy, E, "Cluster Analysis of Multivariate Data: Efficiency vs. Interpretability of Classifications," *Biometrics*, 1965, *21* (1), 768–780.

Foster, Lucia, John Haltiwanger, and Chad Syverson, "Reallocation, firm turnover, and efficiency: selection on productivity or profitability?," *American Economic Review*, 2008, *98* (1), 394–425.

GAO, "Small Business Research Programs: Most Agencies Allow Applicants to Define Needs and Propose Solutions," Technical Report, Government Accountability Office GAO-23-106338 2023.

Gelman, Andrew and Guido Imbens, "Why high-order polynomials should not be used in regression discontinuity designs," *Journal of Business & Economic Statistics*, 2018, pp. 1–10.

Gibbons, Robert, Niko Matouschek, and John Roberts, "Decisions in organizations," *The handbook of organizational economics*, 2013, pp. 373–431.

Glover, Jere, "40 Years of Success: SBIR drives America's High Tech Economy Technology Innovation, Competitiveness and High Quality Jobs," Technical Report, Small Business Technology Council 2021.

Goolsbee, Austan, "Does Government R&D Policy Mainly Benefit Scientists and Engineers?," *American Economic Review*, 1998.

— **and Ben Jones**, *Innovation and Public Policy*, Univiversity of Chicago, 2022.

Gornall, Will and Ilya A Strebulaev, "The economic impact of venture capital: Evidence from public companies," 2015.

— **and** — , "Squaring venture capital valuations with reality," *Journal of Financial Economics*, 2020, *135* (1), 120–143.

Griffin, Michael D., "Terms of Reference - Defense Science Board Task Force on 21st Century Industrial Base for National Defense," 2019.

Gross, Daniel P and Bhaven N Sampat, "Inventing the endless frontier: The effects of the World War II research effort on post-war innovation," Technical Report, National Bureau of Economic Research 2020.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw, "Identification and estimation of treatment effects with a regression-discontinuity design," *Econometrica*, 2001, *69* (1), 201–209.

Halac, Marina, Navin Kartik, and Qingmin Liu, "Contests for experimentation," *Journal of Political Economy*, 2017, *125* (5), 1523–1569.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda, "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 2013, *95* (2), 347–361.

Howell, Sabrina T, "Financing innovation: Evidence from R&D grants," *American Economic Review*, 2017, *107* (4), 1136–64.

— , "Government Intervention in Innovation," *Annual Review of Financial Economics*, 2024, *16.*

— **, Josh Lerner, Ramana Nanda, and Richard R Townsend**, "Financial Distancing: How Venture Capital Follows the Economy Down and Curtails Innovation," Technical Report, National Bureau of Economic Research 2020.

Jacob, Brian and Lars Lefgren, "The impact of research grant funding on scientific productivity," *Journal of Public Economics*, 2011.

Jacobsen, Annie, *The Pentagon's Brain: An Uncensored History of DARPA, America's Top-secret Military Research Agency*, Little, Brown, 2015.

Jaffe, Adam B and Karen Palmer, "Environmental regulation and innovation: a panel data study," *Review of economics and statistics*, 1997, *79* (4), 610–619.

— **and Manuel Trajtenberg**, *Patents, citations, and innovations: A window on the knowledge economy*, MIT press, 2002.

Jensen, Michael C, "The modern industrial revolution, exit, and the failure of internal control systems," *the Journal of Finance*, 1993, *48* (3), 831–880.

King, Andrew and Karim R Lakhani, "Using open innovation to identify the best ideas," *MIT Sloan management review*, 2013.

Kortum, Samuel and Josh Lerner, "Assessing the contribution of venture capital to innovation," *RAND journal of Economics*, 2000, pp. 674–692.

Kotila, Brodi, Jeffrey A. Drezner, Elizabeth M. Bartels, Devon Hill, Quentin E. Hodgson, Shreya S. Huilgol, Shane Manuel, Michael Simpson, , and Jonathan P. Wong, "Strengthening the Defense Innovation Ecosystem," Technical Report, RAND Corporation 2022.

Krieger, Joshua L, Danielle Li, and Dimitris Papanikolaou, "Missing novelty in drug development," Technical Report, National Bureau of Economic Research 2018.

Lach, Saul, "Do R&D subsidies stimulate or displace private R&D? Evidence from Israel," *Journal of Industrial Economics*, 2002.

Lakhani, Karim R and Eric Von Hippel, *How open source software works: "free" user-to-user assistance*, Springer, 2004.

__ , Hila Lifshitz-Assaf, and Michael L Tushman, "Open innovation and organizational boundaries: Task decomposition, knowledge distribution and the locus of innovation," in "Handbook of economic organization," Edward Elgar Publishing, 2013, pp. 355–382.

Lanahan, Lauren and Maryann P Feldman, "Approximating exogenous variation in R&D: Evidence from the Kentucky and North Carolina SBIR State Match programs," *Review of Economics and Statistics*, 2018, *100* (4), 740–752.

Lee, David S, "Randomized experiments from non–random selection in US House elections," *Journal of Econometrics*, 2008, *142* (2), 675–697.

__ and Thomas Lemieux, "Regression discontinuity designs in economics," *Journal of economic literature*, 2010, *48* (2), 281–355.

Lerner, Josh, "The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program," *The Journal of Business*, 1999, *72* (3), 285–318.

__ , *Boulevard of broken dreams: why public efforts to boost entrepreneurship and venture capital have failed–and what to do about it*, Princeton University Press, 2012.

__ and Mark Schankerman, "The comingled code: Open source and economic development," *MIT Press Books*, 2013, *1.*

__ and Ramana Nanda, "Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn," *Journal of Economic Perspectives*, 2020, *34* (3), 237–61.

Lichtenberg, Frank, "The Relationship between Federal Contract R&D and Company R&D," *American Economic Review*, 1984.

— , "Assessing the Impact of Federal Industrial R&D Expenditure on Private R&D Activity in the U.S.," in Philip Gummettm and Judith Reppy, eds., *The Relation Between Defense and Civil Technologies*, 1988.

— , "The Economics of Defense R&D," in K Hartkey and Sandler T, eds., *Handbook of Defense Economics, Volume 1*, 1995.

Lundquist, Jerrold T, "Shrinking fast and smart in the defense industry.," *Harvard Business Review*, 1992, *70* (6), 74–85.

MacDonald, Alistair and Ievgeniia Sivorka, "Meet Bradley, the U.S. Army Veteran Ukrainian Soldiers Love," Technical Report, The Wall Street Journal, September 26 2024.

Mansfield, Edwin, *Technological change*, Norton, 1971.

Manso, Gustavo, "Motivating innovation," *The Journal of Finance*, 2011, *66* (5), 1823–1860.

Mazzucato, Mariana and Gregor Semieniuk, "Public financing of innovation: new questions," *Oxford Review of Economic Policy*, 2017, *33* (1), 24–48.

Mezzanotti, Filippo and Timothy Simcoe, "Innovation and Appropriability: Revisiting the Role of Intellectual Property," *NBER Working Paper*, 2023, (w31428).

Middleton, Andrew, Steven Bowns, Keith Hartley, and James Reid, "The effect of defence R&D on military equipment quality," *Defence and Peace Economics*, 2006, *17* (02), 117–139.

Moretti, Enrico, Claudia Steinwender, and John Van Reenen, "The Intellectual Spoils of War? Defense R&D, Productivity and International Spillovers," *NBER Working Paper No. 26483*, 2020.

Mowery, David C., "The relationship between intrafirm and contractual forms of industrial research in American manufacturing, 1900–1940," *Explorations in Economic History*, 1983, *20*, 351–374.

Mowery, David C, "Defense-related R&D as a model for Grand Challenges technology policies," *Research Policy*, 2012, *41* (10), 1703–1715.

— **and Nathan Rosenberg**, *Technology and the pursuit of economic growth*, Cambridge University Press, 1991.

Myers, Kyle, "The elasticity of science," *American Economic Journal: Applied Economics*, 2020, *12* (4), 103–34.

Nakamura, Emi and Jon Steinsson, "Fiscal stimulus in a monetary union: Evidence from US regions," *American Economic Review*, 2014.

Nanda, Ramana, Ken Younge, and Lee Fleming, "Innovation and entrepreneurship in renewable energy," in "The changing frontier: Rethinking science and innovation policy," University of Chicago Press, 2014, pp. 199–232.

OSD, "Department of Defense Fiscal Year (FY) 2021 Budget Estimates," Technical Report, Department of Defense 2021.

Oster, Emily, "Unobservable selection and coefficient stability: Theory and evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Pellerin, Cheryl, "Carter Seeks Tech-sector Partnerships for Innovation," *Department of Defense Press Office*, 2015.

Pennington, Jeffrey, Richard Socher, and Christopher Manning, "GloVe: Global vectors for word representation," *Proceedings of the 2014 conference on empirical methods in natural language processing*, 2014, pp. 1532–1543.

Pless, Jacqueline, "Are 'Complementary Policies' Substitutes? Evidence from R&D Subsidies in the UK," Technical Report, MIT Working Paper 2019.

Puri, Manju and Rebecca Zarutskie, "On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms," *The Journal of Finance*, 2012, *67* (6), 2247–2293.

Ramey, Valerie, "Identifying Government Spending Shocks: It's All in the Timing," *Quarterly Journal of Economics*, 2011.

Rathje, Jason and Riita Katila, "Enabling Technologies and the Role of Private Firms," *Strategy Science*, 2020, (Forthcoming).

Richardson, Bailey, Kevin Huynh, and Kai Elmer Sotto, "Turn Your Customers into Your Community," *Harvard Business Review*, 2020.

Rogerson, William P, "Economic incentives and the defense procurement process," *Journal of Economic Perspectives*, 1994, *8* (4), 65–90.

Santoleri, Pietro, Andrea Mina, Alberto Di Minin, and Irene Martelli, "The causal effects of R&D grants: Evidence from a regression discontinuity," *Review of Economics and Statistics*, 2022, pp. 1–42.

Sargent, John F. and Marcy E. Gallo, "The Global Research and Development Landscape and Implications for the Department of Defense," Technical Report, Congressional Research Service 2018.

SBIR.gov, "Qualcomm Inducted into SBIR Hall of Fame," Technical Report, https://www.sbir.gov/success-story/qualcomm-inducted-sbir-hall-fame 2011.

Syverson, Chad, "Challenges to mismeasurement explanations for the US productivity slowdown," *Journal of Economic Perspectives*, 2017, *31* (2), 165–86.

Tenenbaum, Joshua B, Vin De Silva, and John C Langford, "A global geometric framework for nonlinear dimensionality reduction," *Science*, 2000, *290* (5500), 2319–2323.

Tirole, Jean, "Procurement and renegotiation," *Journal of Political Economy*, 1986, *94* (2), 235–259.

Tushman, Michael, Karim R Lakhani, and Hila Lifshitz-Assaf, "Open innovation and organization design," *Journal of Organization Design*, 2012, *1* (1).

Wallsten, Scott, "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*, 2000.

Williams, Lauren, "Air Force acquisition chief wants to reshape defense industrial base," Technical Report, FCW, https://fcw.com/articles/2020/06/09/williams-roper-rethink-dib.aspx 2020.

Figure 1: Raw Scores and Award Probability in Four Representative Topics

Note: These plots document the sharp RDD in each topic by showing the probability of winning by raw score. The score perfectly predicts award except occasionally when an awardee is declined in the contracting process because some ineligibility was identified (these instances are dropped in analysis). Note that the range of scores differs across topics, which is we construct a rank normalization for combined analysis.

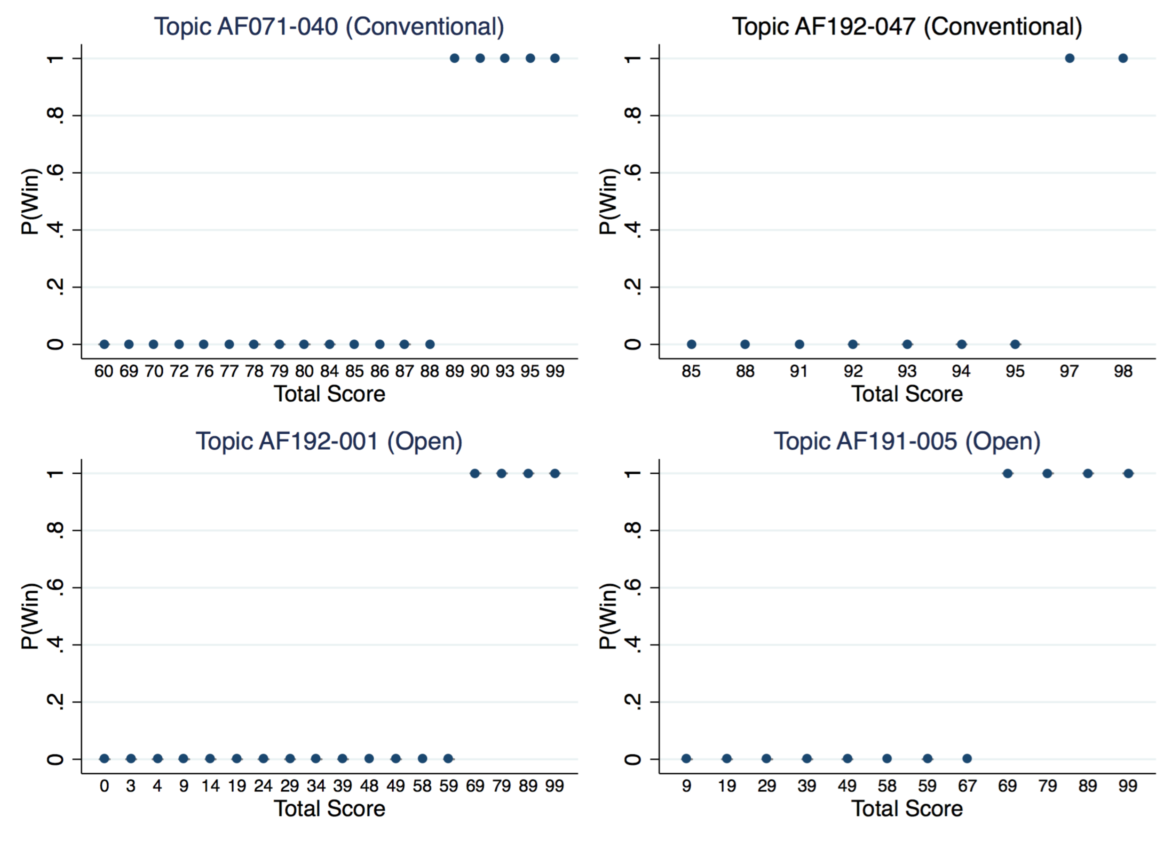


Figure 2: Regression Discontinuity Density Manipulation Test

Note: This figure plots the density of applicants by rank around the cutoff using Phase 1 applicants to the Open (left graph labeled (a)) and Conventional (right graph labeled (b)) programs, to test for bunching near the cutoff. There is more density overall to the left of the cutoff because there are more losers than winners.

(a) Open (b) Conventional (2017-19)

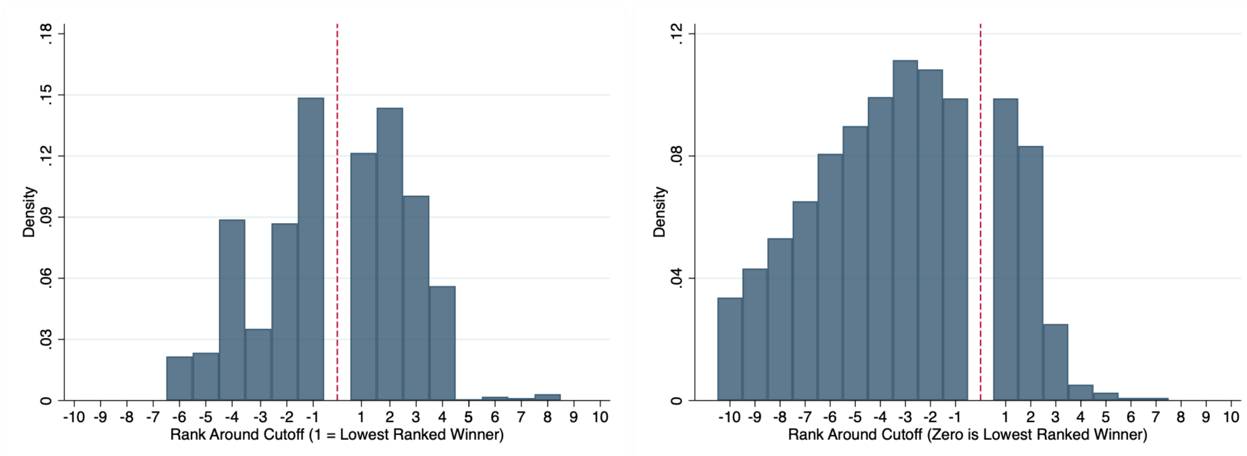


Figure 3: Probability of Technology Adoption (DoD non-SBIR Contract) by Rank Around Cutoff

Note: These figures show the probability that an applicant firm had any non-SBIR DoD contracts valued at more than $50,000 within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. We plot the points and 95% confidence intervals from a regression of the outcome on a full complement of dummy variables representing each rank, as well as fixed effects for the topic. The omitted group is rank=-1. We include first applications from 2017-19.

(a) Open (b) Conventional (2017-19)

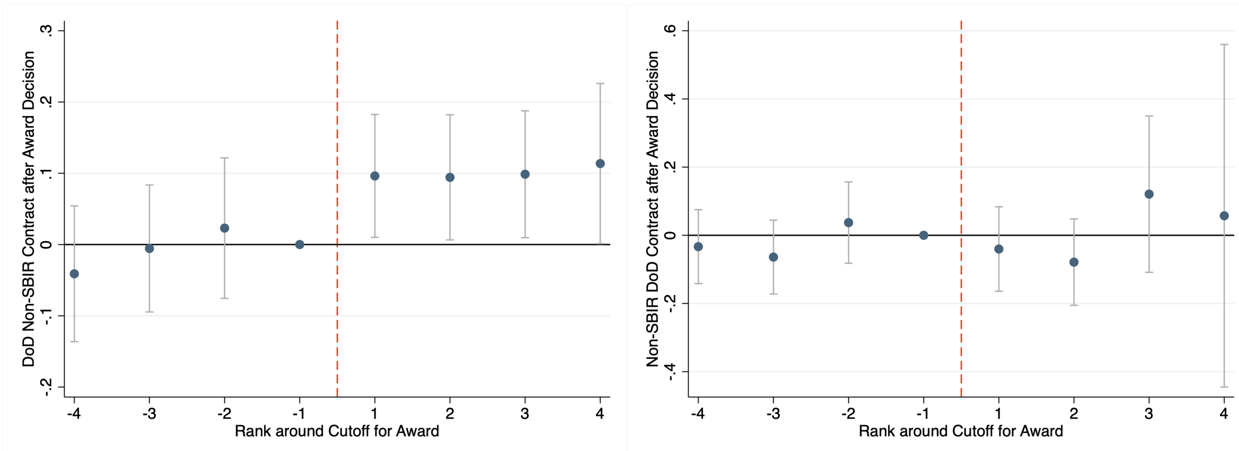


Figure 4: Probability of Venture Capital by Rank Around Cutoff

Note: These figures show the probability that an applicant firm raised venture capital investment (VC) within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. We plot the points and 95% confidence intervals from a regression of the outcome on a full complement of dummy variables representing each rank, as well as fixed effects for the topic. The omitted group is rank=-1. We include first applications from 2017-19.

(a) Open (b) Conventional (2017-19)

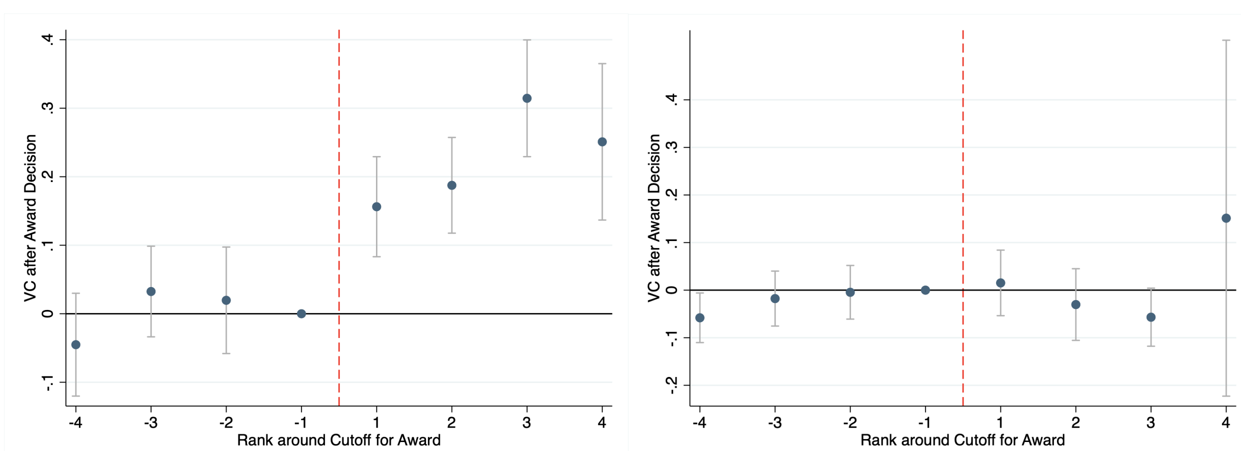


Figure 5: Probability of Patents by Rank Around Cutoff

Note: These figures show the probability that an applicant firm had any ultimately granted patent applications within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. We plot the points and 95% confidence intervals from a regression of the outcome on a full complement of dummy variables representing each rank, as well as fixed effects for the topic. The omitted group is rank=-1. We include first applications from 2017-19.

(a) Open (b) Conventional (2017-19)

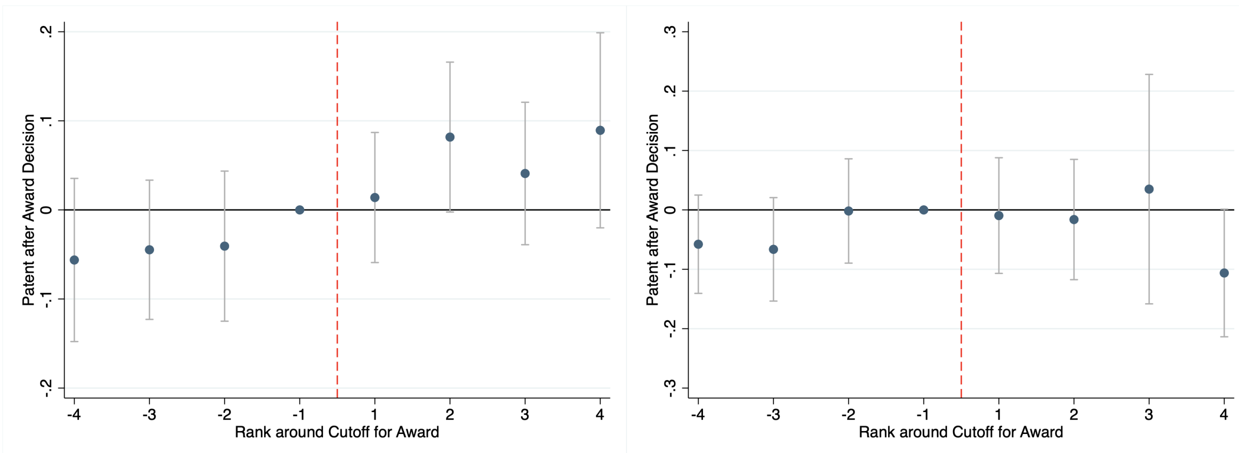


Figure 6: Probability of High-Originality Patents by Rank Around Cutoff

Note: These figures show the probability that an applicant firm had any ultimately granted patent applications within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. We plot the points and 95% confidence intervals from a regression of the outcome on a full complement of dummy variables representing each rank, as well as fixed effects for the topic. The omitted group is rank=-1. We include first applications from 2017-19.

(a) Open (b) Conventional (2017-19)

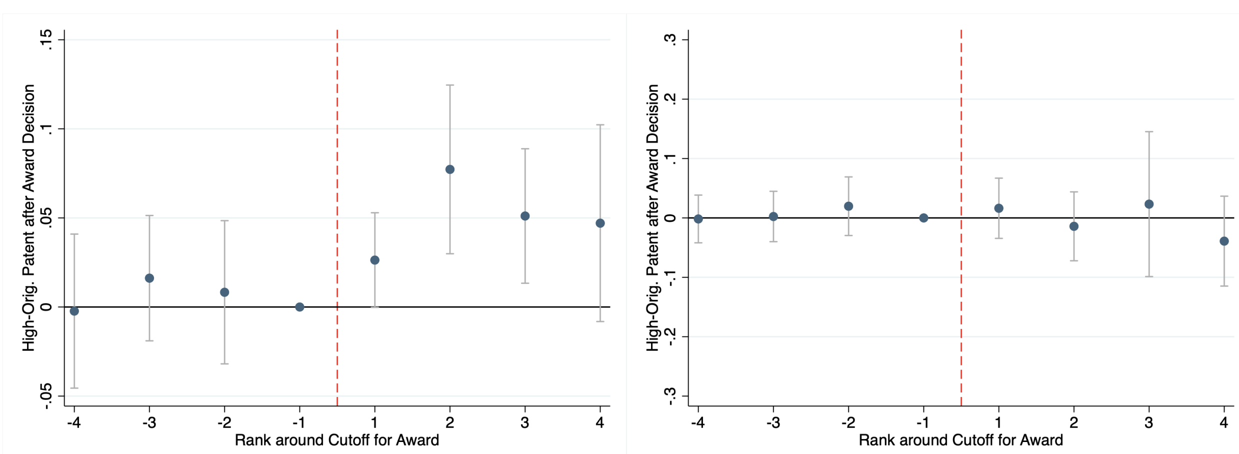
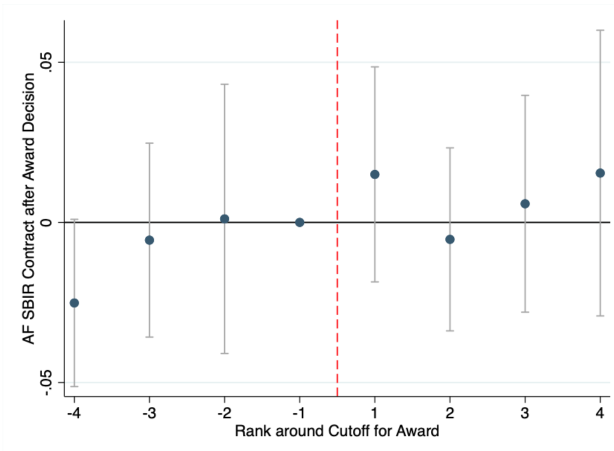


Figure 7: Probability of Air Force SBIR Contract by Rank Around Cutoff

Note: These figures show the probability that an applicant firm had any Air Force SBIR contracts within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. We plot the points and 95% confidence intervals from a regression of the outcome on a full complement of dummy variables representing each rank, as well as fixed effects for the topic. The omitted group is rank=-1. We include all data for Conventional.

(a) Open



(b) Conventional

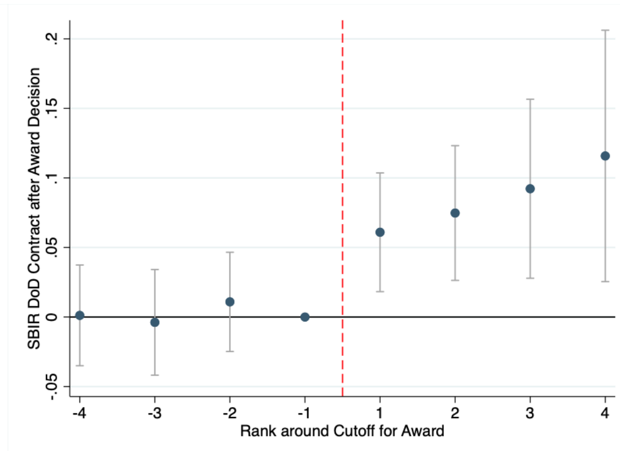


Table 1: Summary Statistics for Main Estimation Sample

Note: This table describes company, pre-award outcomes and competition characteristics. We use all proposals in our main estimation sample between 2017 and 2019, where a firm may only appear once and has not applied before to an SBIR. The left columns contain the applicants to Conventional topics, while the right columns contain the applicants to Open topics. See Section 3 for details on each variable. We report outcome means before the award decision. Outcome means for the full sample are reported in the subsequent regression result tables. We also present the difference of means. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Conventional			Open			
	N	Mean	SD	N	Mean	SD	Diff of Means (Open - Conv)
Company Characteristics							
Lifecycle controls							
Age	1,227	12.206	58.690	1,056	9.095	62.642	-3.111
Number of Employees	1,227	23.235	61.008	1,056	18.205	43.918	-5.030*
Additional controls							
$\mathbb{1}$(in VC Hub)	1,227	0.121	0.326	1,056	0.202	0.401	0.081***
$\mathbb{1}$(in County with AF Base)	1,227	0.209	0.407	1,056	0.172	0.378	-0.037**
$\mathbb{1}$(Immigrant)	1,227	0.063	0.236	1,056	0.083	0.273	0.020*
$\mathbb{1}$(Minority Owned)	1,227	0.170	0.376	1,056	0.128	0.334	-0.042***
$\mathbb{1}$(Woman owned)	1,227	0.155	0.362	1,056	0.113	0.316	-0.042***
Pre-award Outcomes							
$\mathbb{1}$(Previous DoD Contract)	1,227	0.158	0.365	1,056	0.113	0.316	-0.045***
$\mathbb{1}$(Previous VC)	1,227	0.023	0.149	1,056	0.097	0.296	0.074***
$\mathbb{1}$(Previous Patent)	1,227	0.117	0.321	1,056	0.152	0.359	0.035**
$\mathbb{1}$(Previous High Originality Patent)	1,227	0.074	0.262	1,056	0.095	0.293	0.021
$\mathbb{1}$(Previous High Citation Patent)	1,227	0.057	0.232	1,056	0.062	0.242	0.005
$\mathbb{1}$(Previous SBIR Contract)	1,227	0.000	0.000	1,056	0.000	0.000	0.000
Competition Characteristics							
Num Proposals per Topic	328	13.595	10.100	6	274.667	184.268	261.072***
Proposals per Winner	328	5.744	3.726	6	2.120	0.873	-3.624***
Non-specificity Index	328	0.212	0.217	6	0.650	0.058	0.438***

Table 2: Effect of Winning an Open vs. Conventional Award

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on five firm-level outcomes: technology adoption measured by any non-SBIR DoD contract valued at more than $50,000 (column 1), any VC investment (column 2), any patent (column 3), any patent with above-median originality (column 4), and having at least two SBIR awards (column 5). All outcomes are measured as any time after the award decision, through January 2023. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. In Panel B, we include controls for firm age and employment at the application date, as well as a vector of 25 narrow technology fixed effects. Panel C includes all proposals from all years. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline Specification					
	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}$(>1 SBIR)
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.086	-0.006	-0.087*	-0.014	0.093*
	(0.081)	(0.045)	(0.051)	(0.018)	(0.050)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.200**	0.124**	0.176**	0.084***	-0.100*
	(0.096)	(0.060)	(0.069)	(0.028)	(0.053)
Observations	2283	2283	2283	2283	2283
Lifecycle Controls	No	No	No	No	No
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.166	0.092	0.112	0.036	0.031
Panel B: Controls and Technology Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.089	-0.001	-0.087	-0.018	0.102**
	(0.079)	(0.047)	(0.053)	(0.021)	(0.048)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.186**	0.109*	0.163**	0.083***	-0.108**
	(0.094)	(0.064)	(0.072)	(0.029)	(0.050)
Observations	2283	2283	2283	2283	2283
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.166	0.092	0.112	0.036	0.031
Panel C: All Proposals (Including Controls and Technology Fixed Effects)					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.020	0.004	-0.015	-0.025**	0.032**
	(0.013)	(0.004)	(0.014)	(0.012)	(0.014)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.094**	0.108***	0.110***	0.091***	-0.067*
	(0.043)	(0.028)	(0.037)	(0.024)	(0.035)
Observations	21365	21365	21365	21365	21365
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	All	All	All	All	All
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.479	0.024	0.316	0.217	0.457

Table 3: Role of Firm Age and Size in Relative Effect of Open

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on the four firm-level success outcomes, but after dividing the sample in two ways. The first, presented in Panel A, is around median age as a proxy for lifecycle position. The second, presented in Panel B, is around median employment as a proxy for size. All outcomes are measured as any time after the award decision, through January 2023. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Heterogeneity By Age										
	$\mathbb{1}$(DoD Contract)		$\mathbb{1}$(VC)		$\mathbb{1}$(Patent)		$\mathbb{1}$(High Originality Patent)		$\mathbb{1}$(> 1 SBIR)	
	Young	Old	Young	Old	Young	Old	Young	Old	Young	Old
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Award)	-0.115	-0.112	-0.041	0.046	-0.144	-0.037	0.015	0.018	0.128	0.004
	(0.156)	(0.122)	(0.087)	(0.053)	(0.112)	(0.057)	(0.023)	(0.019)	(0.097)	(0.066)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	0.159	0.293**	0.220**	0.004	0.197	0.156	0.024	0.080**	-0.118	-0.028
	(0.170)	(0.148)	(0.108)	(0.072)	(0.129)	(0.095)	(0.030)	(0.040)	(0.099)	(0.070)
Observations	1052	1231	1052	1231	1052	1231	1052	1231	1052	1231
Proposal	First	First	First	First	First	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.122	0.205	0.120	0.069	0.111	0.119	0.035	0.039	0.027	0.031
Panel B: Heterogeneity By Employment										
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Award)	0.166	-0.314**	-0.017	-0.042	-0.179*	-0.058	-0.031	-0.016	0.132**	0.092
	(0.102)	(0.142)	(0.027)	(0.079)	(0.094)	(0.066)	(0.039)	(0.029)	(0.058)	(0.063)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	-0.073	0.376**	0.057	0.192*	0.216**	0.180*	0.049	0.144***	-0.115*	-0.126*
	(0.113)	(0.175)	(0.063)	(0.101)	(0.107)	(0.109)	(0.043)	(0.048)	(0.062)	(0.069)
Observations	1238	1045	1238	1045	1238	1045	1238	1045	1238	1045
Proposal	First	First	First	First	First	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.078	0.265	0.043	0.141	0.076	0.150	0.026	0.048	0.024	0.030

Table 4: Comparison Between Specific and Non-Specific Topics in Conventional Program

Note: This table describes company and outcome characteristics at the topic level, using all proposals in the Conventional program. The left columns contain the applicants to topics identified as more specific, with below 66th percentile non-specificity. The right columns contain the applicants to topics identified as more open, with above 66th percentile non-specificity. See Section 6.2 for details on specificity. We also present the difference of means (non-specific minus specific). We report outcome means before the award decision. Outcome means for the full sample are reported in the subsequent regression result table. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Specific Topics: $\leq$ P66 Non-Specificity			Non-specific Topics: $>$ P66 Non-Specificity			
	N	Mean	SD	N	Mean	SD	Diff of Means
Company Characteristics							
Lifecycle controls							
Age	1,139	17.586	16.102	400	20.838	41.450	3.252
Number of Employees	1,139	50.582	31.422	400	50.081	29.659	-0.501
Additional controls							
$\mathbb{1}$(in VC Hub)	1,139	0.174	0.138	400	0.175	0.147	0.001
$\mathbb{1}$(in County with AF Base)	1,139	0.286	0.166	400	0.289	0.160	0.004
$\mathbb{1}$(Immigrant)	1,139	0.073	0.101	400	0.068	0.096	-0.005
$\mathbb{1}$(Minority Owned)	301	0.123	0.113	111	0.120	0.119	-0.003
$\mathbb{1}$(Woman owned)	419	0.125	0.123	159	0.116	0.105	-0.009
Pre-Award Outcomes							
$\mathbb{1}$(Previous DoD Contract)	1,139	0.399	0.297	400	0.381	0.280	-0.018
$\mathbb{1}$(Previous VC)	1,139	0.061	0.090	400	0.066	0.083	0.005
$\mathbb{1}$(Previous Patent)	1,139	0.452	0.212	400	0.455	0.193	0.004
$\mathbb{1}$(Previous High Originality Patent)	1,139	0.336	0.203	400	0.345	0.182	0.008
$\mathbb{1}$(Previous High Citation Patent)	1,139	0.416	0.205	400	0.418	0.187	0.002
$\mathbb{1}$(Previous SBIR Contract)	1,139	0.516	0.262	400	0.508	0.246	-0.008
Competition Characteristics							
Num Proposals per Topic	1,139	12.354	8.755	400	13.367	8.799	1.014**
Proposals per Winner	1,139	5.582	4.301	400	5.856	4.285	0.274
Non-specificity Index	1,139	0.079	0.070	400	0.526	0.172	0.446***

Table 5: Effect of Relatively more Open (Non-specific) Topics in the Conventional Program

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award within the Conventional program on six firm-level outcomes: any non-SBIR DoD contract valued at more than $50,000, any patent, any patent with above-median originality, any patent with above-median forward citations, any VC, and having at least two SBIR awards. All outcomes are measured as any time after the award decision, through January 2023. The coefficient on Award represents the effect within more specific topics (below the 66th percentile of non-specificity), and the coefficient on Award interacted with high non-specificity represents the differential effect of relatively more open topics within the Conventional program. We control for the interaction between winning an award and the number of proposals per topic in all columns. In Panel B, we include controls for firm age and employment at the application date, as well as a vector of 25 narrow technology fixed effects. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: No Controls

	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}$(High Cite Pat)	$\mathbb{1}$(> 1 SBIR)
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Award)	-0.038**	0.002	-0.034**	-0.044***	-0.041***	0.023
	(0.017)	(0.004)	(0.016)	(0.015)	(0.014)	(0.017)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Non-specific)	0.062*	0.009	0.074**	0.078**	0.064**	0.021
	(0.033)	(0.010)	(0.034)	(0.031)	(0.028)	(0.032)
Observations	19494	19494	19494	19494	19494	19494
Lifecycle Controls	No	No	No	No	No	No
Narrow Tech FE	No	No	No	No	No	No
Proposal	All	All	All	All	All	All
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.498	0.016	0.329	0.230	0.205	0.483

Panel B: Controls & Narrow Technology FE

	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}$(High Cite Pat)	$\mathbb{1}$(> 1 SBIR)
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Award)	0.002	-0.008*	-0.041**	-0.069***	-0.049***	0.045**
	(0.021)	(0.005)	(0.021)	(0.019)	(0.017)	(0.023)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Non-specific)	0.040	0.008	0.058*	0.064**	0.053*	0.007
	(0.031)	(0.010)	(0.033)	(0.030)	(0.028)	(0.031)
Observations	19494	19494	19494	19494	19494	19494
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes	Yes
Proposal	All	All	All	All	All	All
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.498	0.016	0.329	0.230	0.205	0.483

Table 6: Effect of an Open Topic among Firms that Previously Applied to Conventional

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award after restricting the sample to firms that applied to Conventional at least once before 2018 and then applied to Open subsequently. The table includes only Open competitions. This isolates the effect of Open among a sample of firms that selected into both Open and Conventional. We employ the five firm-level outcomes from Table 2. The coefficient on Award represents the effect of winning in an Open topic within this subsample. In Panel B, we include controls for firm age and employment at the application date, as well as a vector of 25 narrow technology fixed effects. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline Specification

	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}$(>1 SBIR)
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	0.164**	0.062*	0.112*	0.091**	0.026
	(0.069)	(0.037)	(0.062)	(0.041)	(0.068)
Observations	507	507	507	507	507
Controls	No	No	No	No	No
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.471	0.059	0.225	0.081	0.381

Panel B: Controls with Technology Fixed Effects

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	0.151**	0.056	0.112*	0.107**	0.021
	(0.071)	(0.034)	(0.064)	(0.045)	(0.068)
Observations	507	507	507	507	507
Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.471	0.059	0.225	0.081	0.381

Table 7: Robustness Tests

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on the five firm-level outcomes from Table 2. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. In all Panels "lifecycle and narrow tech fixed effects" indicate the inclusion of firm age, firm employment, and 25 narrow technology area fixed effects. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. In Panel A, we include "additional controls": whether the firm had any previous non-SBIR DoD contracts, previous VC, previous patents, previous high-originality patents, was located in a VC hub city, was located in a county with an Air Force base, whether the product is software vs. hardware. In Panel B, we restrict the bandwidth to include only two applicants on each side of the cutoff. We construct alternative standard errors through randomization inference, following Cattaneo et al. (2019). The row "Randomization Inference p-value" shows the p-value of the interacted term $\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open) given that standard errors from randomization inference. In Panel C, we consider Conventional effects before the main analysis period (2003-2016). In Panel D, we consider Conventional effects among firms who do not subsequently apply to Open topics before the analysis was implemented.

Panel A: Additional Controls

	$\mathbb{1}$(DoD Contract)		$\mathbb{1}$(VC)		$\mathbb{1}$(Patent)		$\mathbb{1}$(High-Originality Patent)		$\mathbb{1}$(> 1 SBIR)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Award)	-0.098	-0.089	-0.035	-0.029	-0.126**	-0.125**	-0.041*	-0.046*	0.092*	0.101**
	(0.075)	(0.075)	(0.045)	(0.047)	(0.053)	(0.054)	(0.022)	(0.025)	(0.049)	(0.047)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.202**	0.181**	0.136**	0.123*	0.187***	0.180***	0.095***	0.099***	-0.101*	-0.107**
	(0.089)	(0.089)	(0.060)	(0.064)	(0.067)	(0.069)	(0.030)	(0.031)	(0.052)	(0.049)
Observations	2283	2283	2283	2283	2283	2283	2283	2283	2283	2283
Proposal	First	First	First	First	First	First	First	First	First	First
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lifecycle Controls & Narrow Tech FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.166	0.166	0.092	0.092	0.112	0.112	0.036	0.036	0.031	0.031

Table 7: Robustness Tests (continued)

Panel B: Narrow Bandwidth

	$\mathbb{1}$(DoD Contract)		$\mathbb{1}$(VC)		$\mathbb{1}$(Patent)		$\mathbb{1}$(High-Originality Patent)		$\mathbb{1}(> 1$ SBIR)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Award)	-0.078	-0.094	-0.064	-0.059	-0.073	-0.055	0.000	-0.010	0.062	0.079*
	(0.073)	(0.070)	(0.044)	(0.049)	(0.045)	(0.048)	(0.000)	(0.014)	(0.046)	(0.043)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.170**	0.168**	0.195***	0.180***	0.153***	0.125**	0.061***	0.070***	-0.058	-0.076*
	(0.085)	(0.081)	(0.055)	(0.061)	(0.059)	(0.062)	(0.020)	(0.025)	(0.047)	(0.044)
Observations	811	811	811	811	811	811	811	811	811	811
Lifecycle Controls & Narrow Tech FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Proposal	First	First	First	First	First	First	First	First	First	First
Randomization Inference p-value	0.072	0.049	0.000	0.003	0.011	0.060	0.004	0.003	0.370	0.166
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.186	0.186	0.116	0.116	0.125	0.125	0.033	0.033	0.036	0.036

Panel C: Conventional Program Before Open

	$\mathbb{1}$(DoD Contract)		$\mathbb{1}$(VC)		$\mathbb{1}$(Patent)		$\mathbb{1}$(High-Originality Patent)		$\mathbb{1}(> 1$ SBIR)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Award)	-0.026	-0.031**	0.006	0.006	-0.021	-0.022	-0.035**	-0.037***	0.057***	0.055***
	(0.017)	(0.015)	(0.005)	(0.005)	(0.016)	(0.015)	(0.015)	(0.013)	(0.017)	(0.017)
Observations	14743	14743	14743	14743	14743	14743	14743	14743	14743	14743
Lifecycle Controls & Narrow Tech FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Proposal	All	All	All	All	All	All	All	All	All	All
Time Period	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16
Outcome Mean	0.323	0.323	0.021	0.021	0.219	0.219	0.141	0.141	0.241	0.241

Panel D: Conventional Program Before Open, Among Firms that Never Applied to Open

	$\mathbb{1}$(DoD Contract)		$\mathbb{1}$(VC)		$\mathbb{1}$(Patent)		$\mathbb{1}$(High-Originality Patent)		$\mathbb{1}(> 1$ SBIR)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Award)	-0.016	-0.027	0.010	0.010	-0.013	-0.018	-0.028*	-0.033**	0.083***	0.078***
	(0.019)	(0.018)	(0.006)	(0.006)	(0.017)	(0.017)	(0.016)	(0.015)	(0.019)	(0.019)
Observations	12105	12105	12105	12105	12105	12105	12105	12105	12105	12105
Lifecycle Controls & Narrow Tech FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Proposal	All	All	All	All	All	All	All	All	All	All
Time Period	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16	2003-16
Outcome Mean	0.293	0.293	0.022	0.022	0.202	0.202	0.130	0.130	0.210	0.210

Appendix

(For Online Publication)

A Slowing Innovation in the US Defense Industry

In this appendix, we describe some of the economic context for U.S. military R&D and explain the concerns among policymakers about declining innovativeness, which motivated the SBIR reform we study. Despite these concerns, there is no public evidence about the decline. Therefore, in the second part of the appendix, we document the evolution of prime defense contractors' innovation.

A.1 Economic Context for U.S. Defense R&D

Military R&D has shaped technological advances since antiquity, both "pushing" and "pulling" civilian innovation.[31] In the U.S., spillovers from defense R&D to commercial applications occur through two primary channels. First, DoD both conducts and funds basic R&D, and is an important source of basic, open-ended funding for university research. This "pushes" private sector innovation by creating new pools of general engineering or scientific human capital and knowledge (Belenzon and Schankerman 2013, Babina et al. 2020). Second, the military procures new technologies, creating an early market that might otherwise not exist, and shaping the direction of private sector R&D through its vast spending power. DoD has been willing to fund extremely risky, capital-intensive new technologies that have a potential military application.

Since World War II, the U.S. military has invested in innovation primarily through procurement contracts. The theory of procurement, as applied to defense, highlights a hold-up problem in production with large fixed costs in technology innovation and development. As the only customer, once the firm invests, the government can potentially eliminate profits by refusing to pay a high price once the technology is available (Tirole 1986). Furthermore, innovation is a defining characteristic of defense procurement, so incentivizing it effectively is crucial. Other key factors in the government's regulatory problem for defense procurement beyond R&D and monopsony include uncertainty and economies of scale in production (Rogerson 1994). Together, these forces create a rationale for DoD to fund the development stage, in which an innovation is developed for use, tested, and scaled.

Much more so than other Western countries, the U.S. procures defense technologies from

[31] For example, many historians (e.g. Polybius' *Histories)* credit Archimedes with inventing many new technologies in the defense of Syracuse against the Romans in 213–212 BC such as cranes (the "Archimedes' Claw" dragged ships out of the sea).

an industrial base that also supplies commercial markets (Flamm 1988). In the 1950s and 1960s, large orders for early-stage technologies such as transistors and integrated circuits were crucial to reducing their prices while improving quality, such that they could ultimately be applied to commercial products (Mowery 2012). Dual-use technologies have many attractions. As a monopsonist in the defense market, it is difficult for DoD to create competition among defense contractors. A dual-use technology can be exposed to the discipline of the private market, reducing cost inflation and leading to higher quality. In recent decades, there have been increasing concerns that the "virtuous cycle" in which American defense R&D investment yields powerful commercial applications and enables unrivaled military supremacy is failing.

There are at least four challenges. First, procurement regulations have become more complex and onerous, raising barriers to entry for new firms and contributing to the dominance of the prime contractors (Cox et al. 2014). Second, relevant frontier technologies do not seem to be marketed to DoD. Third, the national innovation ecosystem has shifted away from areas most relevant to defense (Sargent and Gallo 2018). Fourth, prime defense contractors have consolidated, often serve only the defense market, and are perceived as increasingly less innovative. For example, in 2019, an Under Secretary of Defense tasking memo noted that

> "The defense industrial base is showing signs of age. The swift emergence of information-based technologies as decisive enablers of advanced military capabilities are largely developed and produced outside of the technologically isolated defense industrial base" (Griffin 2019).

Despite these concerns, to our knowledge, the evolution of defense contractors' innovation has not been previously documented.[32]

A.2 Documenting Declining Innovation

Here, we document innovation trends focusing on the top eight contractors over the past two decades: Boeing, Raytheon, Lockheed Martin, Northrop Grumman, General Dynamics, United Technologies Corp, Harris, and L-3. We researched all of their acquisitions since 1976 of companies that were also defense contractors and linked the eight primes and all their acquisition targets to the NBER/USPTO patent database and Compustat.

[32] Carril and Duggan (2020) show that the substantial consolidation among major defense contractors in the mid-1990s reduced competition and led to a shift to cost-plus contracts in which cost escalations are uncapped.

Figure A.1 shows that between 1976 and 2019, 225 companies consolidated into just six, with L-3 and Harris merging in 2018, and Raytheon and United Technologies merged in 2020. Remarkably, the dollar share of total defense contracts that these firms have won, shown in the grey area, has stayed fairly constant over the years at roughly 35%.[33] The value (in 2019 dollars) of these contracts increased from around $70 billion spread across 225 companies in the late 1970s to $115 billion awarded to just six companies in 2019. The number of firms responsible for the remaining roughly 65% of contract value not represented in the graph declined slightly from 25,339 unique contractors in 1976 to 24,656 in 2018. To confirm that the remaining contracts have not become more dispersed, we present the Herfindahl-Hirschman Index (HHI) of concentration for all non-SBIR DoD contracts, though this measure is not very insightful because the defense market is composed of myriad small markets for items ranging from food supplies at a particular base to a fleet of fighter jets. Nonetheless, the dashed orange line in Figure A.2 Panel A shows that overall concentration has remained relatively stable, albeit volatile.

The dramatic consolidation among the primes has been accompanied by a decline in innovation quality as measured by patent citations, which shed light on private sector spillovers. Figure A.3 shows patent activity for the firms in Figure A.1, weighted by future citations. Patent activity is only one proxy for innovativeness, but it is relevant to DoD-funded innovation. While a patent involves some disclosure, there are often trade secrets that prevent a competitor from copying the invention even once the patent is public, and a patent can coexist with classified aspects of the research that do not appear in the patent itself.

In 1976, the figure includes patents from all 225 companies, and in 2019 we are considering patents from the six companies. Citations are normalized by the average number of citations for all patents in the same CPC3 Technology class by year cohort, so that a number above one indicates the patent is more impactful than the average patent in its class-year.[34] The solid blue line includes all forward citations, and we see a secular decline across the unit threshold, so that defense patents changed from being relatively more innovative to relatively less innovative within their narrow technology areas. This pattern is even starker when we include only outside citations to patents from firms that are not featured in the graph. That is, we exclude citations from firms outside the prime contractor universe. These citations are

[33] We exclude DoD contracts to Humana (health insurance provider) and universities.

[34] We use a kernel-weighted polynomial to smooth the lines (the results are very similar with a binscatter approach).

shown in the dashed green line. They decline from having 17% more citations from outside defense than the average patent in the class year in 1976 to 60% fewer citations in 2019. These trends suggest a prime contractor base that has become markedly more insular over time.

To assess whether firms are innovating in new areas that could have novel defense applications (e.g. software, clean energy), we also calculate a firm's share of "explorative" patents in any given year, following Manso (2011). An explorative patent is a patent filed in technology classes previously unknown to the firm in a given year. Figure A.4 shows the average share of exploratory patents relative to other firms with similar in age, size, and year. As above, all firms from Figure A.1 are included. Age is defined as the year from the firm's first observed patent and size is defined as the firm's patent stock in a given year. As firms merge, they acquire new areas of expertise, and we expect this should lead to increasing exploration since the assignee after the acquisition is usually the acquiring parent firm. This seems to be true to some extent for the big mergers of the 1990s but is not true subsequently. Instead, in Figure A.4 we see a marked decline over time, indicating that the defense contractors are not patenting in new technology areas even as they acquire each other. By 2019, the share of explorative patents was 60% lower than firms with similar patent stocks and age since the first patent.

Figure A.5 shows other variables relevant to prime contractor innovation. In Panel A, we compare the growth in the number of patents for the primes to growth among all other U.S. assignees in the USPTO. Until the early 1990s, the defense contractors were patenting at similar rates as the overall universe, but we see a subsequent divergence, with defense contractors patenting at a lower rate.[35] The subsequent three panels use Compustat data and compare primes to other firms in the same three-digit NAICS industry.[36] Panel B shows that before the mid-1990s, the primes had a higher ratio of profits to R&D than peer firms, but by 2019, they earned $8 for each R&D dollar compared to $5.50 in the comparison group. Panel C shows that the level of profits has increased much more for primes than for other firms and Panel D shows that R&D has grown since 1976, but more slowly than revenue and assets. While these changes clearly increased efficiency, they may also help to explain the decline in innovation we observe in the defense sector and, more directly related to our thesis, have left a remaining cadre of smaller, less innovative, and more locked-in defense contractors.

Finally, our results are consistent with case study evidence. Dial and Murphy (1995)

[35]This coincides with a major merger wave in the mid-1990s when, among others, Northrup merged with Grumman, McDonnell Douglas merged with Boeing, and Lockheed merged with Martin Marietta.

[36]Since many acquisitions were of unlisted firms, the figures only include the acquisition targets after acquisition, so must be treated with more caution.

document how one prime, General Dynamics, generated substantial wealth for shareholders despite facing declining demand in the post-Cold War period. After tying executive pay to stock price increases, the firm dramatically increased stock returns through downsizing, including cutting R&D spending in half, and by shifting resources out of the defense industry (p. 262-3, 277). Lundquist (1992) also explains how the defense industry more broadly created value for shareholders by consolidating and reducing overall research investment. Jensen (1993) specifically explains how these acquisitions transferred large sums to target-firm shareholders so that they could reinvest in more productive sectors, outside of defense.

In short, there has been a big increase in concentration among prime defense contractors. Although their profits and assets have increased substantially, this has been accompanied by a fall in the primes' relative innovation whether measured by citations, patenting or R&D intensity. The key transition appears to have occurred after the Cold War ended, during the period of lower defense budgets and consolidation during the 1990s but continued into the period of higher spending following 9/11 and the Iraq War.

Finally, we conduct a similar analysis for the SBIR program. Since firms must be small to participate, concentration is not a primary concern. The main concern is lock-in and repeat contracts awarded to firms that are interested neither in commercializing innovation nor in seeking scale in the defense market. Such firms specializing in SBIR awards are sometimes derisively called "SBIR mills" (Edwards 2020). Figure A.3 Panel B shows that among winners in the Conventional SBIR program, there has been a decline in relative innovation since the 1990s, similar to that for prime contractors (see Appendix A).[37]

This decline may be related to the difference between the findings of this paper and that in Howell (2017) for the Department of Energy (DoE), where there are large positive effects on innovation of winning a Phase 1 grant. One explanation is that there is more severe lock-in of the SBIR firm base at DoD than at DoE. Indeed, we show that this is the case in Figure A.2 Panel B. Each line shows the share of Phase 1 SBIR contract value awarded to firms that won no contracts in the previous three years from the agency. At the beginning of the sample, in the mid-1990s, the two lines are relatively close together, with about 35% (39%) of DoD (DoE) awards going to new firms. The series diverges subsequently, and during the 2010s only 20-25% of DoD SBIR Phase 1 awards went to new firms. The greater lock-in at DoD might

[37]Furthermore, Figure A.2 panel A uses the Herfindahl-Hirschman Index (HHI) to show that the DoD SBIR program has become more concentrated over time, with more firms winning many awards in a single year.

reflect the large size of DoD's SBIR program and the many similar types of R&D procurement contracts that DoD offers, which can be sustainably lucrative to a small research firm. The higher incidence of repeat contracts in the SBIR offers a parallel to the consolidation among prime contractors in the larger acquisitions programs.

Figure A.1: Consolidation of Prime Defense Contractors

Note: This figure shows the trend of defense contractors' consolidation since the 1980s. We first define prime defense contractors as the top contractors between 2000 and 2020: Boeing, Raytheon, Lockheed Martin, Northrop Grumman, General Dynamics, United Technologies Corp, Harris, and L-3. We then identify all their acquisitions of other defense contractors starting in 1976. The blue line shows the number of unique firms in each year, from 226 in 1976 to just six in 2020. The gray area shows the share of all DoD contracts (in nominal dollars) that are awarded to the top eight prime defense contractors and their acquisition targets. The total value of these contracts (in 2019 dollars) is shown in the orange line. For example, the 226 firms accounted for about $70 billion or 33% of the total defense contract value, in 1976. They consolidated to six companies by 2019, at which point those six accounted for $115 billion, or 35% of the total defense contract value. Data are sourced from the Federal Procurement Data System (FPDS) and Defense Contract Action Data System (DCADS).

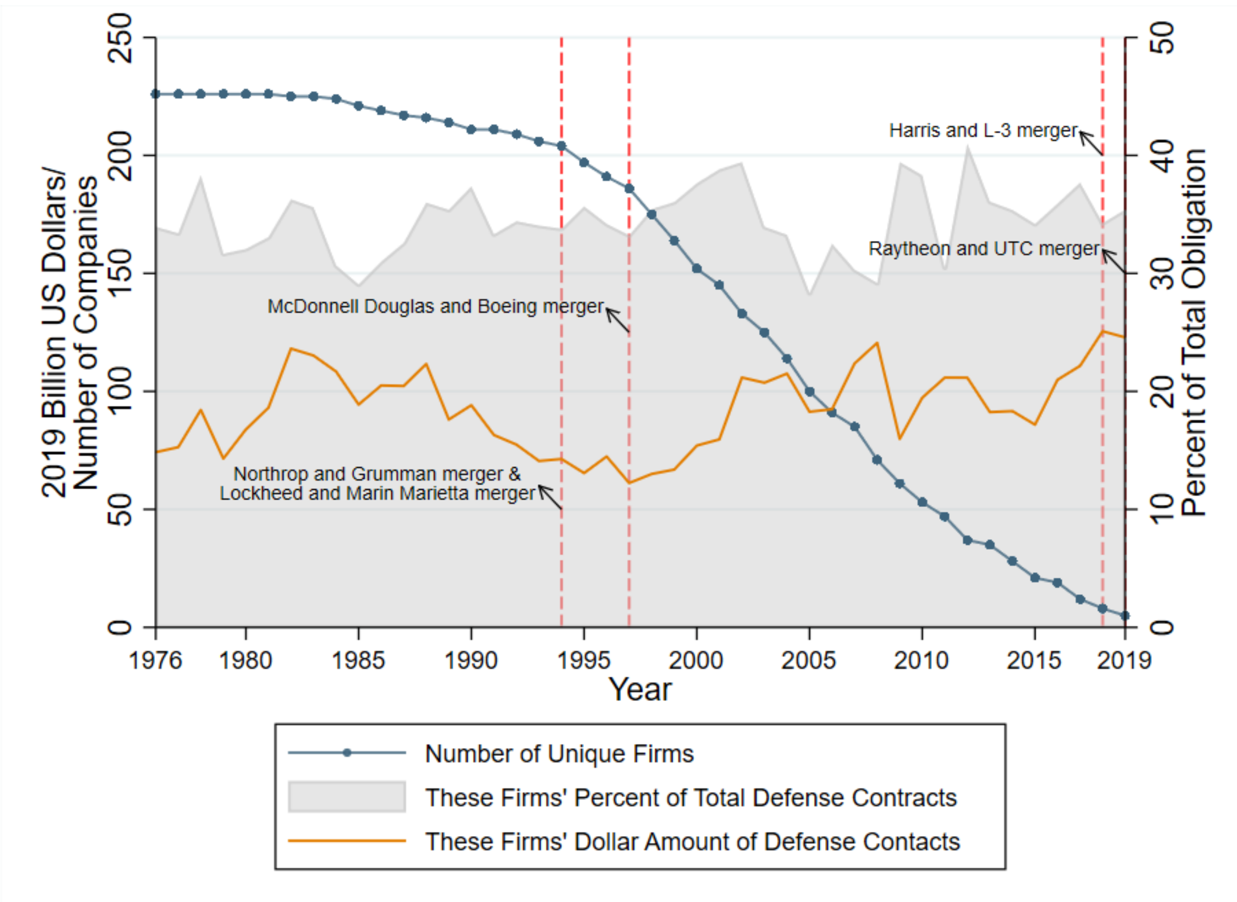
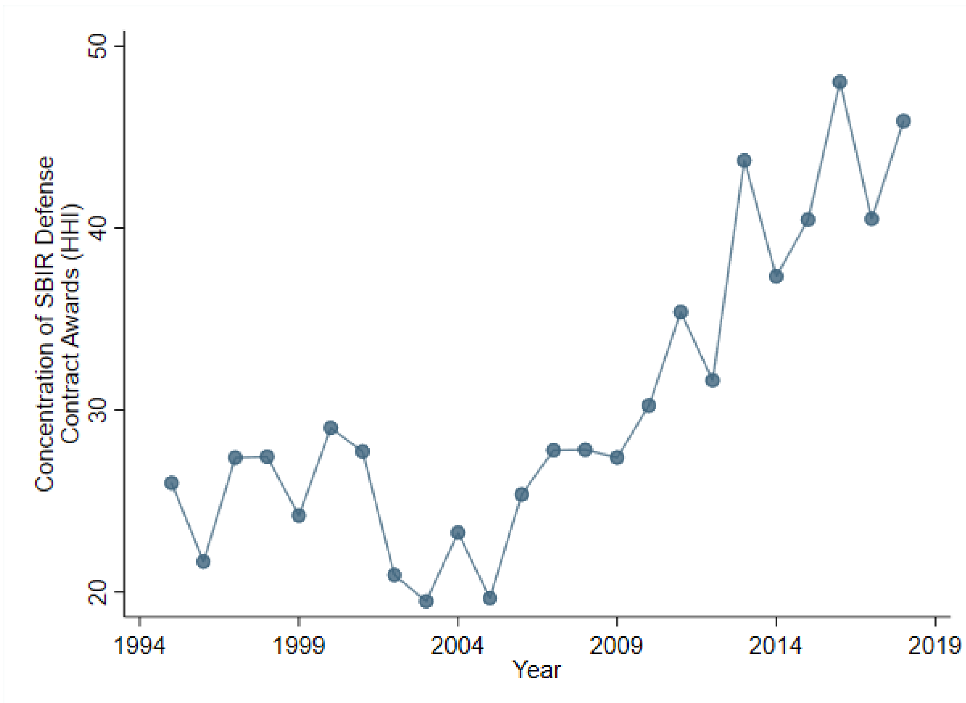


Figure A.2: Concentration of Federal Contracts

Note: Panel A in this figure shows the Herfindahl–Hirschman Index (0-10,000) for Non-SBIR Department of Defense contracts from 1990 to 2018. Panel B shows the share of "new" firms winning awards from the SBIR programs at the Department of Defense (DoD) and the Department of Energy (DoE). Each line plots the percentage of SBIR contract dollars awarded to firms that have not won a contract in the last three years. At the beginning of the sample in the early 1990s, the share of SBIR awards to firms that have not won in the last three years are relatively similar at the two agencies, but the series subsequently diverge. Data from DCADS, FPDS, and the U.S. Small Business Administration.

(a) Concentration of Department of Defense SBIR and Non-SBIR Contracts



(b) Share of Firms without Recent Repeat Contracts in Two SBIR Programs

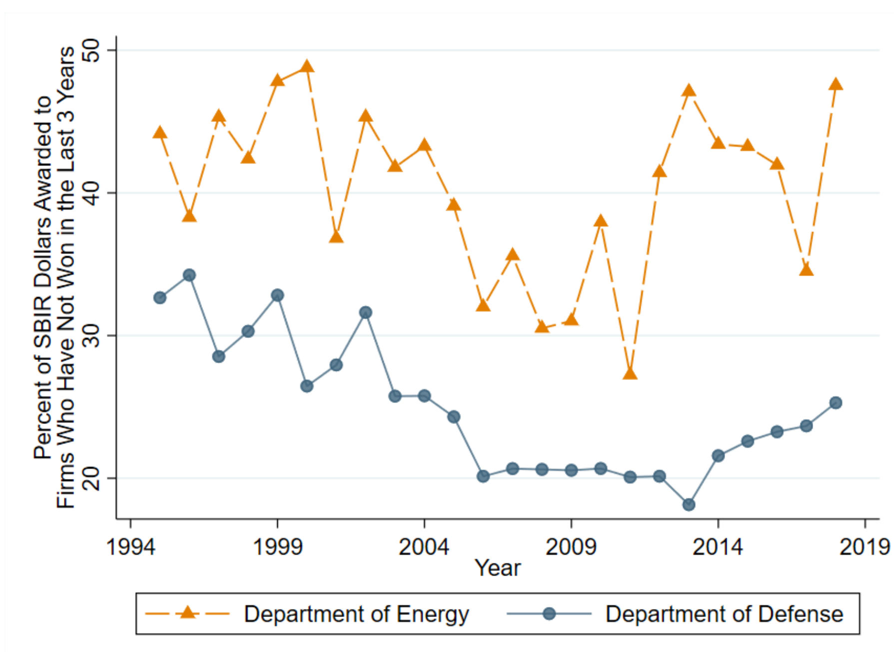
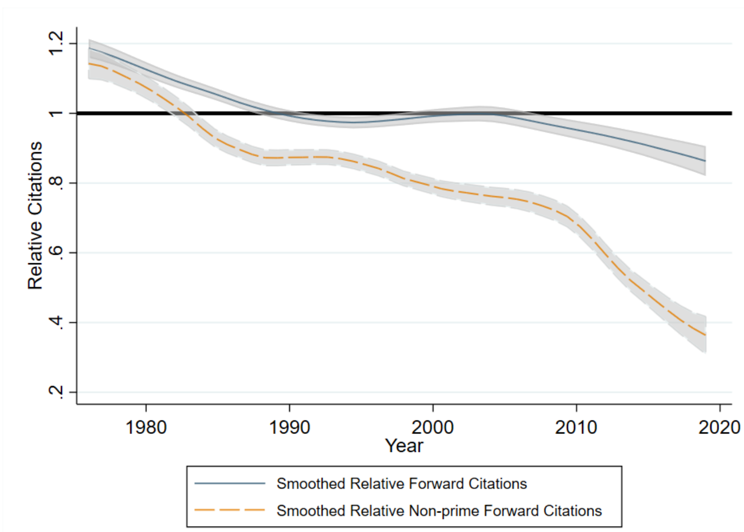


Figure A.3: Declining Relative Innovation Among U.S. Prime Defense Contractors

Note: These graphs describe patent quality for the prime defense contractors and their acquisition targets (depicted in Figure A.1). That is, 226 firms are included in 1976, while only six are included in 2019 (as the 226 have merged into these six). Panel A shows the total number of forward citations (solid blue line) and outside non-prime forward citations (dashed orange line) for these firms relative to the average in the same class-year. A value of 1 means the firm's patents have the same number of citations as the average patent in the same class-year. The dashed line makes two changes relative to the blue line. First, it excludes self-citations, where the company cites one of its own previous patents. Second, it excludes any citations from the firms in the figure (prime defense contractors and their acquisition targets). We do not count future cites of a target firm's patents from its future acquirer as self-cites, so the effect is not mechanical from consolidation. Note that the prime and target share of patents in a class year has declined over time, so there are not "fewer outside patents to cite" in a class-year (see Figure 3). Panel B repeats this exercise but for Air Force SBIR winner firms. In this case, the dashed orange line excludes self-citations citations from other AF SBIR winner firms. The measures in both figures are smoothed using kernel-weighted polynomial regressions. The gray band around the relative citations represents the 95% CI. Data are sourced from the USPTO.

(a) Prime Patent Citations



(b) Conventional SBIR Winner Patent Citations

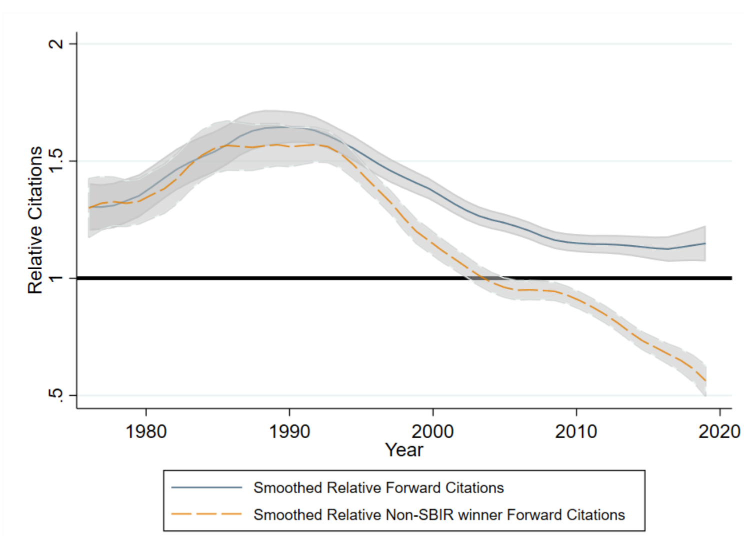


Figure A.4: Exploratory Patents from Prime Defense Contractors

Note: This figure describes the trend of exploratory innovation by the prime defense contractors and their acquisition targets over time. The firms are the same set from Figure A.1. That is, 226 firms are included in 1976, while only six are included in 2019 (as the 226 have merged into these six). The graph shows these firms' average share of exploratory patents relative to other firms with similar in age, size, and year. An exploratory patent is a patent filed in a technology class previously unknown to the firm in a given year. Age is defined as the year from the firm's first observed patent and size is defined as the firm's patent stock in a given year. The measures in both figures are smoothed using kernel-weighted polynomial regressions. The gray band around the relative citations represents the 95% CI. Data are sourced from the USPTO.

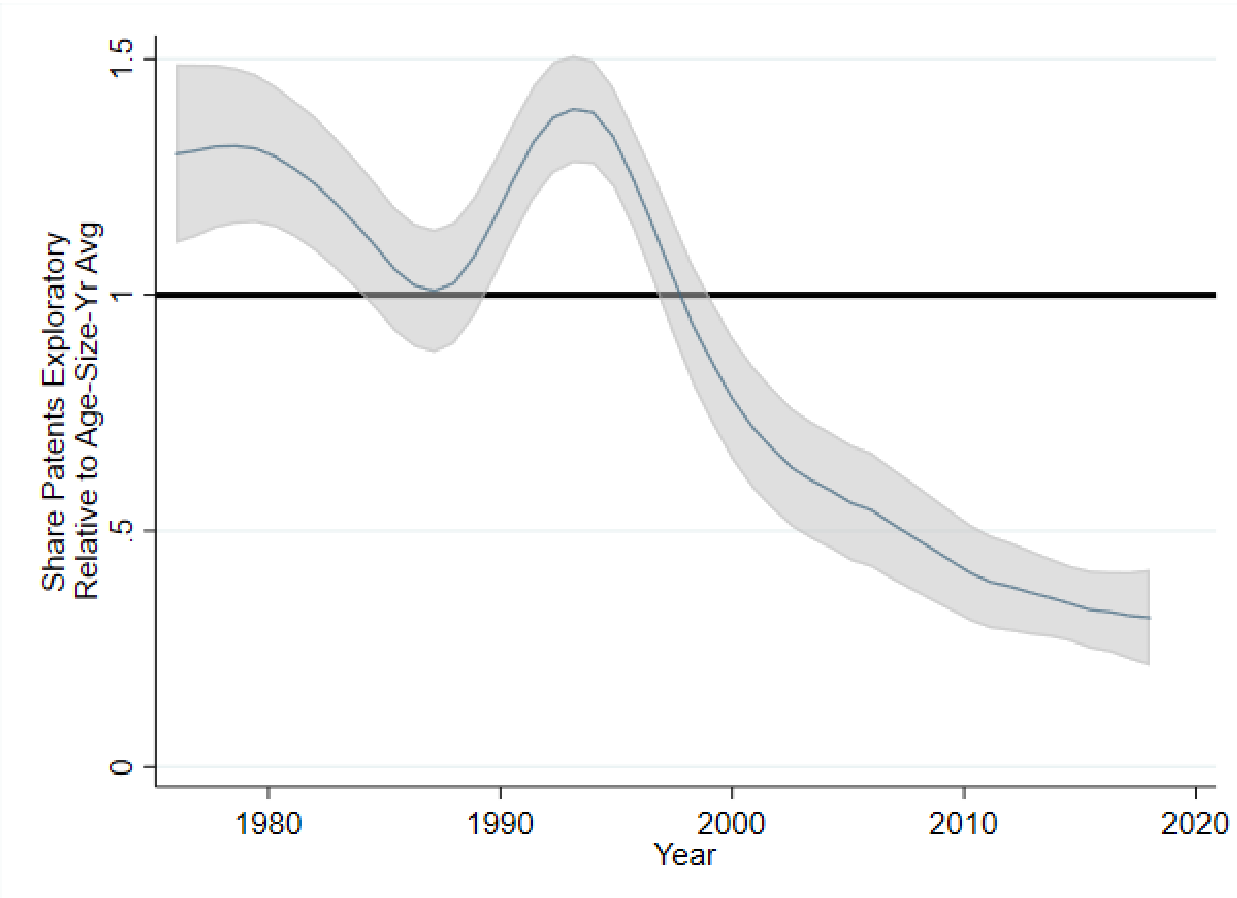
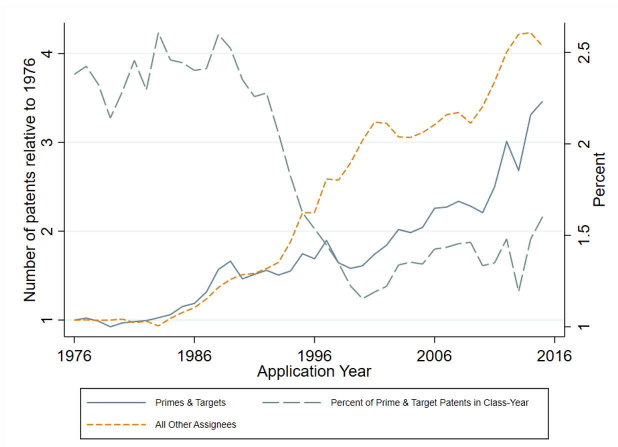


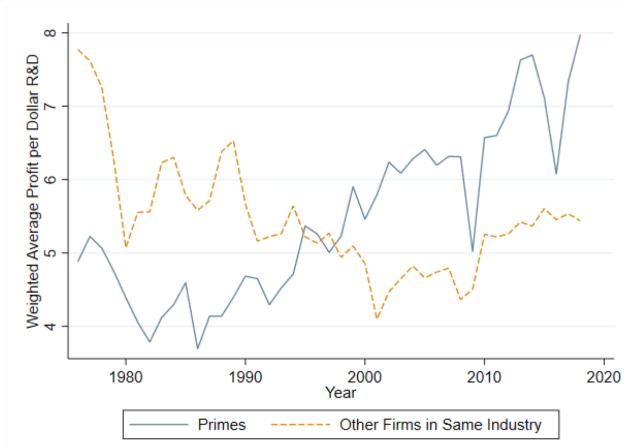
Figure A.5: Historical Dynamics of Prime Defense Contractors

Note: This figure shows the dynamics of prime defense contractors. Panel A shows growth in the number of granted patents for prime defense contractors and their acquisition targets (blue line) and the number of granted patents for all other assignees (orange line) from 1976 - 2016, using data from the U.S.PTO. The teal line shows the share of prime defense contractors and their acquisition targets' patents in their class-year. The number of patents is scaled by 1976 levels (1976=1). We exclude 2016–on because there is a 2-3 year time period between application and patent award, so there are far fewer granted patents in the most recent application years. Panel B shows the weighted average profit per dollar of R&D for prime defense contractors compared to other Compustat firms in the same 3-digit SIC code (334 and 336). Panel C shows the growth of profits for prime defense contractors compared to other Compustat firms in the same 3-digit SIC code (334 and 336) relative to 1976 (1976=1) from 1976 to 2019. Panel D shows the growth of total assets, total revenue, and R&D expenditures in constant 2019 U.S. dollars for prime defense contractors, scaled by the 1976 level. Panel A includes the prime defense contractors and their acquisition targets; Panels B, C, and D only include the prime defense contractors and not their acquisition targets.

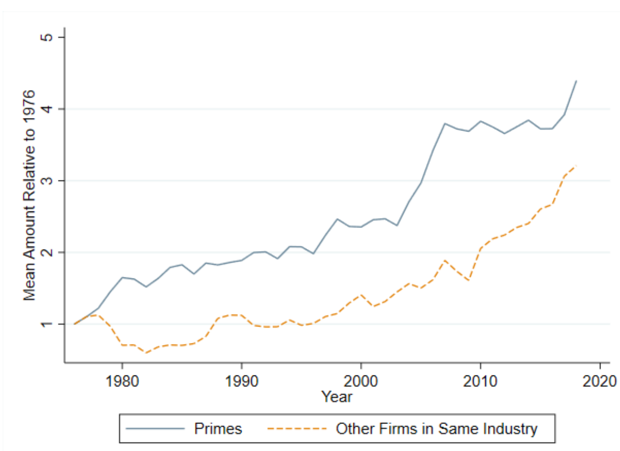
(a) Number of Patents



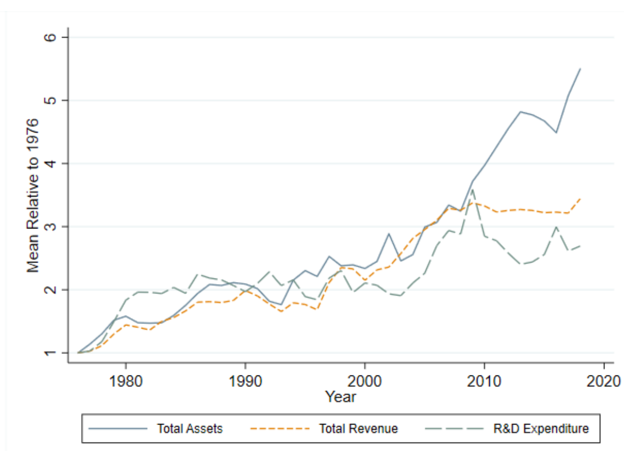
(b) Profit per Dollar R&D



(c) Profits



(d) Total Assets, Revenue, and R&D Expenditure



B Small Business in U.S. Defense Innovation Spending

Small firms have long played an important and economically meaningful role in DoD innovation procurement. The problem that the Open reform program seeks to address is not the absence of small firms *per se*, but the decline of both innovation and new entry in the defense industrial base. Below, we make three points. First, small firms compose a significant portion of overall DoD procurement and DoD innovation procurement. We find that about a third of all DoD R&D dollars goes to smaller firms. Second, large build projects like the F35 have many small firms involved. Third, DoD innovation strategy since 2015 has centered around smaller firms and in particular, startups. We regard this last point as the most important. Fundamentally, DoD innovation policy today is about startups, so there can be nothing more pertinent to defense innovation than studying the main vehicle through which they enter the defense industrial base (SBIR and the use of SBIR by DoD's new innovation organizations, of which AFWERX is a cornerstone). This is not just our perspective - we document that this is the view of leading defense policymakers.

B.1 The Share of Small Firms in Overall DoD Spending is Substantial

Small businesses play a meaningful role in DoD contracting overall and in innovation specifically. There is no consistent reporting in contracting data of business size, and small business designations vary by contract type, firm industry, and award management system. However, many sources indicate that small firms account for a large share of total DoD procurement. In March 2023, a DoD official testified in Congress that "Last fiscal year, the department spent \$85.2 billion on small business prime contracts, and nearly 25% of the department's prime contracts go to small businesses."[38] External to the DoD, Bresler and Bresler (2022) create their own measure using a variety of data sources. They find that in 2021, small businesses were awarded nearly \$91.6 billion in defense contracts, which represents 21.4% of total procurement of \$428.6 billion.

We wish to identify innovation spending specifically, which is not available in public sources. We obtained complete DoD procurement data to identify concrete statistics based on publicly

[38] See https://www.defense.gov/News/News-Stories/Article/Article/3339784/dod-increases-efforts-to-bring-small-businesses-into-defense-industrial-base/

available awards. We begin with direct DoD awards data (this excludes subcontracts) between 2018 and 2021 from USAspending.gov. During this period, we observe a total of 15,153,911 contracts amounting to \$4,253 billion dollars. Within these data, we define R&D spending using two methods. First, we use all contracts with NAICS code 5417, which is Scientific Research and Development Services. Second, we use the product or service code description, which is typically a short phrase. We label as R&D all projects whose description includes any of the following words: "Research", "R&D", "Scientific" and "Science".[39] We observe 59,752 R&D contracts amounting to \$472 billion dollars and we use this as a proxy for total innovation spending.

In order to obtain information on firm employment, we link the contracts data to Dun and Bradstreet (D&B) data using the award recipient and recipient parent DUNS numbers. Out of all R&D contracts between 2018 and 2021, the merged sample covers 79% of total R&D contracts and 89.6% contracted R&D dollars. Thus we can identify the size distribution for \$423 billion (about 89.6% of \$472 billion) of contracted R&D.

D&B coverage improves with firm size, so this exercise will likely be biased towards a lower share for small firms than is true in reality.[40] We define a small firm as having fewer than 500 employees, based on the SBA's criterion for SBIR eligibility. Within our merged sample of R&D contracts, 61% were awarded to small firms. These contracts to small firms amount to \$78 billion, or 18% of the total R&D dollars. Annually, there is a slight increase over in the fraction (and dollar amount) going to small businesses between 2018 and 2021.

Next, we turn to subcontracting data, again between 2018 and 2021. During this period, we observe 769,527 subcontracts amounting to \$916 billion dollars. Since have no description or NAICS for subcontracts, we assume all subcontracts of direct R&D contracts are R&D-related, which leaves us with 96,882 subcontracts worth \$193 billion. We merge subcontracts to D&B data.[41] Finally, we exclude subcontracts where the direct contractor is a small businesses,

[39] Two examples of contract descriptions are "R&D—Defense System: Weapons (Advanced Development)" and "Repair or Alteration of Office Buildings". There are many small contracts that are likely R&D, but we cannot systematically identify as such. For example, a contract with the description "Medium Unmanned Underwater Vehicle (MUUV) Phase 1 - EDM Design & Fabrication" is categorized as NAICS 336611, Shipbuilding and Repairing, but arguably this is innovative.

[40] Since some firms provide erroneous DUNS numbers or do not have DUNS numbers at all, they cannot be merged exactly. The merge percent is roughly equal in the different years. Following the Small Business Administration (SBA), we identify a recipient as "small" if the firm has less than 500 employees across all establishments.

[41] Note that our approach undercounts R&D, because it excludes R&D subcontracts of contracts that were not coded as R&D. The merged sample covers 80% of total R&D subcontracts and 78% of total R&D subcontracted amount.

leaving 71,014 total R&D subcontracts amounting to $148 billion from 4,488 prime awards. We observe that 65% of subcontracts in R&D contracts are to small businesses, accounting for 38.5% of subcontract value ($57 billion).

In sum, this calculation shows that small firms represents a substantial portion of innovation procurement: putting together the direct contracts ($78 billion) and the subcontracts ($57 billion), **small businesses account for 32% (= (78+57)/423) of all R&D dollars.** This represents 66% of all R&D contracts.[42]

It is also worth noting that small firms produce *qualitatively* more innovative output. In 2019, a Congressionally mandated DoD Advisory Panel on Streamlining and Codifying Acquisition Regulations released a report that concluded:[43]

> *"Small businesses produce many of the innovative capabilities, emerging technologies, and complex services DoD must acquire for warfighting dominance in a dynamic and uncertain strategic environment... small companies are more innovative per dollar of research and development funds spent and per employee than large firms."*

It may seem that the small projects of SBIR are not relevant to defense innovation, which happens inside "large build" projects such as the F35 Joint Strike Fighter. But such projects are in practice integrations or platforms. They are composed of large numbers of subcontractors and individual innovations—many of which are sourced from small firms. For example, consider the F35 program itself illustrates the important role of small business in DoD procurement. While Lockheed Martin is the primary contractor, small businesses play a major role in the project. In Figure B.1 below, we copy the landing page of Lockheed Martin's website for the F35 program. Small businesses are the focus of the first substantive point (reading from left to right). It says: *"We are proud to partner with 1,650 high-tech suppliers, of which nearly 1,000 are small business corporations."*[44] Note that they emphasize "high-tech," implying a role for these small firms in innovation.

[42] Among the 4,488 R&D contracts with subawards, 65% of the total subcontracts were awarded to small businesses. Thus, out of a total of 47,399 identified R&D contracts, 28,681 contracts were awarded directly to small businesses and another 2,917 equivalent contracts were awarded to small business through subcontracts.

[43] This report was required by the FY2016 National Defense Authorization Act. More information is here, https://discover.dtic.mil/section-809-panel/, and the quoted section is here: https://discover.dtic.mil/wp-content/uploads/809-Panel-2019/Volume1/Recommendation_21.pdf.

[44] https://www.f35.com/f35/about/economic-impact.html

To quantify this better and generalize beyond the F35, we consider the largest projects in the direct award data to gather a better sense of the role of small businesses in these "large build" programs.[45] We proxy for large build using the very largest ten contracts to the six top prime contractors whose consolidation we document in our paper.[46] Of these, on average each contract has 327 unique firms as subcontractors, and their subawards represent 24% of the total contract value, for an overall amount of $56.5 billion.

Finally, we repeat this analysis but focus on the largest R&D-specific contracts, which proxies for the large build innovation.[47] Of these, on average each contract has 118 unique firms as subcontractors, and their subawards represent 25% of the total contract value, for an overall amount of $11.6 billion. In sum, this exercise shows that large build projects are in practice integrations with many firms involved.

B.2 DoD's Small Firm Innovation Strategy

This brings us to the strategy shift that has occurred over the past two decades, with a notable acceleration starting in 2015. Since 2015, DoD's principal and explicit innovation strategy has been to encourage startups to enter the defense industrial base (Kotila et al., 2022). This shift represents an effort to go beyond the historical focus on small businesses towards a new focus on innovative startups. The shift—and the Open reform program we study—reflect a realization that the traditional defense sector is no longer at the cutting edge of innovation. For example, in 2019, an Under Secretary of Defense tasking memo noted that:

> *"The defense industrial base is showing signs of age. The swift emergence of information-based technologies as decisive enablers of advanced military capabilities are largely developed and produced outside of the technologically isolated defense industrial base"* (Griffin 2019).

Instead, nimble startups and the venture capitalists who fund and guide them are perceived to be at the frontier of innovation in the areas most relevant to the future of warfare, such as autonomy, AI, quantum computing, IoT, and robotics. Military forces around the world are focusing energies on funding and working with high-tech, small businesses that possess

[45] While there are actually multiple direct awards for very large programs like the F35 (as highlighted above), since we cannot typically tie direct awards together into a single program, we use the largest direct contracts.

[46] Table B.1 shows the ten largest contracts.

[47] Table B.2 shows the ten largest R&D contracts.

"dual-use" technologies with commercial as well as defense applications. For the DoD, this has been difficult. The DoD acquisitions Advisory Panel report introduced above concluded:

> *"DoD's challenges in working effectively with small businesses to address critical needs and achieve the strategic objectives of DoD are of substantial concern. DoD would benefit if it aligned its acquisitions from small business with its strategic priorities... DoD's small business policies and programs currently focus on acquiring supplies and services that further socioeconomic goals but do not fully leverage innovative and unique capabilities of small businesses to support DoD's mission."*[48]

To address this issue, DoD's policy shift began under Secretary of Defense Ash Carter and has been expanded by Secretaries Mattis, Esper, and Austin. Three quotes underscore this point. As the new policies were being rolled out, a DoD press release summarized a key speech by Ash Carter as follows:

> *"To invest in the most promising emerging technologies, the department needs the creativity and innovation that comes from startups and small businesses. This is particularly important, because startups are the leading edge of commercial innovation."* (Pellerin, 2015)

Similarly, Secretary Mattis repeatedly emphasized the importance of new, startup-oriented programs such as the Defense Innovation Unit – Experimental (DIUx, located in Mountain View CA). Responding to a question about how DIUx will sidestep DoD bureaucracy, Mattis said the DIUx director "will be talking directly to my deputy secretary... And he will also have direct access to me."[49] In 2021 Secretary Austin announced at the Reagan National Defense Forum that the DoD was expanding efforts to help innovative small firms bring new technology to the military. He specifically highlighted the SBIR, saying:

> *"We're doubling down on our Small Business Innovation Research program... This program helps fuel American firms to pursue R&D tailored to the Department's unique tech requirements. And so far this year, we've awarded funds to more than 2,500 small businesses working on groundbreaking tech. We're also*

[48] https://discover.dtic.mil/wp-content/uploads/809-Panel-2019/Volume1/Recommendation_21.pdf

[49] https://www.defense.gov/News/News-Stories/Article/Article/1276282/mattis-impact-of-industry-innovation-will-continue-to-grow-at-dod/

doing more to integrate the Department's innovators into tech hubs around the country where academics, and business leaders, and innovators thrive."[50]

The vehicles for the policy change are a series of new defense innovation organizations (DIOs). Arguably the first with a startup focus was the Defense Innovation Unit (DIU) within the Office of the Secretary of Defense, established in 2015. In the subsequent years, DoD added the Army Applications Lab, Naval X, AFWERX, SOFWERX (part of the Special Operations Command), DEFENSEWERX, the National Security Innovation Network (NSIN), the Army Venture Capital Initiative, and others. These organizations aim to reduce barriers between defense field missions and commercially focused companies that are not traditionally defense contractors. Among these DIOs, more than 90% of innovation contracts are to small businesses (in part this is by construction since they primarily use SBIR to make direct awards).[51]

Many of these new organizations use Congressional authorization for spending through "Other Transaction Authorities" (OTA), which do not require adherence to the arduous regulations and competition requirements that govern most contracts. Congress noted when making these authorizations in 2016 that *"We believe that expanded use of OTAs will support Department of Defense efforts to access new source[s] of technical innovation, such as Silicon Valley startup companies and small commercial firms."*[52]

The landing page of NavalX, shown in Figure B.2 below, is clear about the focus on startups and the use of SBIR open topics. (We have highlighted the words "open topics" at the bottom, and are showing the menu for "About Us", which shows that the only contracting mechanism for NavalX is SBIR.)

The program we study is at the forefront of the new strategy. Air Force Open SBIR companies that were new to defense contracting have gone on to grow and obtain significant military contracts. For example, Anduril's first contract with the U.S. government was an Air Force Open SBIR award in 2019. It went on to obtain at least $756 million in contracts from the Navy, Special Operations Command (SOCOM), and the Air Force. Further examples of companies that first participated in the Air Force Open SBIR program and are growing into meaningful defense contractors are Scale AI, Epirus, Beta Technologies, Joby, and True

[50] https://www.defense.gov/News/Speeches/Speech/Article/2861931/remarks-by-secretary-of-defense-lloyd-

[51] Based on FPDS and conversations with DoD officials. These agencies' spending cannot be distinguished in the public contracts data.

[52] U.S. Congress, House Committee on Armed Services, National Defense Authorization Act for Fiscal Year 2016, committee print, Legislative Text and Joint Explanatory Statement to accompany S. 1356, P.L. 114-92, 114th Cong., 1st sess., November 2015, pp. 700-701.

Anomaly.

Finally, the effort to encourage startups to participate in defense is not limited to the U.S. For example, France's RAPID program is similar to the AFWERX agenda, taking proposals from small businesses that believe they have a technology relevant to defense, and making awards swiftly (Budden and Murray (2019)). Other examples include the Joint Forces Command Innovation Hub (jHub) and Defense and Security Accelerator in the UK, the Defense Innovation Hub in Australia, the Strategic Innovation Fund within the Canadian Department of National Defense, and the Defense Innovation Organization in India. All of these institutions explicitly focus on funding small, high-tech businesses that are not traditional defense contractors.

Figure B.1: Lockheed Martin's F35 Website (Landing Webpage)

Figure B.2: NavalX Landing Page

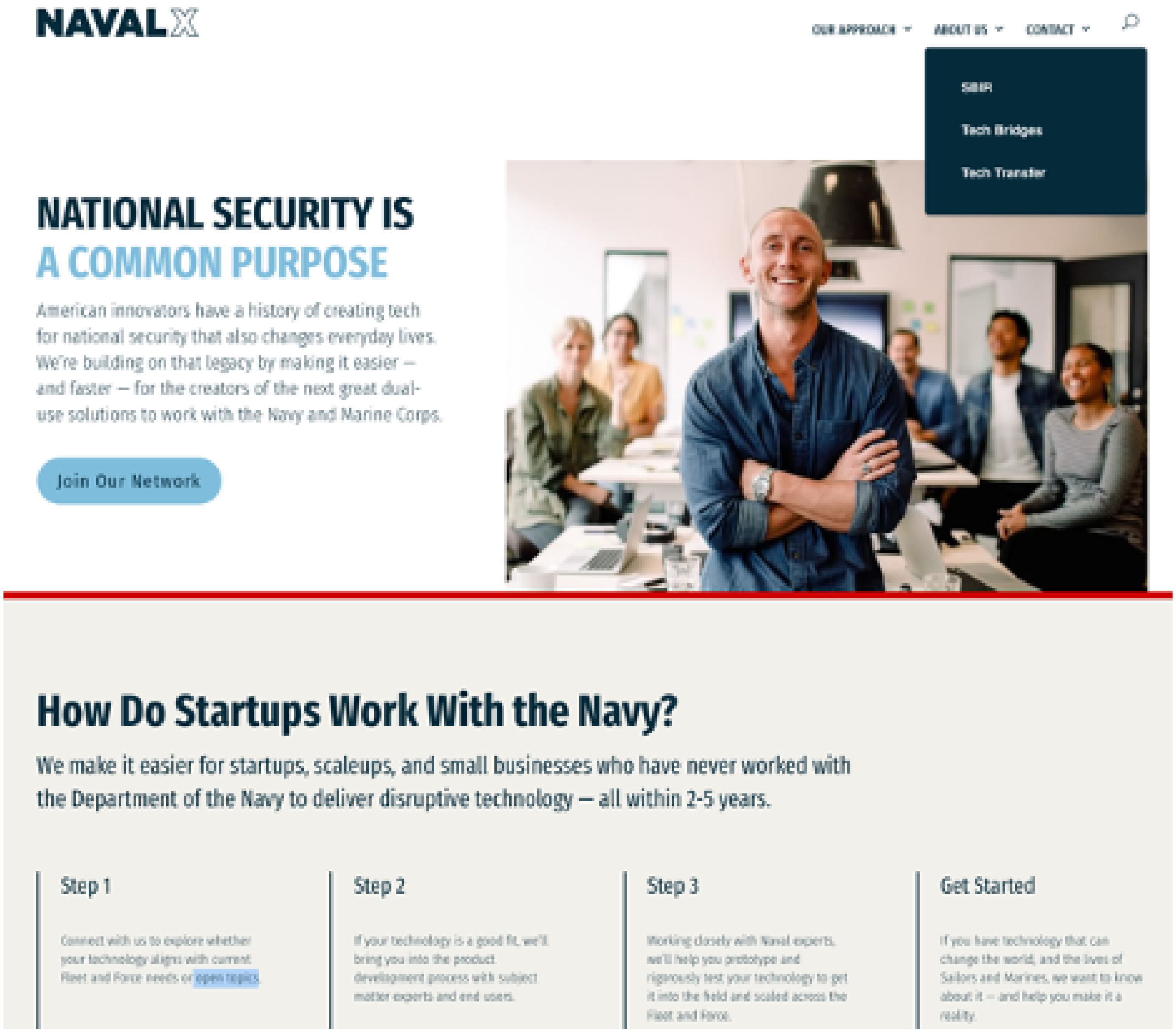


Table B.1: Examples of Large Build Projects

Contractor	Description	Amount (bill)	# Subcontractors	Subcontracted Amount (bill)	Share Amount Subcontracted
Lockheed Martin	LRIP 10 AAC	$172.5	168	$0.53	0.31%
Lockheed Martin	F-35 Lightning II Joint Strike Fighter	$129.5	93	$1.2	0.01%
Boeing	KC-X Modernization Program	$41	174	$1.83	4.40%
Lockheed Martin	LRIP Lot 12	$36	389	$18.9	41.57%
Electric Boat Corp.	SSN 802 and 803 Long Lead Time Material	$24.1	344	$2.82	11.82%
Lockheed Martin	F-35A LRIP 15	$22.6	335	$16.5	72.83%
Boeing	USN P-8A Long Lead Material	$18.7	251	$3.2	17.28%
Electric Boat Corp.	SSN 792 Long Lead Time Material	$18.35	308	$0.23	1.27%
Huntington Ingalls	CVN 80 Engineering Efforts and Steel	$16.43	336	$7.38	44.92%
The Aerospace Corp	FY19 Engineering Services	$15.57	210	$0.07	0.46%
Lockheed Martin	Long Lead-Time Items	$14.5	42	$0.05	0.36%
Sirkosky	H-60 Helicopters	$13.06	180	$550	4.19%
Lockheed Martin	LRIP 11 AAC	$12.3	248	$2.3	19.14%
Boeing	RSAF F-15 Fleet Modernization Program	$11.05	65	$0.06	0.54%
Lockheed Martin	Phase Array Tracking Radar	$10.13	282	$3	29.50%
Boeing	Lot 7 Full Rate Production	$9.97	212	$1.59	15.92%
United Technologies	Lot 12 AAC Propulsion	$8.96	26	$0.24	2.67%
Raytheon	Qatar Fire Units	$8.38	656	$7.27	86.82%
Boeing	F-15 Development	$8.33	375	$3	35.97%
Lockheed Martin	Hellfire Buy 17	$6.91	201	$6.28	90.86%
	Average	$20.92	244	$3.85	18.4%

Table B.2: Examples of Large Build R&D Projects

Prime Recipient Name	Prime Award Description	Prime Award Amount	Num Subcontractors	Subcontracted Amount	Share Amount Subcontracted
The Aerospace Corporation	Engineering Services Aerospace Federally Funded R&D	$15.57 billion	210	$72 million	0.04%
Bell Textron Inc.	Future Long Range Assault Aircraft Program	$7.2 billion	9	$390 million	5.45%
Boeing	Ground-based Mid-course Defense Development	$7.05 billion	144	$2.66 billion	37.71%
Boeing	Ground-based Interceptor & All Up Round Systems Engineering	$5.2 billion	117	$2.27 billion	43.61%
Lockheed Martin	Space Fence Program	$4.78 billion	91	$1.6 billion	33.52%
The Aerospace Corporation	Federally Funded R&D Center	$4.4 billion	192	$46.4 million	1.05%
Lockheed Martin	Next Generation Interceptor & All Up Round	$3.76 billion	178	$1.41 billion	37.41%
The Mitre Corporation	Federally Funded R&D Contract	$3.44 billion	33	$8.77 million	0.25%
BAE Systems	Tank R&D	$3.32 billion	133	$1.18 billion	35.59%
Science Applications International	Missile Hardware in the Loop	$3.29 billion	73	$1.93 billion	58.51%
	Average	$5.8 billion	118	$1.16 billion	25.36%

C Institutional Details about the Open Reform

The SBIR reforms have taken place within a new organization called Air Force Ventures (AFVentures), a business division of AFWERX.[53] AFVenture's stated goals are to leverage private capital to deploy new innovations for the military, to expand the industrial base interested in defense, and to grow the U.S. economy. That is, they hope to address the challenges facing military procurement identified in Section 2. The idea is that if the open approach is successful in this context, it might be applied to the larger acquisition programs with the hope of garnering interest in the defense market among the large tech firms in areas such as cybersecurity and artificial intelligence. Senior leaders perceive commercial innovation metrics as measures of successful Air Force R&D investment, with the idea that an innovative U.S. industrial base will, in the long term, enable military supremacy, especially if the research has early-stage ties to the defense market.

AFWERX and AFVentures are one of a number of initiatives that the Defense Department has instituted, since about 2015, aiming to reduce barriers between defense field missions and commercially focused companies that are not traditionally defense contractors.[54] Many of these programs make use of Congressional authorization for increased spending through "Other Transaction Authorities" (OTA), which do not require adherence to the arduous regulations and competition requirements that govern most contracts. Congress noted when making these authorizations in 2016 that "We believe that expanded use of OTAs will support Department of Defense efforts to access new source[s] of technical innovation, such as Silicon Valley startup companies and small commercial firms."[55]

More broadly, AFWERX is representative of many institutions established in the 2010s around the world reflecting a realization that the traditional defense sector is no longer at the cutting edge of innovation. Instead, the private sector, especially nimble startups and the venture capitalists who fund and guide them are perceived to be at the frontier of innovation in many areas. Important features of this entrepreneurial ecosystem are a willingness to experiment and access, through both co-location as well as pecuniary and non-pecuniary benefits,

[53] https://www.afwerx.af.mil/

[54] Some of the new initiatives include SOFWERX (part of the Special Operations Command), the Defense Innovation Unit (DIU), the Defense Innovation Board, and the National Security Innovation Network (NSIN), the Army Venture Capital Initiative, and the Capital Factory in Austin, an incubator "tech hub" that houses offices of AFWERX, Army Applications Lab, and DIU.

[55] U.S. Congress, House Committee on Armed Services, National Defense Authorization Act for Fiscal Year 2016, committee print, Legislative Text and Joint Explanatory Statement to accompany S. 1356, P.L. 114-92, 114th Cong., 1st sess., November 2015, pp. 700-701.

to high-skill human capital.

DoD SBIR awards are in the form of contracts. This contrasts with some agencies, such as the DoE or the NIH, which deliver SBIR awards in the form of grants. With a grant, the application defines the scope of work, payment is entirely up-front, and the government has little recourse in the event that the firm does not use the money as intended. Conversely, contracts represent a binding agreement between the government and the firm to deliver a good or service. Payment only comes after the firm has accomplished some pre-established milestone. Therefore, risk and liquidity are allocated differently across the two instruments. Grants offer the firm money upfront, and the government takes the risk that the project (or the firm) will fail. Contracts allocate more risk to the firm and require the firm to finance the investment upfront. In the context of financially constrained startups, this may present a challenge.

First conducted in May 2018, Open topics are the centerpiece of AFWERX's reformed SBIR program. Open topic solicitations contain no direction regarding the technology that the applicant may propose. With an reference to seeking "unknown unknowns" in the solicitation, Open topics are designed to let the private sector do the work of identifying military applications for its technology. The solicitation explains:

> "The objective of this topic is to explore Innovative Defense-Related Dual-Purpose Technologies that may not be covered by any other specific SBIR topic and thus to explore options for solutions that may fall outside the Air Force's current fields of focus but that may be useful to the U.S. Air Force. An additional objective of this topic is to grow the industrial base of the U.S. Air Force."

The firm's objective is to demonstrate the feasibility of developing a product or service with an Air Force partner interested in potentially procuring the firm's technology. The Phase 1 deliverable is a white paper, or report describing the outcomes of research. The Open topics are aimed at firms already developing a technology aimed at commercial use, even if it is in the very early stages

In contrast, Conventional topics tend to fund R&D projects nominally geared towards a particular military use. Conventional topics are sourced primarily from the Air Force Research Laboratory (AFRL). They are highly specific; some examples of topics are:

- "Affordable, Durable, Electrically Conductive Coating or Material Solution for Silver Paint Replacement on Advanced Aircraft"

- "Safe, Large-Format Lithium-ion (Li-ion) Batteries for ICBMs"
- "Develop Capability to Measure the Health of High Impedance Resistive Materials"
- "Standalone Non-Invasive Sensing of Cyber Intrusions in FADEC for Critical Aircraft System Protection"
- "Hypersonic Vehicle Electrical Power Generation through Efficient Thermionic Conversion Devices"
- "Cyber Attack model using game theory"

Each year, there are usually three solicitations, each of which has many Conventional topics but only one Open topic since 2018. For example, in the second solicitation of 2019, there was one Open topic and 61 Conventional topics. All Open topics are the same; there are multiple topics because they are issued at different points in time (i.e., in different solicitations). The pool of competitors a given applicant faces in the Open topic depends on when it applies, as scoring and ranking are within-topic. This creates a different distributional structure in Open topics relative to Conventional, as there are many more applicants but also far more winners. The difference in topic structure should not bias the results towards favoring a stronger effect in Open because we estimate the effect of winning within each program, and the cutoff point for winning is lower in the score distribution for Open.

Open topic awards are also smaller than Conventional ($50,000 vs. $150,000) and have shorter time frames (3 vs. 9 months). AFWERX's belief that offering many very small awards can be useful was in part informed by existing research finding strong positive effects on VC and patenting from small, early-stage Phase 1 awards (Howell 2017). The fact we find larger causal effects in Open than in Conventional cannot be explained by the difference in award amounts since Open is less financially generous than Conventional. Note that the budget for each of the hundreds of topics is determined before the competition, and depends on factors such as the overall funding settlement for U.S. Air Force's SBIR program, military priorities, etc. Hence, the precise threshold will be competition-specific and depend on the number and quality of the applicants for each solicitation.

This paper focuses on Phase 1, so we minimize the discussion of further awards. The Phase 2 awards of $300,000 to $2 million are intended to last 12-24 months and fund a prototype. For all but the first two of its Open SBIR topics, AFWERX sought to encourage Phase 1 winners to access outside funding from either private or or government sources with a matching provision in Phase 2. Below, we evaluate the impact of match availability separately from openness. Figure E.11 shows clustering of awards, particularly in Phase 1, around the maximum amount. Some firms apply for less than the maximum, apparently because firms must apply for the amount of money required to do the work they are proposing.[56] Phase 2 contracts are much more detailed, bespoke, with higher and more varied amounts than Phase 1 (see Figure E.11).

[56]There is also apparently some misconception that cost will be a key factor in evaluation, despite explicit information in the solicitation that it will not.

D Details on Data, Sample, and Key Variables

D.1 Data Sources and Sample Construction

Our starting point is a dataset of applications and awards to the Air Force SBIR program between 2003 and 2019. All awards are publicly available, most easily from the SBA's website www.sbir.gov. Our causal analysis, however, requires applications and evaluations; that is, knowing which firms applied and lost as well as the internal scores that determine award status for all applications. We observe complete evaluation data for all topics between 2017 and 2019, and further evaluation data for Conventional topics in select earlier years: 2003-2007, 2015, and part of 2016. The remaining years' data were, unfortunately, inadvertently destroyed in 2016. The application and evaluation materials are not public information.

We analyze the effect of winning a Conventional award using all our data, but the main focus of this paper is to compare Open and Conventional. To do this, we restrict the sample to the three years of 2017-2019 and to firms who have not won a previous SBIR award, so that the relevant economic environment and defense procurement factors are similar across the sample. We start with 21,365 Phase 1 proposals across all years for which we can observe their abstracts, restricting to 2017-2019 leaves us with 6,622 proposals. Of these 6,622 proposals, 2,753 are from applicants who have not previously won an SBIR award. Finally, 2,283 of these 2,753 proposals are from first-time Air Force SBIR applicants. In 2017, all applicants are Conventional. In 2019, four-fifths of applicants are Open. Table E.2 describes counts of topics, firms, and proposals for all programs.

Conventional topics average 14 applicants and 2.5 winners (i.e., awardees). Open topics have a very different model, leading to many applicants and winners per topic (on average, 275 and 147, respectively). Table F.1 shows similar statistics for the whole Conventional sample.

D.2 Outcome Variables

The two main outcomes of interest are subsequent VC investment and technology adoption measured by DoD non-SBIR contracts, which correspond to the two key metrics of success from AFWERX's perspective. The current Air Force leadership views commercial innovation as evidence of initial success, based on the idea that a strong U.S. industrial base (especially if its research has early-stage ties to DoD) will ultimately enable strong defense (Williams 2020). From an economic perspective, VC investment is a useful proxy for high-growth innovation potential. Although VC-backed startups make up only 0.11% of new firms, over 44% of public company R&D is performed by formerly VC-backed startups (Puri and Zarutskie 2012, Gornall and Strebulaev 2015).

We obtain unique private financing deals from Pitchbook, CB Insights, SDC VentureXpert, and Crunchbase. The majority of deals come from Pitchbook, which we observe through January 10, 2023. While there are likely VC investments that do not appear in these databases, they are the industry state-of-the-art and are widely used (Lerner and Nanda 2020, Gornall and Strebulaev 2020). We match firms to these datasets on name and state, and then check manually for false positives. Clearly there may be some errors, in particular as firms can change names. However, there is no reason the error rate should be systematically different across Open and Conventional in the 2017-19 time frame.

The second outcome is non-SBIR DoD contracts, representing defense procurement success in the sense that the research has led to a practical application for the military; in the DoD jargon this is often termed "transition to programs of record." An example of a successful Open applicant from the perspective of "transitioning" to Air Force operations is Alabama-based Aevum, which designs drone-launched rockets in a former textile mill. After winning a $50,000 Open Phase 1 award in July 2019, Aevum was awarded a $4.9 million Air Force launch contract in September 2019. An example from the Conventional program is Ascendant Engineering Solutions. After winning a $149,000 Conventional Phase 1 award in September 2016, Ascendant Engineering Solutions has been awarded with a $7.5 million Air Force contract for its tactical gimbals in February 2018.

To construct this outcome, we use complete data from the Federal Procurement Data System (FPDS) and USASpending through March 2023. The FPDS dataset is a single, comprehensive dataset of all federal contracts. The FPDS archives were discontinued in 2021, so we turn to USASpending for contracts from 2021 to 2023. In practice, the data obtained is exactly the same since USASpending reports data from FPDS. We remove all non-DoD and SBIR contracts and then match to our data on firm DUNS number. For the portion that do not match on DUNS, we use firm name and state, and manually check for false positives. Among the matched contracts, 64% were matched on DUNS. While it is possible that we are missing some contracts, the error rate should be small. We restrict to contracts worth at least $50,000 so that we do not capture very small add-on type awards or minor purchases. Among the matched contracts, 42% of contracts by volume and 99% by value are over this threshold. The results are similar using all matched contracts.

We consider patents from the USPTO to assess technical innovation with potential commercial applications. We match SBIR applicants to patent assignees on firm name and state. One outcome is an indicator for the firm having any granted patents that were applied for after the award date. That is, we use the application date (as opposed to the award date), but we restrict to granted patents. The second measure is originality. The originality score will be low if a patent cites previous patents in a narrow set of technologies, whereas citing patents in a wide range of fields leads to a high score.[57]

We also consider the number of forward citations, which we normalize by patent class and by year to adjust for the systematic differences across classes and years.[58] Forward citations are informative about the impact of a patent on future research. Finally, we looked at the number of patent applications, which could represent innovation effort and is less truncated due to the lag between application and award. We obtained application data courtesy of Liat Belenzon, and merged these data to the SBIR data on firm name and state.

The final outcome measure is subsequent SBIR awards across all agencies, using data from the Small Business Administration (results are similar using Air Force or all-DoD SBIR awards). We examine whether winning one SBIR award causally increases the probability of winning a future one, to assess lock-in to the SBIR program.

D.3 Machine learning to classify applications and topics

Here we give further details on how we measured characteristics of applications from their text, which is used both to assign firms to technology areas and to identify the non-specificity (i.e. openness) of topics. As noted in the main text, the raw applications data is not classified by industry or technology. As a way of classifying application types, we make use of the abstracts in the application proposals. We employ a machine learning algorithm called "k-means clustering" (see Forgy (1965) in the statistics literature or Bonhomme and Manresa (2015) in the econometrics literature) to classify each abstract based on its word "embedding."

We first map each word of the abstract into vector space using a pre-trained model that, based on corpuses of text, is able to identify words that are conceptually similar. For example, the vectors for words such as "happy" and "joy" would be close in distance, while vectors for words such as "happy" and "toolbox" would be quite distant from each other. Specifically, we

[57] Originality for patent i is defined as $1 - \sum_j c_{ij}^2$, where c_{ij} is the percentage of citations that patent i makes that belong to patent class j.

[58] The citations data are from the USPTO.

use the SpaCy pipeline in Python, whose model is trained on OntoNotes with GloVe (Global Vectors for Word Representation) vectors trained on Common Crawl.[59] Each word embedding vector consists of 300 elements where an element is a value between -1 and +1. We then estimate the abstract embedding as the average of the word embeddings that make up the abstract. In this way, we can capture how similar abstracts are to one another using the average embedding. Next, we reduce the dimensionality of the abstract embeddings from three hundred dimensions to two. We do so nonlinearly using isometric mapping, following the framework in Tenenbaum et al. (2000).

Next, we cluster these abstract embeddings using the k-means clustering algorithm, whose objective is to minimize the total within-cluster variance. Note that this is unlike traditional topic modeling methods such as Latent Dirichlet Allocation, which focuses on the co-occurrence of words within topics and within the corpus of the given text but does not take into account the semantics and context of the words (i.e. the relationship between words themselves). We present the two- and twenty five-cluster model. The former yields a clear dichotomy between software- and hardware-based technologies and the latter provides narrow technology classifications. The word clouds for the two-cluster model is in Figure E.2. The top words in each of the 25 clusters are listed in Table E.14. They show the keywords that form a topic cluster, with the word's size scaled to reflect its prevalence in the topic. For the two-cluster model we have a cluster over what could describe as "Training/Software" and one which we could describe as "Hardware." We remove the most prevalent 75 words across all topics from the word clouds for clarity, as these are mostly filler words.

To calculate the "non-specificity" of a topic, we take the following steps. First, we calculate the cossine similarity of each application embedding to the centroid of each topic. Next, we calculate the topic's standard deviation of cossine similarity. The higher the standard deviation in a topic, it implies that there is considerable spread in the similarity between proposals. The lower the standard deviation, the lower the spread in similarity between proposals in a topic. In general, we would expect Open topics to be more non-specific than Conventional topics as there is little restriction on what can be proposed. This is indeed what we see in practice.

We validate our approach to measuring topic non-specificity by manually examining the top

[59] OntoNotes is a large corpus consisting of various texts from news, conversational telephone speech, blogs, broadcasts, and talk shows. It is available at catalog.ldc.upenn.edu/LDC2013T19. GloVe is an unsupervised learning algorithm where training is done on global word-word co-occurrence statistics from a corpus (Pennington et al., 2014). Common Crawl is an open repository of web crawl data, available at www.commoncrawl.org.

and bottom 1% of topic titles. Among the top 1% of topics by non-specificity are "Wearable Device to Characterize Chemical Hazards for Total Exposure Health" and "Extended Weather Measurements in Support of Remotely Piloted Aircraft." Among the bottom 1% (most specific) are "Landing Gear Fatigue Model K Modification" and "Mitigation of Scintillation and Speckle for Tracking Moving Targets." This gives us confidence that the non-specificity measure indeed reflects topic specificity.

E Additional Tables and Figures

Figure E.1: Histogram of Normalized Total Score in Analysis Sample

Note: This figure shows the distribution of each proposal's total score relative to the topic mean, so a value of 2 means twice the topic mean, etc. This is on our analysis sample (2017-2019).

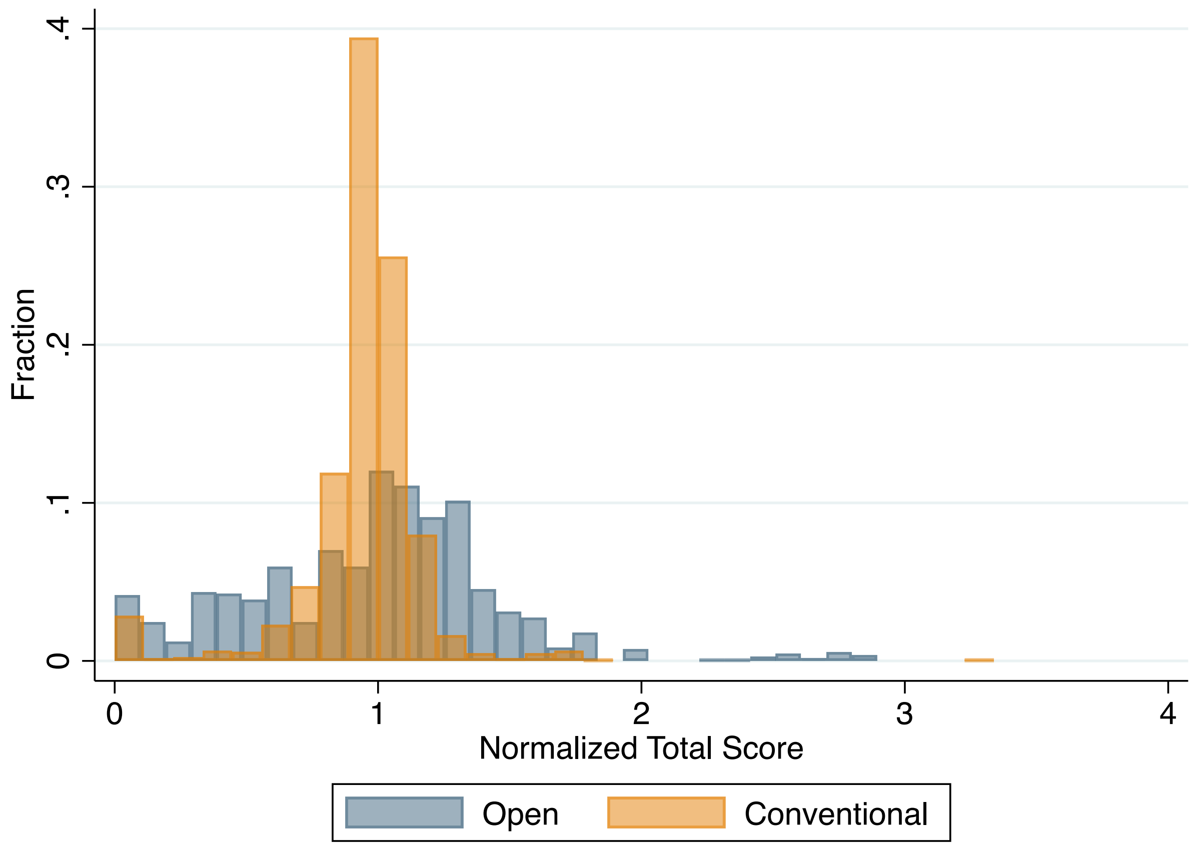
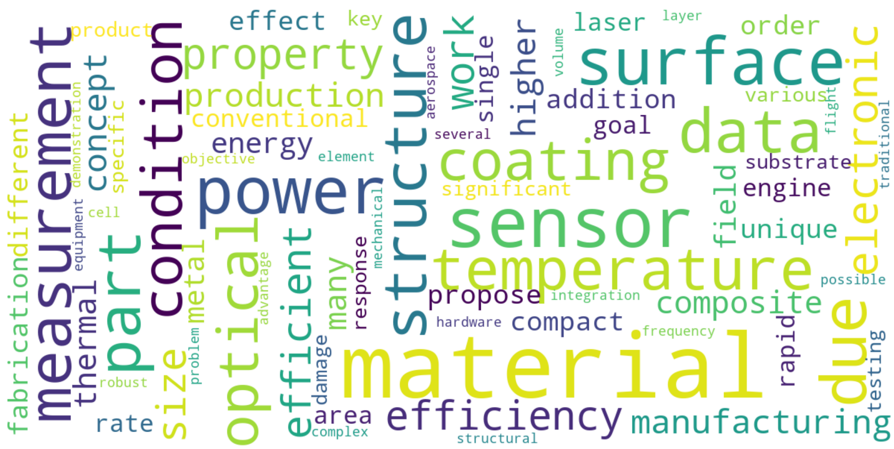


Figure E.2: Keywords for K-means 2 Cluster Model Scaled by Importance to Topic

Note: These figures show the keywords that are identified as a topic cluster by the k-means cluster algorithm, where the algorithm has been assigned to find two clusters. The word's size reflects its prevalence in the topic.

(a) Hardware

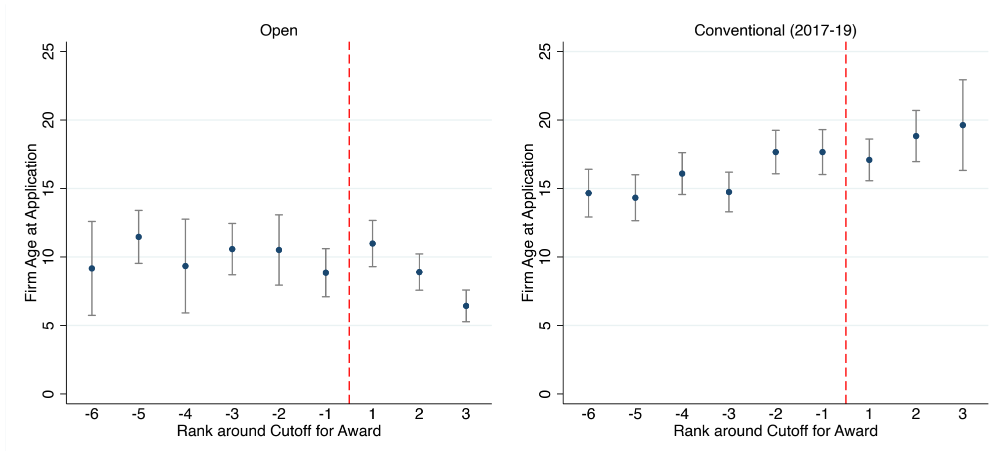


(b) Training/Software

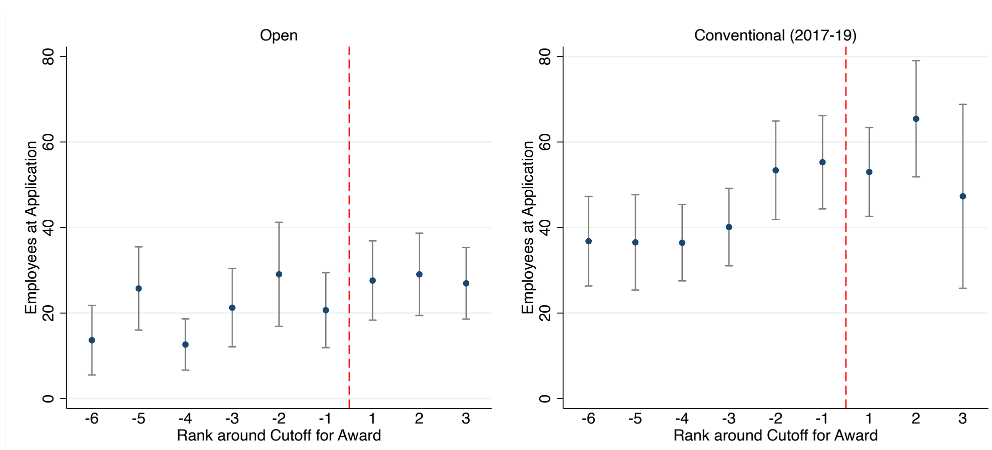
Figure E.3: Continuity of Baseline Characteristics by Rank around Cutoff (Part 1 of 4)

Note: These figures show applicant firm age (top figures), employment (middle figures), and the k-means 2 cluster abstract classification which yields a software and a hardware group (bottom figures) at the time of the application. In all cases, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. The grey capped lines represent 95% confidence intervals.

(a) Firm Age at Application



(b) Firm Employment at Application



(c) Software vs. Hardware Technology

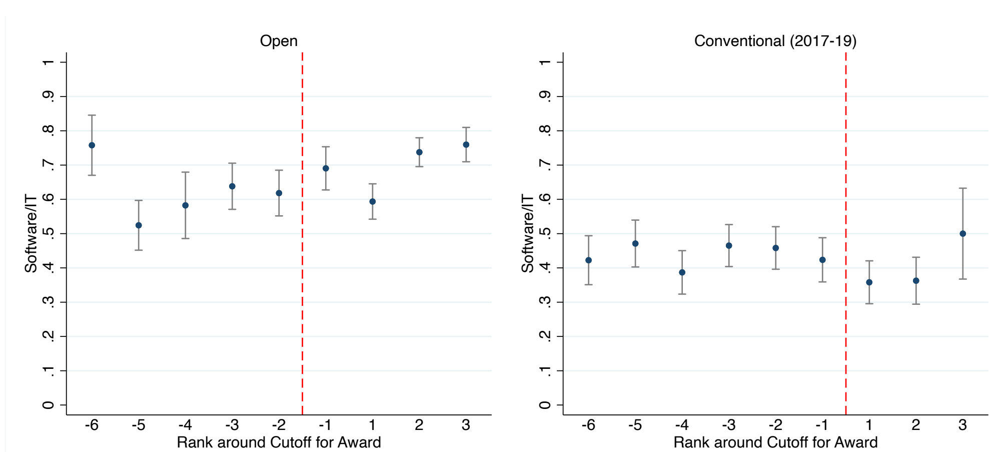
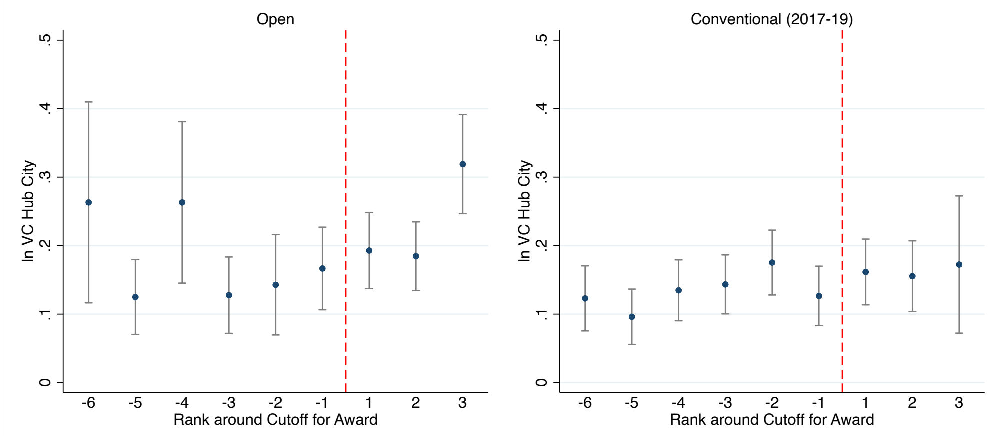


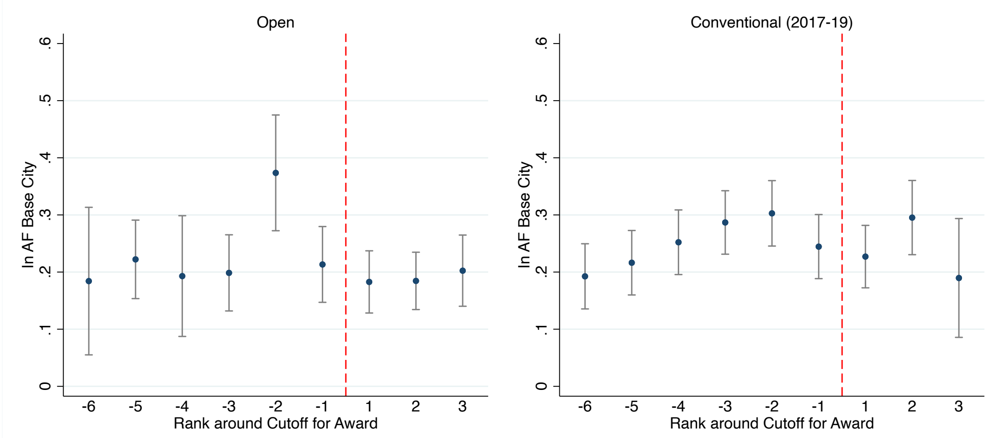
Figure E.4: Continuity of Baseline Characteristics by Rank around Cutoff (Part 2 of 4)

Note: These figures show the probability that an applicant firm is located in either San Francisco/San Jose, Boston, or New York City (top figures), located in a county with a U.S. Air Force base (middle figures), and woman-owned (bottom figures) at the time of the application. In all cases, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. The grey capped lines represent 95% confidence intervals.

(a) Probability Firm Located in VC Hub City



(b) Probability Firm Located in a County with an Air Force Base



(c) Probability Firm Woman-Owned at Application

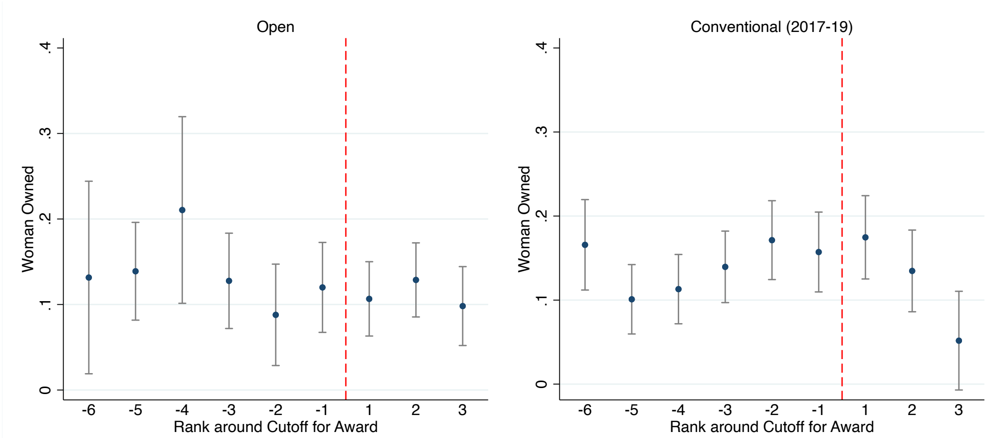
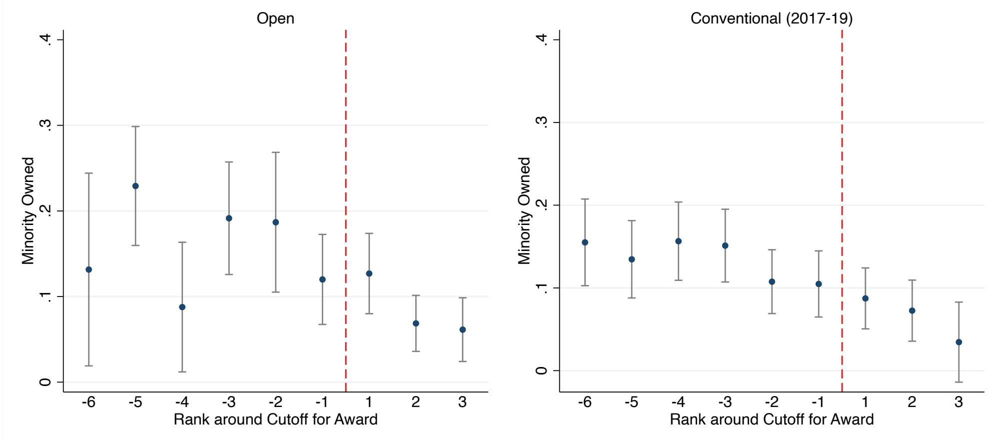


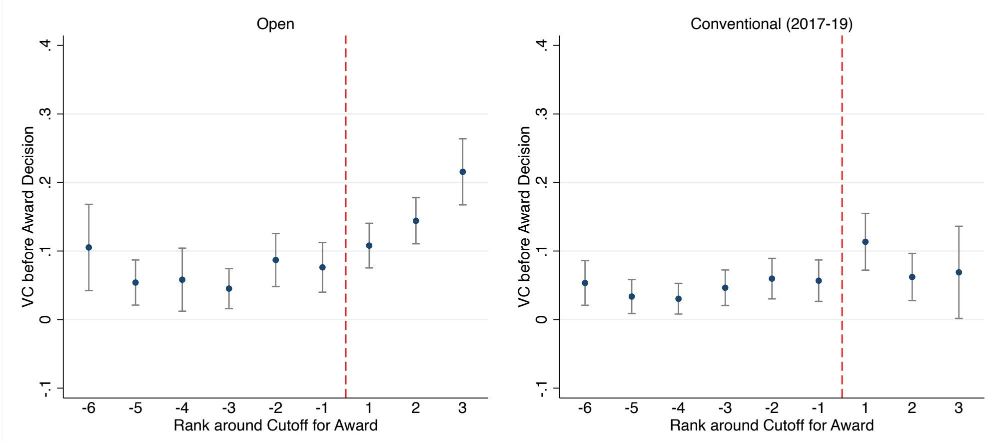
Figure E.5: Continuity of Baseline Characteristics by Rank around Cutoff (Part 3 of 4)

Note: These figures show the probability that an applicant firm is minority-owned (top figures), raised venture capital investment (VC, middle figures), and had any patents at the time of the application (bottom figures) at the time of application. In all cases, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. The grey capped lines represent 95% confidence intervals.

(a) Probability Firm Minority-Owned at Application



(b) Probability of Venture Capital Before Award Decision



(c) Probability of Patent Before Award Decision

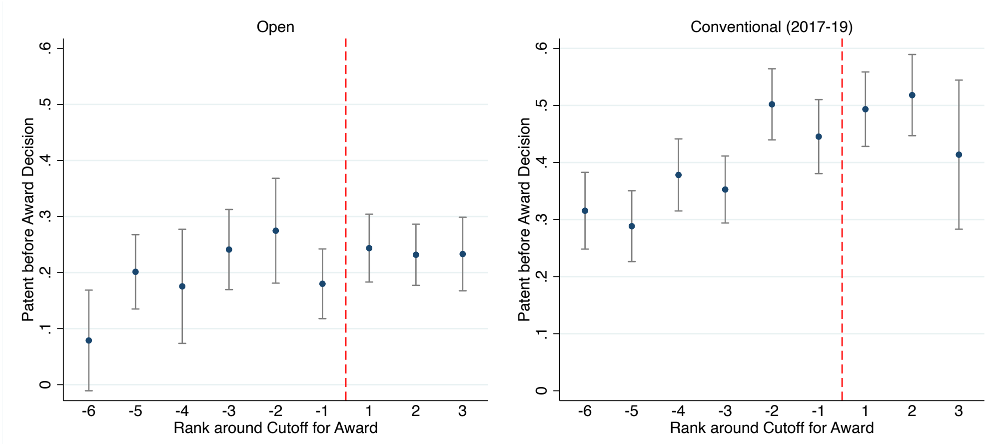
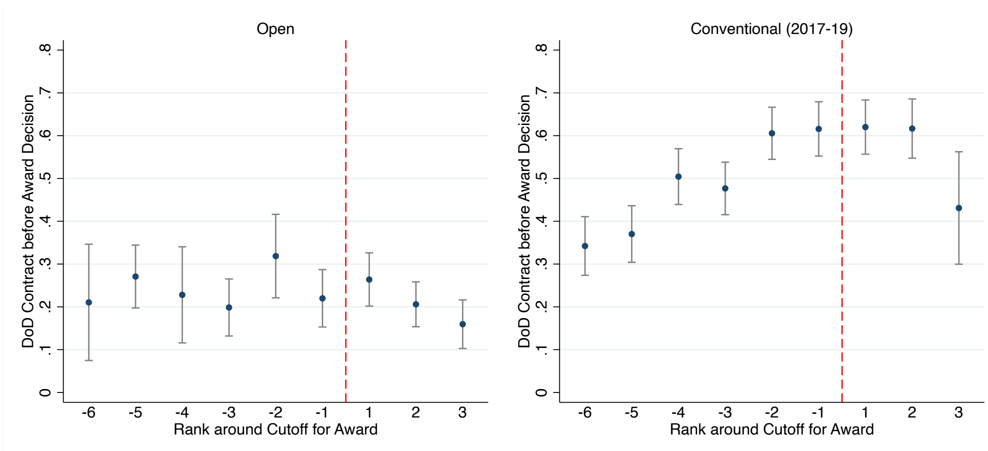


Figure E.6: Continuity of Baseline Characteristics by Rank around Cutoff (Part 4 of 4)

Note: These figures show the probability that an applicant firm had any SBIR contracts after the award decision (top figures) and had any non-SBIR DoD contracts valued at more than $50,000 at the time of the application (bottom figures). A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. The grey capped lines represent 95% confidence intervals.

(a) Probability of DoD Non-SBIR Contract Before Award Decision



(b) Probability of SBIR Before Award Decision

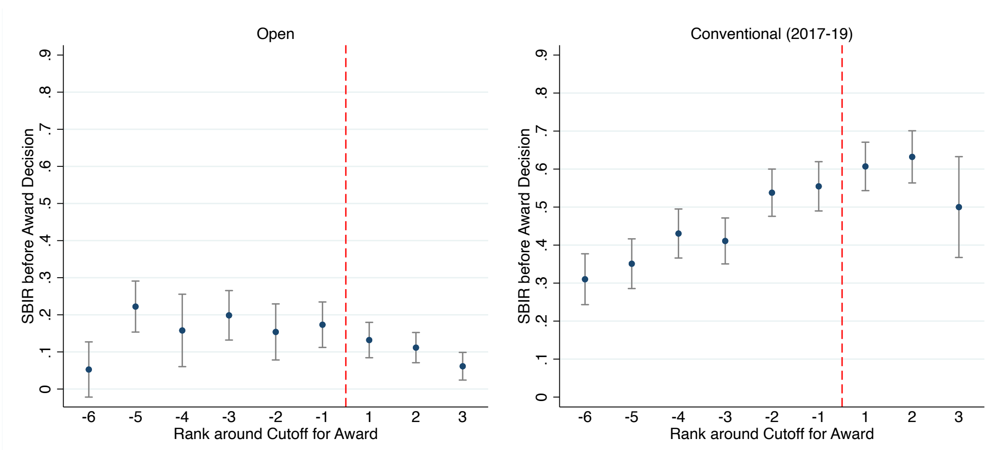
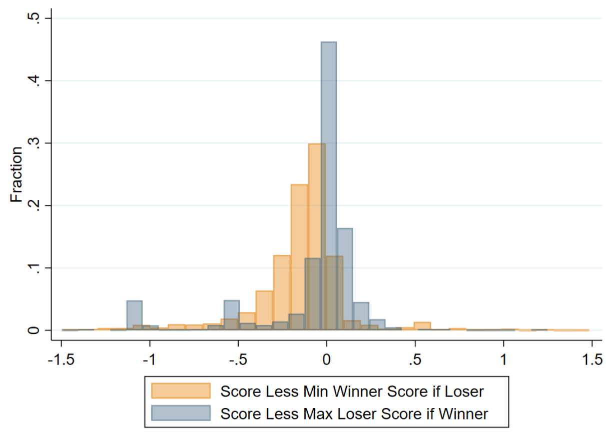


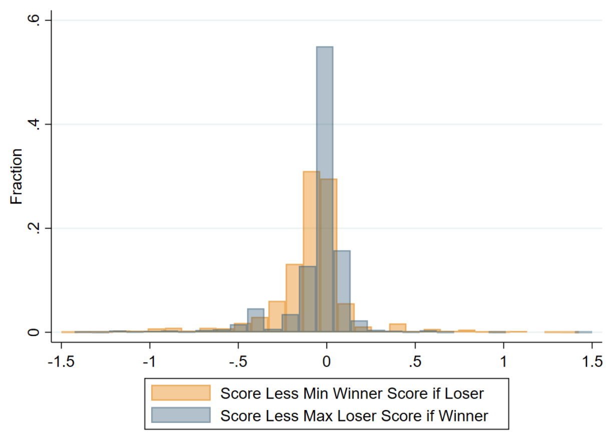
Figure E.7: Prevalence of Crossover Sub-scores

Note: These histograms demonstrate the substantial variation in the three sub-scores (tech, team, commercialization) around the cutoff. The red bars to the right side of zero show that many unsuccessful applicants (losers) have a sub-score that exceeds the lowest sub-score among winners. Similarly, the blue bars to the left side of zero show that many winners have sub-scores that are lower than the highest loser sub-score. Altogether, 81% of applicants have at least one sub-score that is a "crossover." All topics 2017-19 are included.

(a) Tech Score



(b) Team Score



(c) Commercialization Score

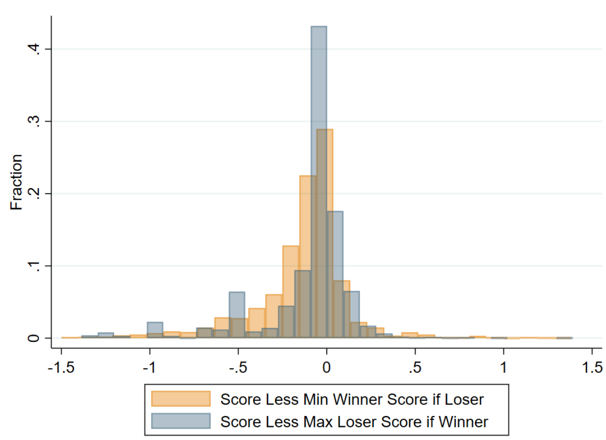
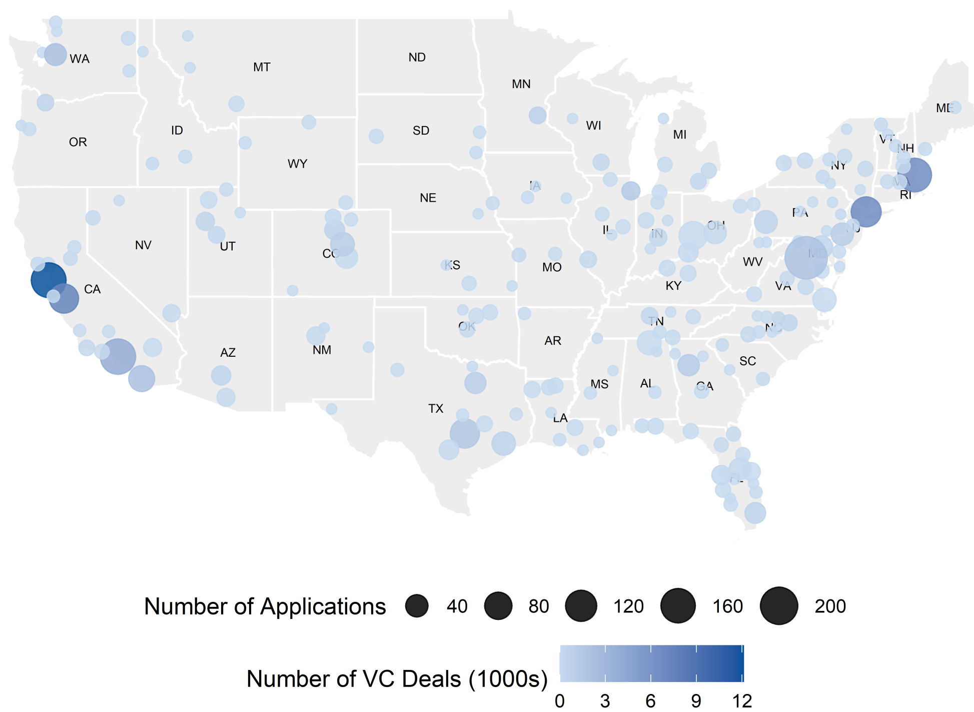


Figure E.8: Geographic Dispersion of Applications (2017-19)

Note: These maps show the number of applications to open (Panel A) and conventional SBIR topics (Panel B) by MSA from 2017 to 2019. The size of the bubble represents the relative number of applications. The color gradient in both maps also show VC activity by MSA.

(a) Open Topic Applications and VC Deals



(b) Conventional Topic Applications and VC Deals

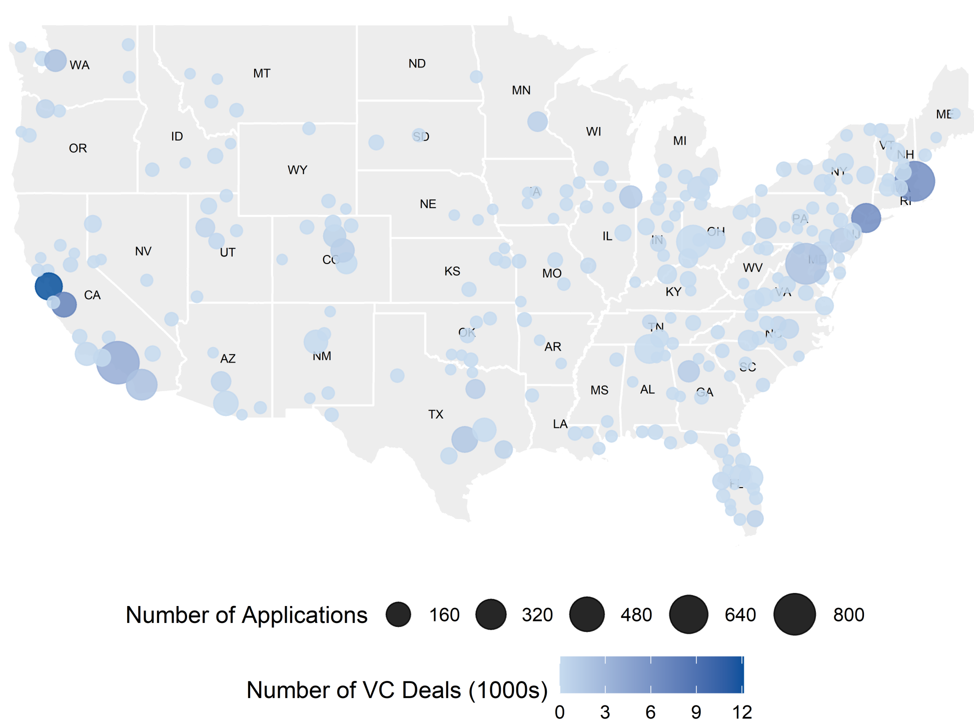
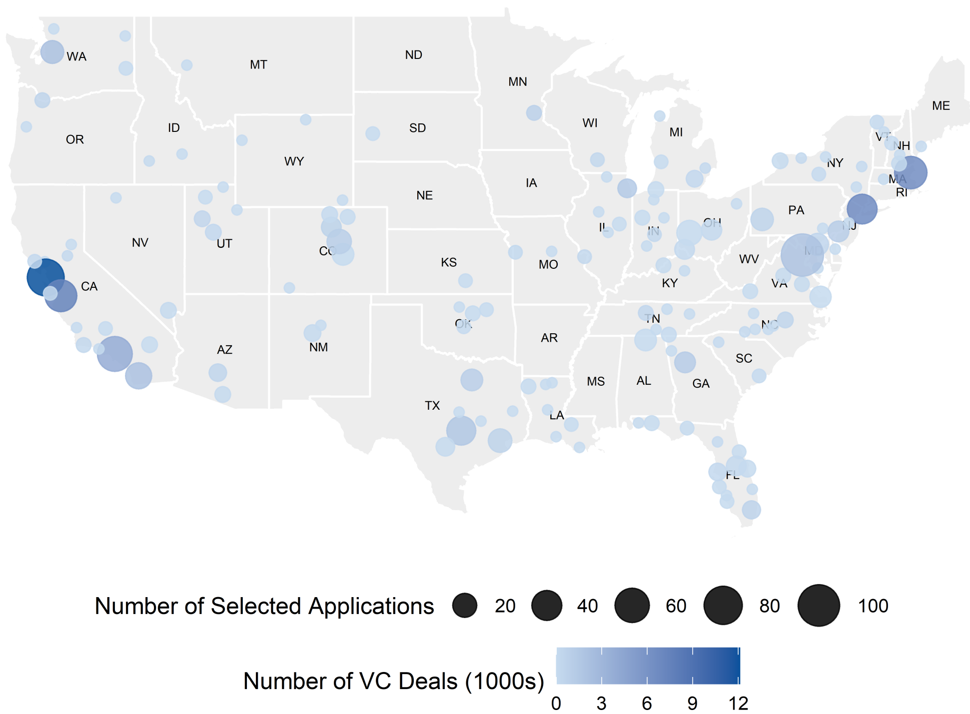


Figure E.9: Geographic Dispersion of Awards (2017-19)

Note: These maps show the number of awards (i.e. contracts) for open (Panel A) and conventional SBIR topics (Panel B) by MSA from 2017 to 2019. The size of the bubble represents the relative number of applications. The color gradient in both maps also show VC activity by MSA.

(a) Open Topic Awards and VC Deals



(b) Conventional Topic Awards and VC Deals

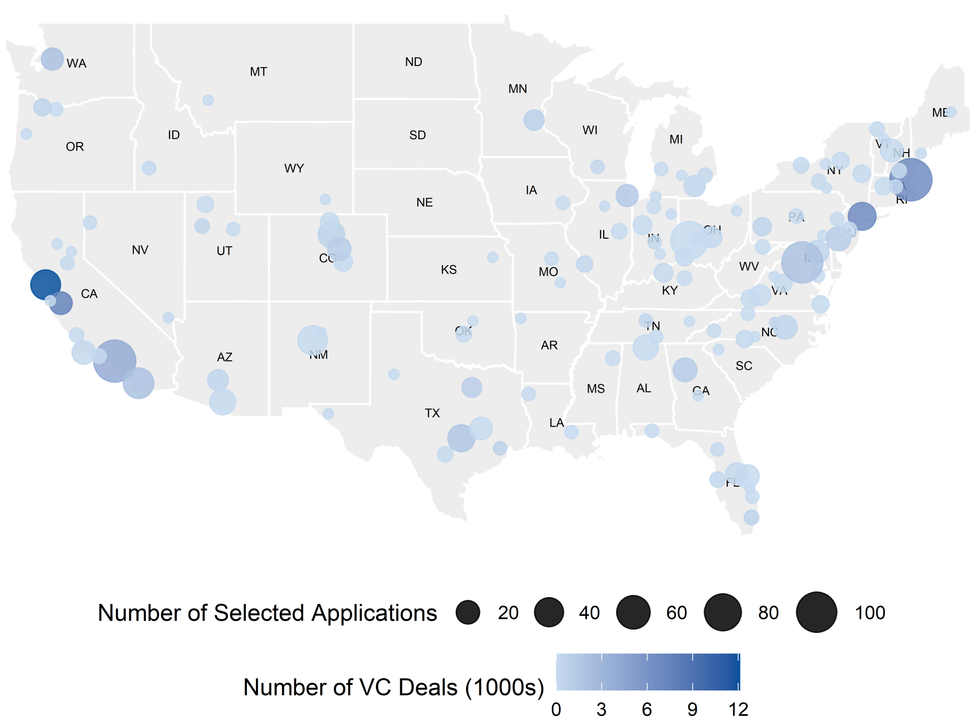


Figure E.10: Lock-in for Open and Conventional over Three-Year Window

Note: This figure contains a histogram of the number of Open and Conventional applicants in categories defined by the number of Air Force SBIR awards in the past three years. For the Open applicants, we use 2020 data so that we have three years in which to look back for lock-in. For Conventional, we use 2019 data and also look back for three years. We do not observe Conventional application data in 2020, and this approach also aligns the sample with that of our main analysis (2017-19, where 2017 only contains Conventional applicants).

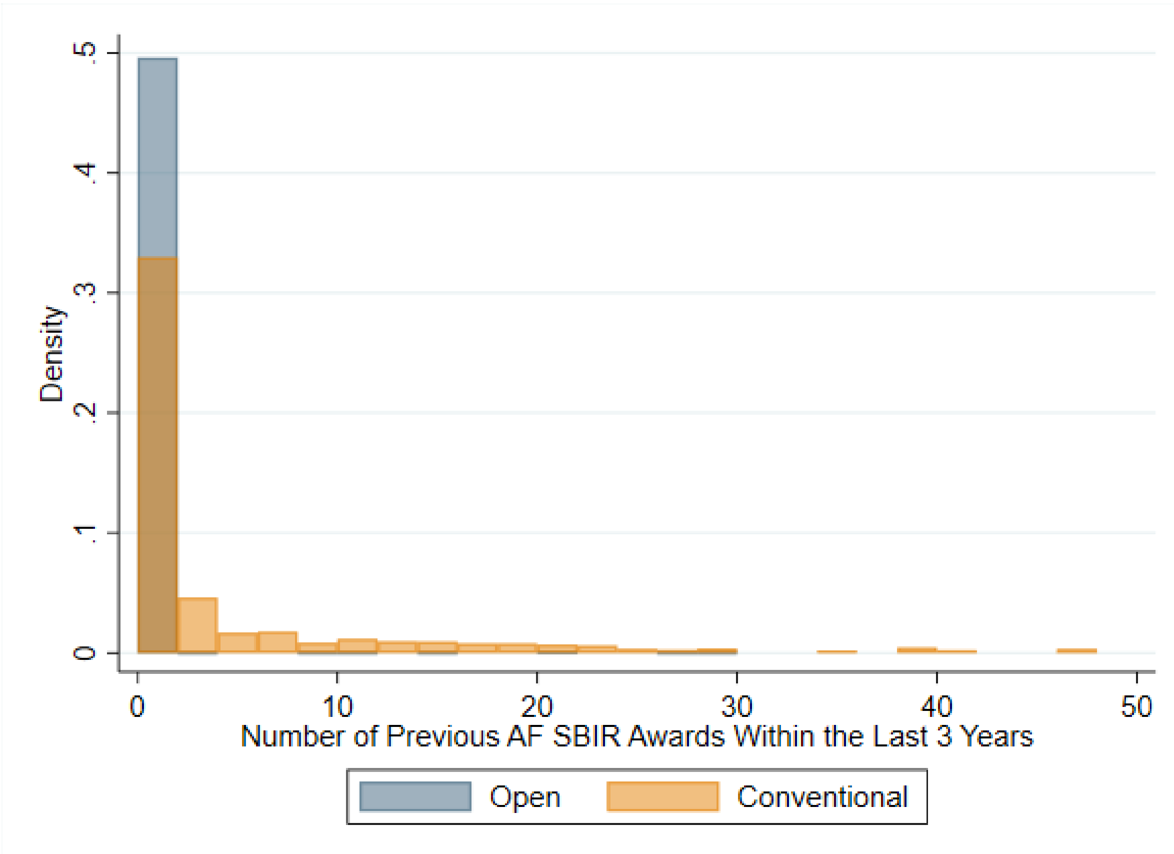
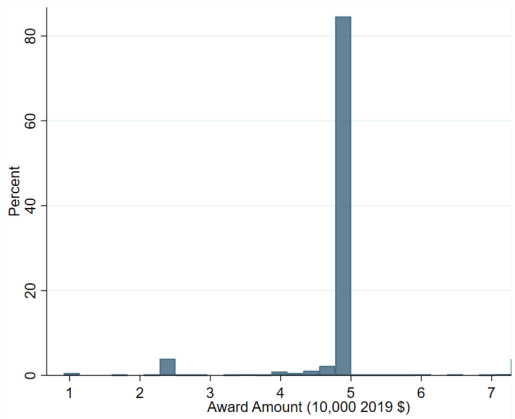


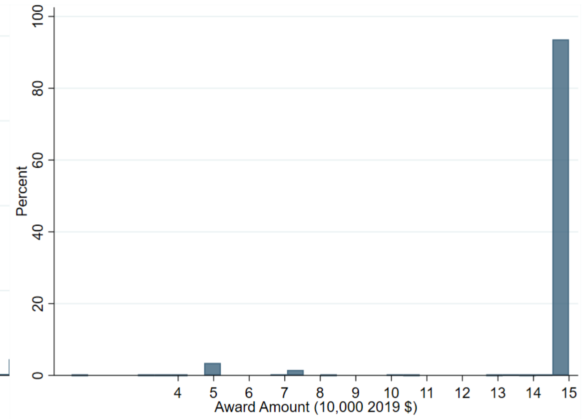
Figure E.11: Histograms of Award Amounts by Topic Type and Phase

Note: These histograms show the share of awards by amount, in real 2019 dollars. For the bottom right graph (Phase 2 <2017), we omit one outlier $12 mill contract.

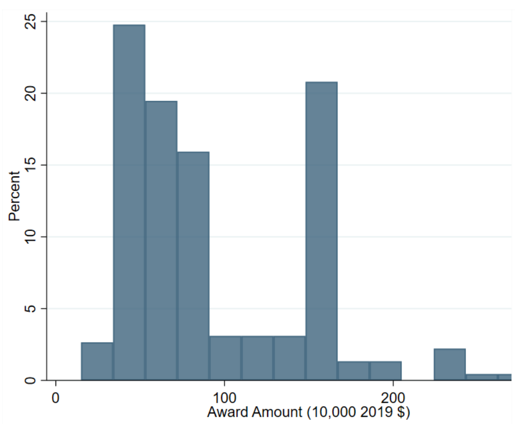
(a) Open Phase 1



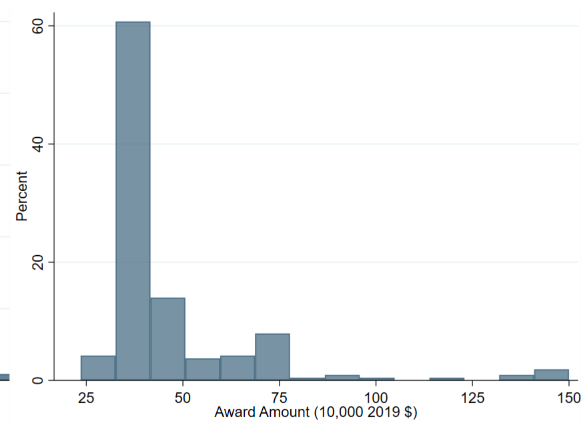
(b) Conv Phase 1 2017-19



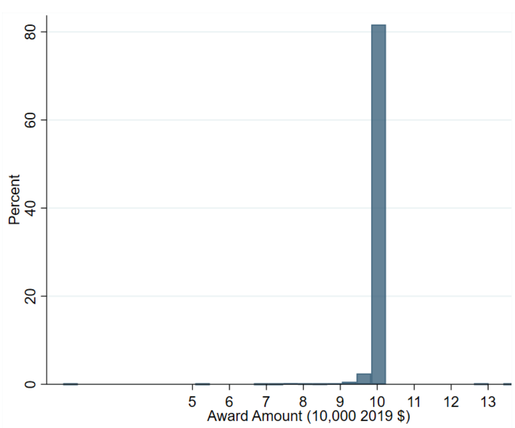
(c) Open Phase 2



(d) Conv Phase 2 2017-19



(e) Conv Phase 1 < 2017



(f) Conv Phase 2 < 2017

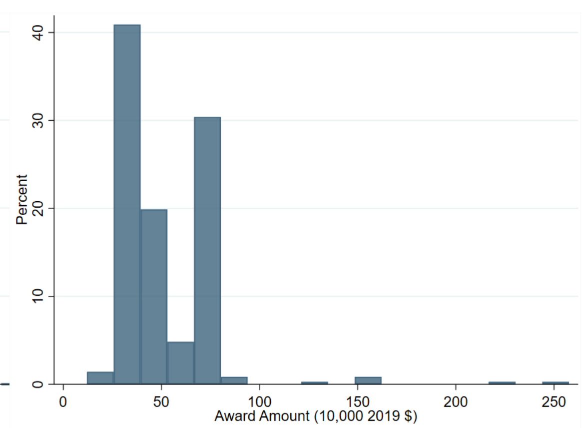
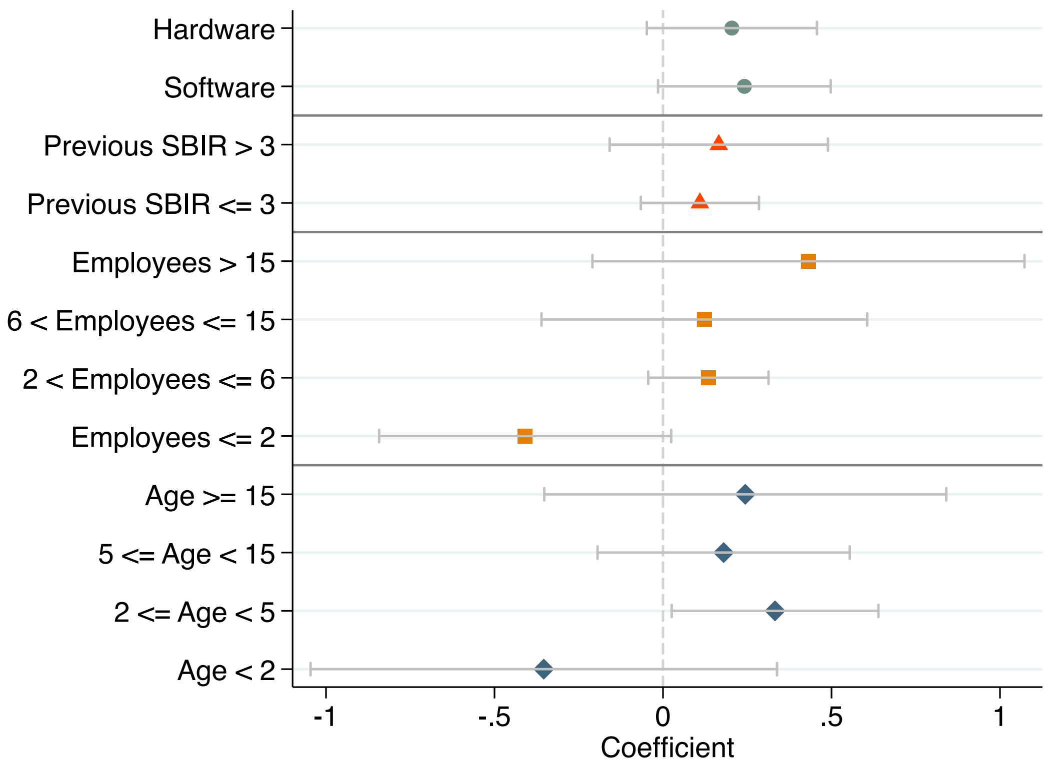


Figure E.12: Relative Effect of Open within Narrow Subsamples by Firm Characteristic

(a) Any DoD Contract



(b) Any VC

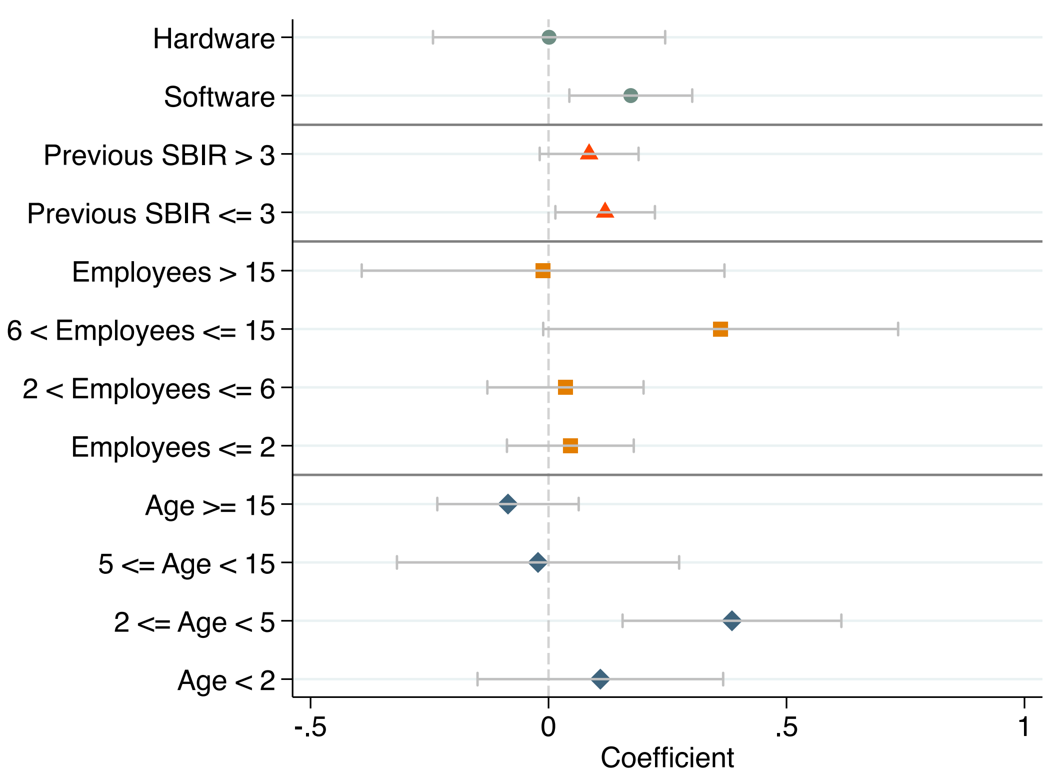
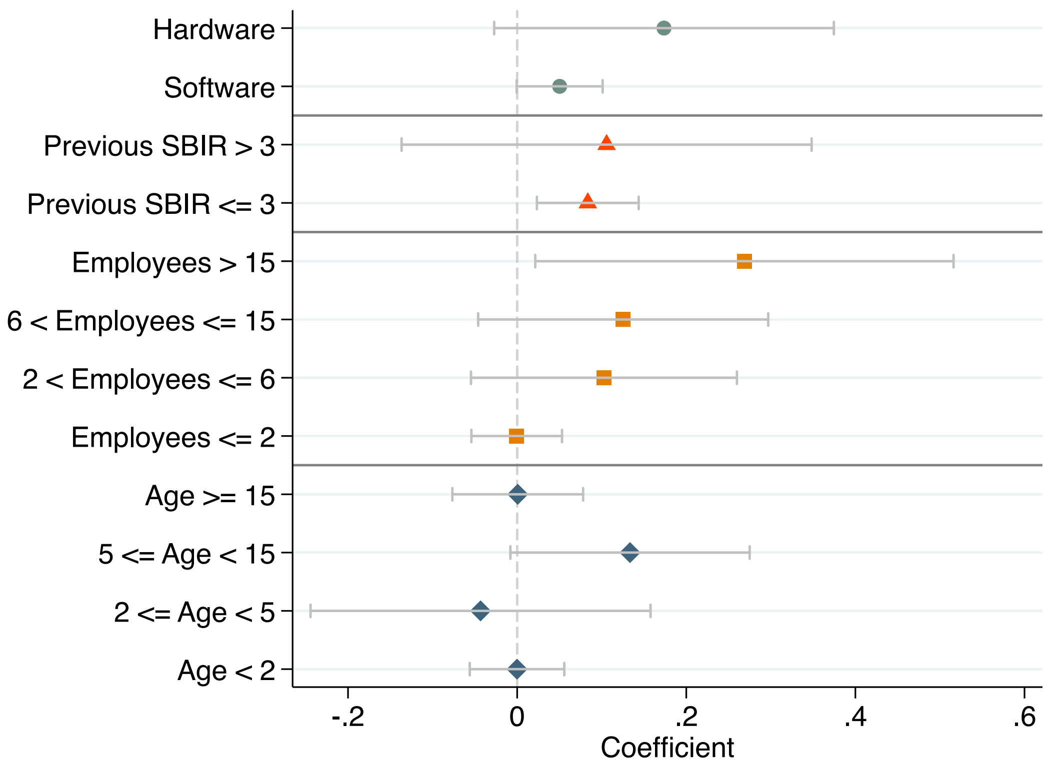


Figure E.13: Relative Effect of Open within Narrow Subsamples by Firm Characteristic

(a) Any High Originality Patent



(b) Any Patent

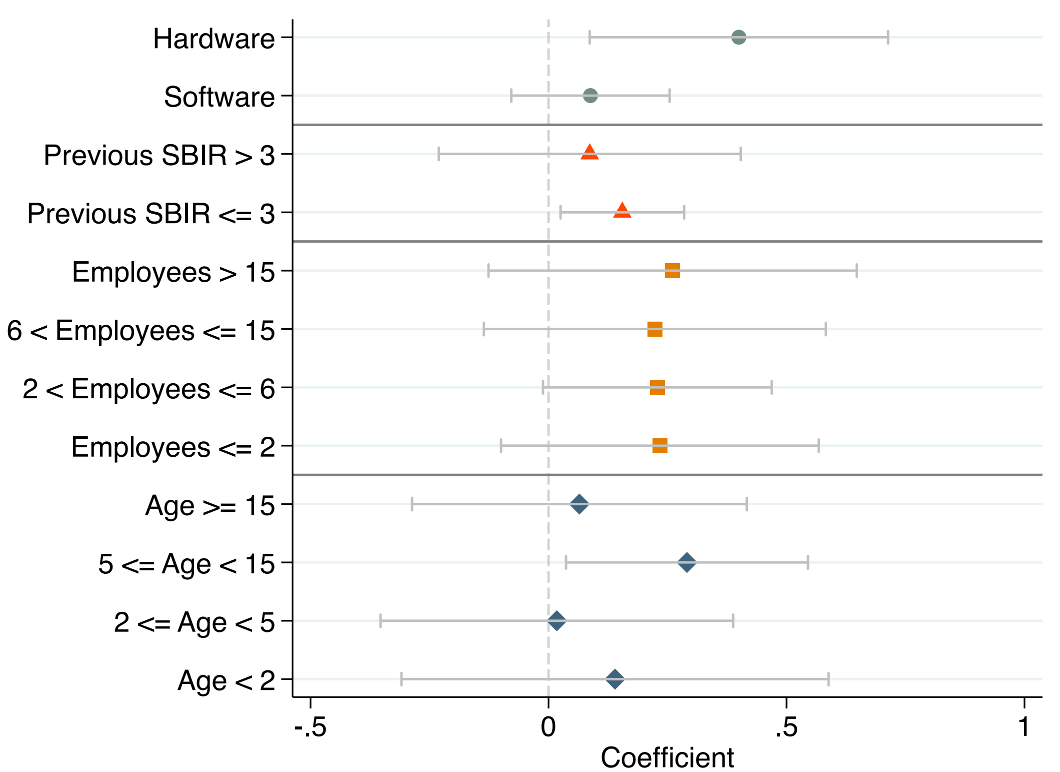


Table E.1: Use of Open Topic Awards in the SBIR Program by Agency, FY 2019-21

Note: This table shows statistics on SBIR awards by U.S. agency, from GAO (2023).

	Number of Awards			Dollars Awarded		
Agency	Open	All	Percentage	Open	All	Percentage
National Science Foundation	1,481	1,481	100%	\$575,669,487	\$575,669,487	100%
Dept. of Agriculture	327	327	100%	\$80,154,963	\$80,154,963	100%
Dept. of Education	72	76	95%	\$32,617,869	\$34,881,003	94%
Dept. of Health and Human Services	3,121	4,378	71%	\$2,197,971,958	\$3,236,558,049	68%
Dept. of Commerce	75	178	42%	\$14,977,936	\$44,704,049	34%
Dept. of Defense	3,329	10,705	31%	\$1,143,431,049	\$5,065,679,798	23%
Dept. of Energy	156	1,939	8%	\$55,220,007	\$962,360,023	6%
Dept. of Homeland Security	0	128	0%	\$0	\$56,533,211	0%
Dept. of Transportation	0	97	0%	\$0	\$35,190,146	0%
Environmental Protection Agency	0	98	0%	\$0	\$16,805,499	0%
National Aeronautics and Space Administration	0	1.631	0%	\$0	\$566,294,601	0%
Total	**8,561**	**21,038**	**41%**	**\$4,100,043,269**	**\$10,674,830,829**	**38%**

Table E.2: Proposal and Firm Counts

Note: This table shows the counts of topics, proposals (i.e. applications), and unique firms that applied for the Open and Conventional programs in 2017-19 (Panel A) and 2003-19 (Panel B) in our analysis sample.

Panel A: Open & Conventional (2017-19)			
	Both	Open Topic	Conventional
Number of Topics:			
Phase I	334	6	328
Number of Proposals:			
Phase I	2283	1056	1227
Number of Firms:			
Applied to Type	1938	1040	1443
Exclusively Applied to Type	545	495	898

Panel B: Full Sample (2003-19)			
	Both	Open Topic	Conventional
Number of Topics:			
Phase I	1778	6	1772
Number of Proposals:			
Phase I	21365	1648	19717
Number of Firms:			
Applied to Type	6701	1361	6174
Exclusively Applied to Type	834	527	5340

Table E.3: Summary for Continuous Measures of Main Outcomes

Note: This table describes company and outcome characteristics at the applicant level, using all proposals in our main estimation sample, where a firm may only appear once). The left columns contain the applicants to Conventional topics, while the right columns contain the applicants to Open topics. See Section 3 for details on each variable. We also present the difference of means. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Conventional			Open			
	N	Mean	SD	N	Mean	SD	Diff of Means
Pre-award Outcomes							
Previous DoD Contract	1,227	2.588	23.073	1,056	1.321	18.414	-1.267
Previous VC	1,227	0.023	0.149	1,056	0.097	0.296	0.074***
Previous Patent	1,227	0.568	3.089	1,056	0.800	4.999	0.232
Previous High Originality Patent	1,227	0.266	1.693	1,056	0.344	2.741	0.078
Previous High Citation Patent	1,227	0.218	1.484	1,056	0.230	1.735	0.013
Previous SBIR Contract	1,227	0.000	0.000	1,056	0.000	0.000	0.000

Table E.4: Summary Statistics on Firms Applying to Both Open and Conventional

	N	Mean	SD
Company Characteristics			
Age	507	16.473	12.384
Number of Employees	507	46.420	86.266
$\mathbb{1}$(in VC Hub)	507	0.164	0.370
$\mathbb{1}$(in County with AF Base)	507	0.250	0.434
$\mathbb{1}$(Immigrant)	507	0.057	0.228
$\mathbb{1}$(Minority Owned)	507	0.142	0.349
$\mathbb{1}$(Woman owned)	507	0.124	0.330
Pre-award Outcomes			
$\mathbb{1}$(Previous DoD Contract)	507	0.574	0.495
$\mathbb{1}$(Previous VC)	507	0.069	0.254
$\mathbb{1}$(Previous Patent)	507	0.420	0.494
$\mathbb{1}$(Previous High Originality Patent)	507	0.316	0.465
$\mathbb{1}$(Previous High Citation Patent)	507	0.323	0.468
$\mathbb{1}$(Previous SBIR Contract)	507	0.586	0.493

Table E.5: Effect of a Conventional Topic among Firms that Applied to Conventional and Open

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Conventional Phase 1 award after restricting the sample to firms that applied to Conventional at least once before 2018 and then applied to Open subsequently. The table includes only Conventional competitions. This isolates the effect of Conventional among a sample of firms that selected into both Open and Conventional. We employ the five firm-level outcomes from Table 2. The coefficient on Award represents the effect of winning in an Conventional topic within this subsample. In Panel B, we include controls for firm age and employment at the application date, as well as a vector of 25 narrow technology fixed effects. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline Specification					
	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}(\geq 2$ SBIR)
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.284	-0.020	-0.219	-0.017	-0.060
	(0.224)	(0.075)	(0.253)	(0.162)	(0.176)
Observations	636	636	636	636	636
Controls	No	No	No	No	No
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.471	0.059	0.225	0.081	0.381
Panel B: Controls with Technology Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.258	-0.019	-0.326	-0.086	-0.097
	(0.237)	(0.093)	(0.314)	(0.174)	(0.197)
Observations	636	636	636	636	636
Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	First	First	First	First	First
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.471	0.059	0.225	0.081	0.381

Table E.6: Effect among Firms that Applied to Conventional and Open (Pooled Model)

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Conventional Phase 1 award after restricting the sample to firms that applied to Conventional at least once before 2018 and then applied to Open subsequently. The table includes only Conventional competitions. This isolates the effect of Conventional among a sample of firms that selected into both Open and Conventional. We employ the five firm-level outcomes from Table 2. The coefficient on Award represents the effect of winning in an Conventional topic within this subsample. In Panel B, we include controls for firm age and employment at the application date, as well as a vector of 25 narrow technology fixed effects. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline Specification					
	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}(\geq 2$ SBIR)
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.255	-0.026	-0.230	-0.048	-0.044
	(0.155)	(0.051)	(0.168)	(0.103)	(0.116)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.423**	0.090	0.350*	0.142	0.068
	(0.183)	(0.072)	(0.186)	(0.114)	(0.140)
Observations	1143	1143	1143	1143	1143
Controls	No	No	No	No	No
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.471	0.059	0.225	0.081	0.381
Panel B: Controls with Technology Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.278	-0.047	-0.244	-0.066	-0.045
	(0.171)	(0.066)	(0.175)	(0.108)	(0.120)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.438**	0.110	0.362*	0.171	0.073
	(0.199)	(0.081)	(0.195)	(0.121)	(0.147)
Observations	1143	1143	1143	1143	1143
Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	First	First	First	First	First
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.471	0.059	0.225	0.081	0.381

Table E.7: Formal Test for Continuity of Baseline Covariates

Note: This table shows the t-test results on the marginal winners and losers (Rank = -1 or 1).

	Open (N= 422)			Conventional (N= 960)		
	Rank = -1	Rank = 1		Rank = -1	Rank = 1	
	Mean	Mean	p	Mean	Mean	p
Age	9.571	10.714	0.320	20.196	19.603	0.463
Employees	21.367	29.909	0.169	76.663	77.592	0.882
Firm in VC Hub City	0.172	0.202	0.434	0.168	0.168	0.999
Firm in AF Base County	0.200	0.202	0.950	0.294	0.270	0.393
Woman-owned	0.117	0.095	0.473	0.143	0.176	0.166
Minority-owned	0.117	0.116	0.976	0.092	0.093	0.949
Software	0.298	0.271	0.547	0.586	0.591	0.874
Any Pre-Appplication Patent	0.206	0.252	0.264	0.552	0.590	0.234
Any Pre-Appplication VC	0.067	0.095	0.297	0.059	0.100	0.020
Any Pre-Appplication Non-SBIR Contract	0.239	0.277	0.381	0.734	0.705	0.313
Any Pre-Appplication SBIR Contract	0.211	0.194	0.670	0.695	0.726	0.293

Table E.8: Effect of Open vs. Conventional Among the Highest-Quality Applicants

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award. Rank within the topic (competition) is controlled separately as a linear function on either side of the cutoff. In all cases, we control for previous Air Force SBIR awards. Columns (1), (3), (5), and (7) restrict the sample to the firm's first application within the sample time period while columns (2), (4), (6), (8) include all proposals over the sample time period. We interact winning an award with an indicator that is equal to one if the proposal is in an Open topic (and zero otherwise) and an indicator that is equal to one if the proposal is in the top 15 percentiles of scores among winners within topic (and zero otherwise). All columns include topic fixed effects. Standard errors (in parentheses) are below coefficients and are clustered by firm. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Any DoD Contract		Any VC		Any Patent		Any High-Originality Patent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	-0.075	-0.017	0.003	0.004	-0.096	-0.016	-0.020	-0.026*
	(0.084)	(0.015)	(0.040)	(0.004)	(0.060)	(0.014)	(0.022)	(0.013)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open)	0.189*	0.116**	0.116**	0.109***	0.184**	0.127***	0.089***	0.104***
	(0.098)	(0.045)	(0.057)	(0.028)	(0.076)	(0.038)	(0.031)	(0.024)
$\mathbb{1}$(High Rank)	0.073	0.018	0.060	0.001	-0.052	-0.039	-0.033	-0.038
	(0.183)	(0.044)	(0.123)	(0.014)	(0.162)	(0.043)	(0.053)	(0.035)
$\mathbb{1}$(Open) × $\mathbb{1}$(High Rank)	-0.059	-0.039	-0.031	0.022	0.046	0.022	0.023	0.031
	(0.194)	(0.072)	(0.143)	(0.057)	(0.172)	(0.067)	(0.062)	(0.051)
Observations	2283	21365	2283	21365	2283	21365	2283	21365
Proposal	First	All	First	All	First	All	First	All
Time Period	2017-19	2003-19	2017-19	2003-19	2017-19	2003-19	2017-19	2003-19
Outcome Mean	0.166	0.479	0.092	0.024	0.112	0.316	0.036	0.217

Table E.9: Intensive Margin Outcomes

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on five firm-level outcomes: the total value of non-SBIR DoD contracts (column 1), total value of VC investment (column 2), number of patents (column 3), number of patents with above-median originality (column 4), and the total value of future SBIR contracts (column 5). All outcomes are measured as any time after the award decision, through January 2023, and are defined as $\log(1+x)$. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. In Panel B, we include controls for firm age and employment at the application date, as well as a vector of 25 narrow technology fixed effects. Panel C includes all proposals from all years. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline Specification					
	DoD Amount	VC Amount	Num Patent	Num High Orig Pat	SBIR Amount
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-1.378	-0.270	-0.069	-0.007	0.817***
	(1.152)	(0.261)	(0.063)	(0.026)	(0.255)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	2.938**	1.079***	0.194**	0.089**	-0.519*
	(1.374)	(0.413)	(0.093)	(0.042)	(0.281)
Observations	2283	2283	2283	2283	2283
Lifecycle Controls	No	No	No	No	No
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	2.626	0.664	0.117	0.036	0.265

Panel B: Controls and Technology Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-1.366	-0.258	-0.064	-0.014	0.866***
	(1.103)	(0.293)	(0.066)	(0.030)	(0.249)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	2.628**	0.984**	0.165*	0.089**	-0.546**
	(1.331)	(0.451)	(0.094)	(0.043)	(0.273)
Observations	2283	2283	2283	2283	2283
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	2.626	0.664	0.117	0.036	0.265

Panel C: All Proposals					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.271	0.027	-0.055**	-0.051***	0.184***
	(0.186)	(0.033)	(0.025)	(0.020)	(0.059)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	1.174*	0.678***	0.187***	0.110***	-0.139
	(0.635)	(0.218)	(0.057)	(0.032)	(0.169)
Observations	21365	21365	21365	21365	21365
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	All	All	All	All	All
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	7.451	0.179	0.480	0.279	2.144

Table E.10: Effect on Acquisitions

Note: This table shows the effect of winning in Open and Conventional on two supplementary outcomes: the probability that the firm is acquired (Panel A) and the log of one plus the acquisition amount (Panel B). Standard errors are clustered by firm. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Any Acquisition			Log Acquisition Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Award)	-0.016	-0.016	0.002	-0.069	-0.096	-0.018
	(0.012)	(0.013)	(0.007)	(0.093)	(0.093)	(0.026)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.023	0.020	0.010	0.146	0.145	0.201**
	(0.019)	(0.019)	(0.014)	(0.177)	(0.174)	(0.102)
Observations	2283	2283	21365	2283	2283	21365
Lifecycle Controls	No	Yes	Yes	No	Yes	Yes
Narrow Tech FE	No	Yes	Yes	No	Yes	Yes
Proposal	First	First	All	First	First	All
Time Period	2017-19	2017-19	2003-19	2017-19	2017-19	2003-19
Outcome Mean	0.018	0.018	0.040	0.083	0.083	0.082

Table E.11: Flexible Controls for Age and Employment

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on five firm-level outcomes: technology adoption measured by any non-SBIR DoD contract valued at more than $50,000 (column 1), any VC investment (column 2), any patent (column 3), any patent with above-median originality (column 4), and having at least two SBIR awards (column 5). All outcomes are measured as any time after the award decision, through January 2023. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. Panel A controls for a quadratic function of age and employment at the application date, as well as technology type (hardware vs. software). In Panel B, we indicators for above median firm age and employment at the application date, as well as technology type (hardware vs. software). Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Quadratic Age and Employment Controls					
	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}(\geq 2$ SBIR)
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.085	-0.004	-0.081	-0.011	0.094*
	(0.079)	(0.045)	(0.051)	(0.018)	(0.050)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	0.193**	0.124**	0.165**	0.077***	-0.102*
	(0.094)	(0.060)	(0.069)	(0.028)	(0.052)
Observations	2283	2283	2283	2283	2283
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.166	0.092	0.112	0.036	0.031
Panel B: Above Median Age and Employment					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.092	-0.015	-0.089*	-0.014	0.092*
	(0.075)	(0.046)	(0.052)	(0.019)	(0.050)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	0.177**	0.131**	0.170**	0.079***	-0.098*
	(0.090)	(0.061)	(0.070)	(0.028)	(0.052)
Observations	2283	2283	2283	2283	2283
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.166	0.092	0.112	0.036	0.031

Table E.12: Alternative Analysis Sample

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on five firm-level outcomes: technology adoption measured by any non-SBIR DoD contract valued at more than $50,000 (column 1), any VC investment (column 2), any patent (column 3), any patent with above-median originality (column 4), and having at least two SBIR awards (column 5). All outcomes are measured as any time after the award decision, through January 2023. The sample here departs from the main analysis sample in Table 2. Here, we restrict to firms who have not won a SBIR award in the five years prior to application, instead of the whole pre-application period. We also restrict to a firm's first application across both Open and Conventional topics. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. Panel B adds controls for the number of employees, firm age, and whether the technology is software or hardware, as well as a vector of 25 narrow technology fixed effects. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline Specification

	$\mathbb{1}$(DoD Contract)	$\mathbb{1}$(VC)	$\mathbb{1}$(Patent)	$\mathbb{1}$(High Orig Pat)	$\mathbb{1}$(> 1 SBIR)
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.085	0.000	-0.117**	-0.047*	0.062
	(0.079)	(0.042)	(0.054)	(0.025)	(0.051)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	0.197**	0.123**	0.213***	0.116***	-0.086
	(0.094)	(0.059)	(0.071)	(0.032)	(0.055)
Observations	2327	2327	2327	2327	2327
Controls	No	No	No	No	No
Narrow Tech FE	No	No	No	No	No
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.172	0.087	0.111	0.039	0.037

Panel B: Controls and Technology Fixed Effects

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.081	0.006	-0.117**	-0.047*	0.065
	(0.076)	(0.044)	(0.055)	(0.027)	(0.048)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	0.181*	0.108*	0.201***	0.111***	-0.088*
	(0.092)	(0.063)	(0.073)	(0.032)	(0.052)
Observations	2327	2327	2327	2327	2327
Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.172	0.087	0.111	0.039	0.037

Table E.13: Main Results, Restricting to Non-Defense Firms

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on five firm-level outcomes: technology adoption measured by any non-SBIR DoD contract valued at more than $50,000 (column 1), any VC investment (column 2), any patent (column 3), any patent with above-median originality (column 4), and having at least two SBIR awards (column 5). The sample is restricted to firms identified in Pitchbook as non-defense oriented. All outcomes are measured as any time after the award decision, through January 2023. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. We include controls for firm age and employment at the application date, as well as a vector of 25 narrow technology fixed effects. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.039	0.011	-0.005	-0.022	0.023
	(0.030)	(0.014)	(0.032)	(0.030)	(0.031)
$\mathbb{1}$(Award) $\times$ $\mathbb{1}$(Open Topic)	0.164**	0.135**	0.144**	0.123**	-0.075
	(0.076)	(0.061)	(0.072)	(0.052)	(0.065)
Observations	6326	6326	6326	6326	6326
Lifecycle Controls	Yes	Yes	Yes	Yes	Yes
Narrow Tech FE	Yes	Yes	Yes	Yes	Yes
Proposal	All	All	All	All	All
Time Period	2003-19	2003-19	2003-19	2003-19	2003-19
Outcome Mean	0.591	0.067	0.450	0.304	0.551

Table E.14: Most Prevalent Words by Narrow Technology Class

Note: This table shows the five most prevalent words in each 25 technology class classified through k-means clustering.

Topic	Word 1	Word 2	Word 3	Word 4	Word 5
0	aircraft	analysis	power	component	sensor
1	material	power	temperature	energy	use
2	software	tool	information	environment	analysis
3	sensor	power	range	device	component
4	material	composite	component	aircraft	program
5	sensor	algorithm	power	requirement	target
6	material	power	program	component	energy
7	power	sensor	optical	device	laser
8	material	aircraft	program	research	component
9	signal	frequency	communication	algorithm	processing
10	material	temperature	composite	property	coating
11	tool	operation	research	military	current
12	optical	signal	array	frequency	power
13	information	tool	mission	operation	environment
14	material	coating	composite	surface	property
15	material	device	power	optical	temperature
16	information	network	software	analysis	tool
17	material	power	sensor	device	technique
18	aircraft	analysis	vehicle	model	research
19	algorithm	sensor	software	image	processing
20	information	tool	environment	user	software
21	material	temperature	surface	property	polymer
22	algorithm	sensor	software	information	network
23	optical	laser	power	wavelength	device
24	tool	training	information	environment	research

F Supplementary Analysis: Phase 2 and Matching

F.1 Analysis of Phase 2

In this Appendix, we consider the effect of Phase 2 awards which, as noted above, are more generously-funded, larger-scale follow-ups to Phase 1 awards (a Phase 1 award is a necessary condition for a Phase 2). We must be cautious, however, in interpreting the results because the main models using data from 2017-19 Phase 1 awards have only a very short time frame for evaluating Phase 2. Furthermore, the sample is quite small, making it impossible to perform an analysis on Open, so we limit ourselves to Conventional Phase 2 competitions. An interesting aspect of Phase 2 is that it enables considering the amount of award, as unlike Phase 1, there is substantial variation in the Phase 2 award amounts (Figure E.11).

Table F.2 show RDD estimates of the effect of winning a Phase 2 award on all four outcomes of interest. We find no effects of the Conventional topic Phase 2 on any outcome, even over the long term (the even columns of each panel), which is consistent with Howell (2017), where Phase 2 grants also have no effects, in part because firms with successful innovation tend to go to the private sector for funding rather than come back to the government for research grants.

If Phase 2 is important for VC but only through a dynamic channel – via its implications for the Phase 1 treatment effect – this would help explain both why the small Phase 1 award is so impactful for Open and why there is no observable Phase 2 effect on VC. The expectation of a Phase 2 award, which averages about $830,000, may help to explain the large Phase 1 treatment effect on VC. VCs may believe that if they invest, the chances of a Phase 2 award are very high. In practice, about half of applicants to Phase 2 win, but this rises to all among Phase 2 applicants that raised VC in the 12 months after the Phase 1 award (12 months is roughly the period between the two phases). VC after Phase 1 may affect the Phase 2 decision firstly because VC is one measure the evaluators use to gauge commercialization, and secondly because the VC can provide support in the Phase 2 process. For these reasons, VCs may be responsive to Phase 1 because they expect it to be associated with substantially more non-dilutive cash. Under this hypothesis, there would be little marginal effect of winning Phase 2 because it has been, in a sense, "priced in" to the Phase 1 effect.

F.2 Role of the Matching Program

In Section 5 we found a large effect of winning an Open topic contract on VC and argued that one reason appears to be the potential of these contracts to serve as a gateway to much larger contracts at the Air Force beyond the SBIR program, which will support technology development and ultimately lead to off-the-shelf procurement in concert with commercial sales. There is also a second possible reason: the SBIR Phase 2 matching program. As explained in Section 2, an additional reform in the Open topics was to offer matching in Phase 2. Phase 2 applicants could request additional funds to match private or government money that they secured during the Phase 1 period. While the matching reform makes it more difficult to establish a pure treatment effect of openness, it also offers to our knowledge the first opportunity to evaluate a VC matching program. Researchers have long been interested in whether government programs that match VC solve information problems for the government agency or crowd out private capital (Lerner 2012).

Several features of the program's implementation facilitate evaluation. First, we can redefine the VC outcome to exclude VC investments that were matched in the Phase 2 stage. Second, the matching was not available at all for the first Open topic, and for the second topic, it was made available only just before firms submitted their Phase 2 applications. We can therefore assess whether the effect of winning an Open topic Phase 1 is concentrated in the later topics, where matching could have affected selection into applying for Phase 1. Third, we can assess whether the causal effect of Phase 1 on VC is driven by firms that apply for a Phase 2 match.

At the firm level, the fraction of Phase 1 winners that raised VC but never had a private match is 6.1%. The fraction that raised VC and also obtained a private match from the Phase 2 program is 1.3%. Table F.3 provides summary statistics on the matching program within the sample of firms that applied to Phase 2. The average confirmed private funding amount – that is, the event for which a matching contract was awarded for up to $750,000 – is $1.3 million.[60] Among Phase 2 applicants, 20.6% applied for a private match and 14.2% both won Phase 2 and received a matching award. Private funds are categorized as either VC, which means the matching came from an institutional VC fund or any other private source. Almost 40% of the private matches are from VC.

We are interested in whether the matching program was successful in driving subsequent

[60]It is also possible to have an outside government match (as the table shows, 13% of Phase 2 applicants had matching government funds). We find no relationship between the government match and VC.

VC, and also whether there are effects of winning an Open Phase 1 award on VC independently of whether the firm ultimately received a Phase 2 matching contract. In Table F.4, we repeat the main specification from Table 2 Panel A column (1) but make certain adjustments. In column (1) we redefine the outcome variable to be an indicator for subsequent VC if the firm did not receive a Phase 2 VC match. That is, the outcome of VC is zero if the firm did receive VC and got it matched in Phase 2. The effect is 4 percentage points. This is 52% of the mean. Comparing it with the main result from Table 2 of 5.2 percentage points (60% of the mean) suggests that while matching may increase the effect, the majority of the Open Phase 1 effect cannot be explained by subsequent matching. In column (2), we consider the complement. The dependent variable is redefined to be zero for firms that got VC but had no private match. As we would expect, the effect is larger relative to the mean, at 1.5 percentage points relative to a mean of 2.7%.

Even if it does not lead to differential effects of winning, potential matching could affect selection into Phase 1 and perhaps VC decision-making. However, this is not possible for the topics that did not offer VC matching. We split the samples into topics that offer VC matching (column (3)) and topics that do not offer VC matching (column (4)). There is not a statistically significant effect in column (3). The effect in column (4), topics with no matching offered, sees a large but not statistically significant effect of 7.4 percentage points (double the mean). Finally, we interact winning with an indicator for the topic having no match, and exclude topic fixed effects, in column (5). The coefficient on the interaction is small and insignificant, reflecting the fact that the effect in topics without matching is very similar to the effect in topics with matching.

F.3 Role of Unobservable Selection

To further examine the role selection in explaining our results, we conduct several tests. We first consider the degree to which comprehensive controls for observables attenuate differences in treatment effects between conventional and open programs. The key concerns for the review team in the first round were selection based on industry and lifecycle. In Table F.5, we reproduce 2 columns for each of our main outcomes of interest: one without controls (Table 2 Panel A) and another that adds controls for pre-award outcomes, pre-award firm characteristics, and narrow technology fixed effects (Table 7 Panel A). We find that adding the full suite of controls attenuates the effect on DoD contracts by 10%, on VC by 3%, on patents by 1.7%, on highly original patents by 1.7%, and on subsequent SBIR awards by 6%. Overall, this represents little attenuation after imposing granular and economically relevant controls, so they offer comfort that selection does not play a major role.

Next, we follow the method of Altonji et al. (2005) and Oster (2019), which uses variation in observables to draw inferences about the likely maximum bias due to unobservables. We make a conservative assumption that all of the variation in outcomes can be explained by observing the full set of controls, which implies in the notation of Oster (2019) that $R_{\max} = 1$. This is essentially a worst case scenario assumption; the lower the $R_{\max}$, the the more is left over besides the pure treatment effect to explain variation in the outcome. To construct the bounds, we make an additional assumption, which is that there is equal selection in observable and unobservables ($\delta = 1$). Note that δ represents the importance of selection on unobservables relative to selection on observables. These assumptions are strong but standard in the literature (Altonji et al., 2005; Oster, 2019; Finkelstein et al., 2021).

We continue to use the full suite of controls from Table 7 Panel A to learn about maximum possible selection on unobservables. For each specification, we generate bounds, $[\beta(R_{\max}, \delta), \tilde{\beta}]$, where $R_{\max} = \delta = 1$ as per our assumptions and $\tilde{\beta}$ represents the estimated coefficient using observable controls. We present these bounds at the bottom of each column in Table F.5, in the row labeled "Selection-Corrected Bounds." By construction, one of the bounds is the estimate from the right-hand column. The other bound is a function of the coefficient change after adding observables and the amount of variation explained by the observables, together with the assumed $R_{\max}$ and δ. Roughly, if the coefficient increases in magnitude with controls, then δ is negative, and the estimated bound is larger, suggesting that unobservable selection biases down the effect. The reverse is true when the coefficient declines with controls. The first situation is true for patents, high-originality patents, and SBIR contracts, while the second situation is true for DoD contracts and VC.

The bounds suggest that accounting for selection on unobservables could maximally attenuate the difference in treatment effect of winning an Open vs. Conventional award on future DoD contracts and VC by 52% and 55% (relative to columns 1 and 3). Accounting for this selection on unobservables would *increase* the difference in treatment effects on any future patents, high-originality patents, and SBIR contracts.

We also present the degree of relative importance of unobservable selection that would reduce the difference in treatment effects between open and conventional program to zero. This is at the bottom of each column in Table F.5 in the row labeled "δ". Regardless of the direction of δ, we find that selection on unobservables would have to be roughly *twice* as important as selection on observables to reduce differences in treatment effects on future DoD contracts and VC between Open and Conventional to zero. We find that the selection would have to go in the *opposite* direction of observable by $14\times$ and $1.3\times$ to attenuate the differences in treatment effects on future patents and high-originality patents to zero. Lastly, unobservable selection would need to go in the opposite direction of observable selection by $0.43\times$ to reduce differences in treatment effects on future SBIR contracts to zero.[61]

[61] Another common assumption in the literature is to assume that selection on unobservables go in the same direction as selection on observables. If we make this assumption, selection on unobservables would never attenuate our results on patents, high-originality patents, and SBIR contracts to zero.

Table F.1: Summary Statistics for Phase 2

Note: This table repeats the summary statistics from Table 1 for all Phase 2 proposals from 2003-2019.

	Conventional			Open			
	N	Mean	SD	N	Mean	SD	Diff of Means
Company Characteristics							
Age	1,672	20.504	70.059	627	8.495	9.760	-12.010***
Number of Employees	1,672	60.193	81.087	627	30.512	72.708	-29.681***
$\mathbb{1}$(in VC Hub)	1,672	0.165	0.371	627	0.166	0.372	0.001
$\mathbb{1}$(in County with AF Base)	1,672	0.310	0.463	627	0.091	0.288	-0.219***
$\mathbb{1}$(Immigrant)	1,672	0.090	0.286	627	0.104	0.262	0.015
$\mathbb{1}$(Minority Owned)	27	0.000	0.000	111	0.099	0.300	0.099***
$\mathbb{1}$(Woman owned)	732	0.060	0.238	442	0.115	0.320	0.055***
Pre-award Outcomes							
$\mathbb{1}$(Previous DoD Contract)	1,672	0.464	0.499	627	0.262	0.440	-0.203***
$\mathbb{1}$(Previous VC)	1,672	0.069	0.253	627	0.158	0.365	0.089***
$\mathbb{1}$(Previous Patent)	1,672	0.532	0.499	627	0.295	0.456	-0.237***
$\mathbb{1}$(Previous High Originality Patent)	1,672	0.409	0.492	627	0.185	0.389	-0.224***
$\mathbb{1}$(Previous High Citation Patent)	1,672	0.481	0.500	627	0.131	0.337	-0.351***
$\mathbb{1}$(Previous SBIR Contract)	1,672	0.638	0.481	627	0.183	0.387	-0.455***
Competition Characteristics							
Num Proposals per Topic	776	2.192	2.115	6	107.833	61.846	105.641***
Proposals per Winner	724	1.537	0.678	6	1.990	0.693	0.454
Non-specificity Index	556	0.088	0.212	6	0.543	0.041	0.455***

Table F.2: Effect of Phase 2 Award on VC and AF Contracts (non-SBIR)

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 2 award on the main outcomes within 24 months after the award decision. We include both an indicator for award and the award amount in real 2019 dollars. Note the coefficient on the award amount is not shown here. This is possible as the award amount varies, which it does not for Phase 1. Standard errors are clustered by firm. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Any DoD Contract and VC						
	Any DoD Contract			Any VC		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Award)	0.048	0.008	0.044	-0.035	-0.036	-0.037
	(0.066)	(0.065)	(0.066)	(0.023)	(0.024)	(0.024)
Observations	1672	1672	1672	1672	1672	1672
Controls	No	Yes	No	No	Yes	No
Narrow Tech FE	No	No	Yes	No	No	Yes
Proposal	First	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.593	0.593	0.593	0.019	0.019	0.019
Panel B: Any Patent and High Originality Patent						
	Any Patent			Any High-Originality Patent		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Award)	0.089	0.070	0.061	0.053	0.040	0.038
	(0.068)	(0.067)	(0.070)	(0.057)	(0.056)	(0.059)
Observations	1672	1672	1672	1672	1672	1672
Controls	No	Yes	No	No	Yes	No
Narrow Tech FE	No	No	Yes	No	No	Yes
Proposal	First	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.385	0.385	0.385	0.236	0.236	0.236

Table F.3: Phase 2 VC and Government Matching (Open Topics Only) Summary Statistics

Note: This table contains summary statistics about the private and government matching among Open Phase 2 awardees.

	N	Mean	Median	SD
Share Government Match	647	0.131		0.338
Share Private Match	647	0.145		0.353
Confirmed Govt Match Amt	79	\$ 769,446	\$ 600,000	\$ 810,078
Confirmed Private Match Amt	23	\$ 1,273,499	\$ 1,500,000	\$ 468,870
Share Applied Government Match	647	0.182		0.386
Share Applied Private Match	647	0.206		0.404
Applied Govt Match Amt	118	\$ 680,240	\$ 529,618	\$ 538,458
Applied Private Match Amt	133	\$ 1,355,232	\$ 1,500,000	\$ 940,224

Table F.4: Effect of Winning Phase 1 Interacted with Phase 2 Match

Note: This table contains regressions showing the effect of winning a Phase 1 award on measures of VC within 24 months of the award decision interacted with indicators for private and government matching (only available to Open Phase 2 awardees) on subsequent venture capital. In column 1, the dependent variable is redefined to be zero for firms that got a VC match. That is, the dependent variable is zero if a firm got VC and also got a VC match. In column 2, we consider the complement. The dependent variable is redefined to be zero for firms that got VC but had no VC match. That is, the dependent variable is only equal to one for firms that got VC and a VC match and is zero otherwise. Column 3 includes only those topics that offered a match, (19.1, 19.2, and 19.3), while column 4 includes the remaining topics that did not offer a match (18.2 and 18.3). Column 5 shows the interaction. All models include topic fixed effects. The sample is restricted to first-time applicants only. Standard errors are clustered by firm. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	VC If No Prvt Match	VC If Prvt Match	Any VC		
Sample:			Match Offered	No Match Offered	
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	0.093**	0.018	0.078	0.024	0.057
	(0.037)	(0.016)	(0.064)	(0.098)	(0.062)
$\mathbb{1}$(Award $\times$ Match Offered in Topic)					-0.009
					(0.084)
Observations	1056	1056	821	235	1376
Outcome Mean	0.132	0.031	0.183	0.162	0.152

Table F.5: Robustness to Selection on Unobservables

Note: This table shows regression discontinuity (RD) estimates using Equation 1 of the effect of winning a Phase 1 award on the five firm-level outcomes from Table 2. The coefficient on Award represents the effect within Conventional topics, and the coefficient on Award interacted with Open represents the differential effect of Open relative to Conventional. The odd columns reproduce the estimates from Table 2 Panel A. The even columns replicate the specification in Table 7 Panel A, which includes lifecycle controls (firm age and number of employees at time of application), narrow technology controls, and "additional controls": whether the firm had any previous non-SBIR DoD contracts, previous VC, previous patents, previous high-originality patents, was located in a VC hub city, was located in a county with an Air Force base, whether the product is software vs. hardware. Standard errors are clustered by topic. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$\mathbb{1}$(DoD Contract)		$\mathbb{1}$(VC)		$\mathbb{1}$(Patent)		$\mathbb{1}$(High-Orig Patent)		$\mathbb{1}$(SBIR Contract)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Award)	-0.086	-0.089	-0.006	-0.028	-0.087*	-0.125**	-0.014	-0.046*	0.093*	0.100**
	(0.081)	(0.075)	(0.045)	(0.047)	(0.051)	(0.054)	(0.018)	(0.025)	(0.050)	(0.047)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open)	0.200**	0.181**	0.124**	0.120*	0.176**	0.179***	0.084***	0.098***	-0.100*	-0.106**
	(0.096)	(0.089)	(0.060)	(0.064)	(0.069)	(0.069)	(0.028)	(0.031)	(0.053)	(0.049)
Observations	2283	2283	2283	2283	2283	2283	2283	2283	2283	2283
Lifecycle Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Narrow Tech FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Proposal	First	First	First	First	First	First	First	First	First	First
Time Period	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19	2017-19
Outcome Mean	0.166	0.166	0.092	0.092	0.112	0.112	0.036	0.036	0.031	0.031
R^2	0.191	0.335	0.129	0.185	0.143	0.303	0.080	0.223	0.266	0.285
Selection-Corrected Bounds	[0.095, 0.181]		[0.056, 0.120]		[0.179, 0.192]		[0.098, 0.171]		[-0.365, -0.106]	
δ	2.086		1.843		-14.594		-1.346		-0.430	