Opening up Military Innovation:

An Evaluation of Reforms to the U.S. Air Force SBIR Program

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Abstract

The U.S. military has historically been an important investor in transformational technologies, but this model faces challenges from a less innovative and more concentrated defense industrial base. This paper examines reforms to the Air Force Small Business Innovation Research (SBIR) program, which are part of an effort to address these challenges by bringing new firms with frontier technologies into the defense market. The "Open topic" reform takes a bottom-up approach to innovation, encouraging a broad set of ideas. This contrasts with the traditional "Conventional topics," which solicit highly specific technologies in a top-down approach. We show that the Open program attracts new entrants (younger firms and those without previous defense SBIR awards). In a regression discontinuity design that offers the first causal evaluation of a defense R&D program, we show that winning an Open award increases future venture capital investment, non-SBIR defense contracting, and patenting. These treatment effects are driven by new entrants. Conventional awards have no effects on these outcomes but do increase the chances of future defense SBIR contracts, creating a kind of persistent dominance. The results suggest that government (and perhaps private sector) innovation could benefit from more bottom-up, decentralized approaches that reduce barriers to entry, minimize lock-in advantages for incumbents, and attract a wider range of new entrants.

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1 Introduction

The U.S. military has historically been an important financier and early customer for transformational technologies such as GPS, radio, cryptography, nuclear power, jet engines, and the Internet (Mowery and Rosenberg 1991, Mazzucato and Semieniuk 2017). The fact that frontier defense technology has always had dual-use (i.e., commercial and defense) components can lead to opportunities for large spillovers from defense R&D investment to the private sector.

Unfortunately, this successful story of U.S. military R&D and its large private sector spillovers faces challenges, even as defense R&D now comprises about 60% of total federal government R&D.[1] We document how the U.S. defense sector has been growing progressively *less* innovative compared to the rest of the U.S. economy since the early 1990s, a period which coincides with extensive M&A activity that substantially increased the concentration of the defense industrial base.[2] To explain falling defense innovation, policymakers point to a shift from a creative approach to innovation with broad-based private sector collaboration to a more top-down approach in which military procurement is narrowly specified, leaves little room for more radical thinking, and is siloed in a small group of defense-specialist firms (Cox et al. 2014, Griffin 2019). From the perspective of the Department of Defense (DoD), it is problematic if the best technologies are no longer marketed to the military. From a broader social perspective, there are significant productivity growth implications from DoD's attenuated role in funding capital intensive, "tough tech" frontier ideas.

To address these issues, the U.S. Air Force experimented with "Open topics" in its Small Business Innovation Research (SBIR) contracts starting in 2018. The DoD accounted for $1.32 billion of the $3.11 billion total SBIR spending in 2018. Within DoD, the Air Force has the largest SBIR program, at $664 million in 2018. The goal of "Open topics" is to reach non-traditional firms with frontier dual-use technology, and to source ideas that the Air Force may not yet know it needs. The SBIR program is a useful venue for experimentation as it has flexibility and lends itself to rapid, staged financing. While questions of consolidation and competitive bidding in overall defense contracting are not relevant to the SBIR program, it faces a similar challenge in the form of incumbent contractors repeatedly applying and winning research contracts yet relying on SBIR for revenue and failing to transition the results of their R&D to sustained acquisition programs ("SBIR mills," Edwards 2020).

In an Open topic, a firm can propose *any* idea or technology that may be relevant to Air

[1] See Congressional Research Service (2018)).

[2] See Figures 1-2 and Figure A.1. The causes of the increased consolidation are not fully understood. Part of it reflects the fact that procurement regulations became increasingly complex and onerous from the early 1990s. Part of if may also reflect general trends in the U.S. economy towards higher concentration. See Carril and Duggan (2020) for a discussion of the trends in the US defense sector.

Force, in contrast to the narrowly specified Conventional SBIR topics, which like most mission-oriented R&D programs are top-down, with particular research ideas generated within the Air Force and then firms invited to complete them. The hope was that the Open topic reforms might revive DoD's historical role as a large, early customer for risky new technologies from new firms.

While SBIR is a small, particular program, the idea is that if the bottom-up 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 (AI).[3] Sourcing innovative ideas via open solicitations is not unique to this reform, as other government agencies both in the U.S. and the U.K. have developed similar programs.[4] Moreover, companies are increasingly experimenting with this approach through customer-driven, outsourced, or open innovation approaches, especially in R&D-intensive industries (Chesbrough 2003, de Villemeur and Versaevel 2019).[5]

Whether this sort of bottom-up approach can be successful is a longstanding question in innovation and organizational economics (Azoulay and Li 2020). In many cases a research funder does not know what opportunities exist and cannot spell out exactly what promising projects will look like, making a bottom-up approach appropriate. At the same time, there are potential downsides, particularly in the defense context. For example, companies oriented towards private sector commercialization may not deliver technologies that are useful to the Air Force.[6] This is why DoD R&D funding has often been held up as the quintessential example of a top-down approach, compared to say the bottom-up approach of NIH grants.

In this paper we assess how these reforms affected selection into applying for an SBIR award as well as the causal effect of winning an award (this is to our knowledge, the first causal analysis of a defense R&D program). We use administrative data on applications and evaluations of Air Force SBIR proposals over the 2003-2019 period, with a focus on the last three years to facilitate comparison of Open and Conventional topics, which were run simultaneously in 2018

[3]With the notable exception of Palantir, the large West Coast-based tech firms do minimal work with the DoD.

[4]These include the U.K.'s Defense and Security Accelerator Open Call for Innovation (UK Defence and Security Acceleator 2020), DoD's DARPA, and the U.S. Department of Energy's ARPA-E (Advanced Research Projects Agency-Energy 2020)

[5]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. See https://www.unilever.com/about/innovation/open-innovation/ and https://www.warc.com/newsandopinion/news/open_innovation_boosts_unilever/30488

[6]Despite this concern, the current Air Force leadership claims that commercial innovation is evidence of initial success, and says it takes a long-term view that a strong U.S. industrial base (especially if its research has early-stage ties to DoD) will ultimately enable strong defense (e.g. https://fcw.com/articles/2020/06/09/williams-roper-rethink-dib.aspx).

and 2019. In the 2017-19 sample, the data include 7,300 proposals across 3,200 firms. The larger sample of applications from 2003 includes 19,500 proposals over 6,500 firms.

We first show that the Open topics reached a dramatically different type of firm from the Conventional topics. They are about 50% younger and smaller than firms applying to Conventional topics, are less likely to have previous DoD SBIR awards, and are more likely to be located in an entrepreneurial hub than in a county with an Air Force base

Next, we assess the effect of winning an SBIR contract on two primary future outcomes, obtaining Venture Capital (VC) funding and non-SBIR DoD contracts, which correspond to the key metrics of success from the perspective of the program administrators. VC success represents high-growth innovation potential and creates more general social spillovers. DoD contracts reflects that the technology can be directly used by the DoD, so has direct private benefit to the funders. Our design compares firms by rank around the cutoff for an award. Importantly, the rank that determines the award decision is constructed by forced ordering of independent scores from three evaluators, making manipulation of any particular firm around the cutoff extremely unlikely. We document a smooth density around the cutoff and continuity in baseline covariates.

We find robust evidence that winning an Open topic competition increases the probability of subsequent VC investment by 5.7 percentage points (71% over the mean of 8%), while there is no effect of winning a Conventional competition. Second, we find that winning an Open award increases the chances of a subsequent non-SBIR DoD contracts by 6.6 percentage points (45% over the mean of 14.8%). The treatment effect for both outcomes is significantly stronger for new entrants: firms that are young or have no previous defense SBIR awards. Indeed, the only specifications where we find any effect of the Conventional program is (sometimes) among these new entrants when we consider a long (2003-2019) time period. This suggests that a reason for the success of Open is that it encouraged more new entrants into the SBIR program.

As an alternative measure of innovation, we consider patenting. We find that winning an Open award increases the probability of any patenting by more than twice the mean rate, though this outcome is quite sparse. In the Conventional program, there is a much higher average rate of patenting, but the estimated effects of winning are not significantly different from zero (though they are positive). Our final outcome is future DoD SBIR awards. Winning an initial Conventional award increases the chances of winning a future SBIR award by more than 50%, while there is no such effect in the Open program. This implies that Open competitions do not appear to suffer from the same lock-in and persistent dominance of recurring SBIR-winners that seem prevalent in the Conventional program.

In sum, the Conventional SBIR program at the Air Force has weak if any effects on measures of innovation and commercialization, and instead has powerful effects on winning subsequent SBIR awards. By contrast, our results show that the Open topics – where a small minority of applicants have previous DoD SBIR awards – have meaningful effects on measures of commercial innovation. The results for both programs suggest that they are most useful for firms that are young or new to the SBIR program. The finding that effects decline with previous awards is consistent with Howell (2017)'s evaluation of U.S. Department of Energy (DoE) SBIR grants. However, the DoE SBIR program appeared to have much stronger effects overall than the Conventional Air Force program. There are many possible reasons for the difference, but an obvious one is DoD's massive procurement capability and much larger SBIR program, which allows firms to focus solely on the defense market. We show that overall, DoD's SBIR program has more repeat-firms than the DOE program (Figure A.2).

While it is difficult to know whether "openness" per se, some other aspect of the program, or the composition of applicants drives our effects, we can use other, smaller reforms to Air Force R&D programs where we also have administrative data to probe this question. In particular, we consider two other DoD SBIR reform efforts, which had specific topics but, due to other features such as faster contracting and outreach to startup hubs, attracted firms with features closer to Open applicants than to Conventional applicants. We find that the Open program had significantly larger effects than these other programs, suggesting that part of its success goes beyond attracting new applicants, and is due to the causal impact of encouraging bottom-up innovation.

The Open topics seem to work because they provide firms with an avenue to identify customers in the Air Force who did not previously know that they needed the firm's innovative new product. While high-growth startups are poorly aligned with the Conventional SBIR program, which requires awardees to produce a very particular, ex-ante specified technology, the Open program allows firms to bring something to the SBIR program that is their own existing idea oriented primarily to the civilian commercial market. The Open contracts may have such a large effect on VC because they represent an entry point to much larger DoD contracts. The goal of the Open Phase 1 program is to demonstrate the feasibility of a novel technological development to meet an Air Force customer's demand who can supplement commercial sales and support subsequent development, while the goal of the Conventional program is focused on the technical feasibility of developing a narrowly specified novel technology. Startups with a successful Open Phase 1 process 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.

The structure of this paper is as follows. First, we describe our contribution to the literature in Section 1.1. Next, Section 2 discusses the historical importance of U.S. military R&D and documents the decline in innovation in recent decades. We also discuss the SBIR program and its recent reform in detail. Section 3 contains the data and descriptive statistics and Section 4 explains the empirical design. The results are described in Section 5. Section 6 offers some concluding comments.

1.1 Contribution to the Literature

This paper contributes to several strands of literature. First, to our knowledge we are the first to offer a causal evaluation of a defense R&D program. Defense is unique because the ultimate buyer is a monopsonistic government agency providing a public good. Particularly in the U.S., this implies a narrow market, but one with a historically high tolerance for capital-intensive early stage risk-taking (at least in some circumstances, such as DARPA investments), and essentially unlimited buying power in the event of success. This situation is quite different from other R&D-funding agencies seeking to promote innovation for private sector deployment in a particular location or sector. There are few attempts to unravel the causal impact of military spending or defense research on economic performance. The focus of the general literature has been on using military spending as an exogenous shock to demand (Ramey 2011, Nakamura and Steinsson 2014, Barro and Redlick 2011, and Perotti 2014).

Our focus is more on the supply side. Here, there is rich historical evidence, but it is mainly anecdotal (e.g. Braddon 1999, Senor and Singer 2009, and Mazzucato 2013). Building on the earlier econometric work in the U.S. of Lichtenberg (1984; 1988; 1995), Moretti et al. (2020) show the crowd-in effects of defense R&D on private R&D and subsequent productivity growth in industry and firm level panel data across OECD countries. Akcigit et al. (2017) use the spatial location of defense spending within the U.S. as a shock to innovation. Draca (2013) estimates the impact of U.S. defense spending on firm-level innovation and finds that increases in procurement contracts are associated with increases in patenting and R&D. There is also work documenting an important role for federal research funding at both private firms and universities (Fleming et al. 2019, Babina et al. 2020, Rathje and Katila 2020).

Second, we contribute to the burgeoning literature on innovation policies, especially the role of direct government subsidies (for a recent survey on the evaluation of innovation policies, see Bloom et al. (2019)). The literature focuses on two types of R&D policies. First, there are fiscal policies encouraging R&D analyzed in Hall (1993), Bloom et al. (2002), Moretti and Wilson (2014), Dechezlepretre et al. (2019), Chen et al. (2018), and Rao (2016). These studies generally find positive effects (see Akcigit and Stantcheva (2020) for a recent survey). Second, there is a body of empirical research on the effect of public R&D on private R&D (e.g. David et al. 2000, Lach 2002, Goolsbee 1998, Wallsten 2000, Wallsten 2000, and Rathje 2019). The results here are mixed – see for example the meta-study of Dimos and Pugh (2016).

There is a small number of recent papers that have clear causal identification strategies. For example, Jacob and Lefgren (2011) and Azoulay et al. (2019) study the effect of NIH grants on publications and patenting; Bronzini and Iachini (2014) focus on the effect of R&D subsidies on capital investment by Italian firms; and Slavtchev and Wiederhold (2016) study the effect of government procurement on innovation. Pottelsberghe De La Potterie and Lichtenberg (2001) and Pless (2019) are rare exceptions that look at multiple types of R&D policies. Other work on the U.S. SBIR program includes Lerner (1999), Howell (2017), and Lanahan and Feldman (2018). Bhattacharya (2018) presents a structural model of R&D in the context of the U.S. Navy SBIR program, suggesting that increasing competition (and forced sharing of IP) would be socially beneficial.

Third, our paper is related to studies of how to motivate innovation, such as Manso (2011), Azoulay et al. (2011), Nanda, Younge and Fleming (2014), and Krieger et al. (2018). Azoulay and Li (2020) explore how research grant programs can best stimulate innovation. We offer the first effort to compare a bottom-up with a top-down strategy for funding frontier innovation, and explore how these strategies interact with firm incumbency. Finally, our work documenting the changing degree of concentration and innovation trends in the defense sector relates to work on increasing concentration and the rise of superstar firms in the economy more broadly (Autor et al. 2020, De Loecker et al. 2020 and Philippon 2019).

2 Institutions and Policy: Defense R&D and SBIR Reforms

This section first explains how military investment in innovation is relevant to the rest of the economy (Section 2.1). We then discuss challenges facing defense innovation (Section 2.2) and the SBIR context at the Air Force (Section 2.3).

2.1 The Relationship between Defense and Commercial Innovation

Military R&D has shaped technological advance since antiquity.[7] Defense R&D can serve to both "push" and "pull" civilian innovation. 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 through creating new pools of general engineering or scientific human capital and knowledge, for example by funding MIT's Lincoln Lab, or basic research on crucial technologies such as GPS (Belenzon and Schankerman 2013,

[7]For example, many historians (e.g. Polybius' *Histories)* credit Archimedes in 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).

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 procurement power. DoD has been willing to fund extremely risky, capital-intensive new technologies that have a potential military application. As an early and major customer of certain technologies, the defense sector can pull firms to work on "tough-tech" problems.

Since World War II, the U.S. military has invested in innovation primarily through procurement contracts. Much more so than other Western countries, the U.S. has procured defense technologies from an industrial base that also supplies commercial markets (Flamm 1988). In the early decades, large orders for early stage new technologies such as transistors and integrated circuits were crucial in 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.

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.

2.2 Consolidation and Declining Innovation in the Defense Sector

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 being undermined. There are also particular challenges facing the SBIR program at DoD. In this subsection, we explain these concerns and challenges, as they motivate the reforms we study.

There are at least four broad and interrelated challenges for U.S. defense innovation. First is the consolidation and lock-in of prime defense contractors with weakening innovation (see below). Second, procurement regulations have become more complex and onerous, raising barriers to entry for new firms and contributing to the dominance of the primes (Cox et al. 2014). Third, relevant frontier technologies are no longer being marketed to DoD, partly as a result of the first two problems. The challenge of lagging behind the civilian sector and failure to make better use of civilian technology has been observed since the early 1990s (Alic et al. 1992, Stowsky 1992), but concerns have intensified in the past decade with the rise of technologies such as AI, autonomous mobility, cyber-security, and biotechnology (Harrison 2016). Indeed, DoD may not even know *which* aspects of these and other technologies could apply to its operations. Finally, the national innovation ecosystem has shifted away from the "tough tech" areas most relevant to defense (Sargent and Gallo 2018), consistent with evidence that corporate basic science research has declined (Arora et al. 2018).

Several senior defense officials have highlighted the perceived scope of the problem. 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.[8] Consequently, Appendix A.1 documents 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. Figure 1 shows that between 1976 and 2019, 225 companies consolidated into just six. 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%. The value of these contracts increased from around $70 billion (in 2019 dollars) for the 225 companies in the late 1970s to $115 billion awarded to just six companies in 2019. The remaining 65% of contracts did not become more dispersed and the total number of remaining contractors declined slightly over this period.

This dramatic consolidation was accompanied by a decline in innovation quality as measured by patent citations. Figure 2 shows patent activity for the firms in Figure 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. Citations are normalized by the average number of citations for all patents in the same IPC3 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.[9] The solid blue line includes all forward citations, and we see a secular decline across the unit threshold, so that

[8]Though they do not study innovation, Carril and Duggan (2020) show that the substantial consolidation among major defense contractors in the mid-1990s reduced competition.

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

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. This measure omits self-citations, which occur when a company cites one of its own previous patents. Outside citations offer a proxy for knowledge spillovers to the broader economy.[10] On this measure, presented in the dashed orange line, defense contractor patents exhibit a steeper downward trend, from having 22% more outside citations than the average patent in 1976 to 11% fewer in 2019.[11] Finally, we restrict outside citations to patents from firms that are not featured in the graph, that is, from firms outside the prime contractor universe. These citations are 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. As we explain in Appendix A.1, the declines are not mechanical and are based on conservative assumptions.

Although their profits and assets have increased substantially (Figure A.1 Panels C and D), this has been accompanied by a fall in the primes' relative innovation whether measured by citations, patenting (Figure A.1 Panel A) or R&D intensity (Figure A.1 Panels B and D).

2.3 Air Force SBIR Program: Context, Process and Reform

This section describes how the SBIR program operates, focusing on facts relevant to our main set of questions.

2.3.1 SBIR Context and Challenges

Congress first authorized the Small Business Innovation Research (SBIR) program in 1982 to strengthen the U.S. high technology sector and support small firms. Congress requires SBIR to have two Phases: smaller Phase 1 awards fund proof-of-concept work, after which a firm may apply for a larger Phase 2 awards to support later stage demonstration.[12] In 2018, the total SBIR/STTR budget across all 11 participating agencies was $3.11 billion, of which DoD

[10] Self citation is calculated by matching the USPTO assignees of cited and citing patents. For example, if Boeing cited a McDonnell Douglas patent in 2000, it would not be counted as a self citation. If McDonnell Douglas and Boeing file for patents solely under "Boeing" as the assignee after the merger, then those citations will be counted as self citations.

[11] We do not count cites of a target firm's patents from its future acquirer as self-cites, so the effect is not mechanical from consolidation. Also, 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 A.1 Panel A).

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

accounted for \$1.32 billion, with the Air Force having the largest SBIR program in the DoD. In 2018, the Air Force SBIR program gave out \$664 million in awards.

SBIR applicant firms are typically small, high-tech, and intend to perform innovation. While this type of firm represents is a small fraction of the overall economy, the subset that succeed and grow become the primary drivers of future U.S. job creation, innovation, exports, and many other key metrics defining a dynamic economy (Haltiwanger et al. 2013). Amid a decline in large corporate R&D labs performing basic science, new firms have become an increasingly important source of innovation; especially VC-backed startups, which benefit from a surge of private capital in the 2010s.[13] Startups possess frontier technology that is highly relevant for 21st century defense, including products based on AI, autonomous mobility, and cyber-security.

The SBIR program has different features and challenges than overall DoD procurement. Perhaps most importantly, firms must be small to participate and do not compete directly against one another to deliver a particular product. Therefore, consolidation is not a primary concern. The primary concern in the SBIR program 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). The blue line in Figure A.2 Panel A uses the HHI measure to show that the DoD SBIR program has become more concentrated over time, with more individual firms winning many awards in a single year.[14]

A locked-in, repeat SBIR base appears to be a more severe problem at DoD relative to other agencies, in part reflecting 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. To provide a benchmark, we consider the DOE, which has a marginal procurement dimension and is where Howell (2017) finds large positive effects on innovation of winning a Phase 1 grant. Each line in Figure A.2 Panel B 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 diverge subsequently, and during the 2010s only 20-25% of DoD SBIR Phase 1 awards went to new firms. This evidence of higher incidence of repeat contracts offers a parallel to the consolidation

[13] See Kortum and Lerner (2000), Foster et al. (2008), Puri and Zarutskie (2012), Decker et al. (2016), Puri and Zarutskie (2012), Gornall and Strebulaev (2015), Arora et al. (2018), Howell et al. (2020), and Bloom et al. 2020.

[14] As with overall contracts, the large number of small contracts and diverse "markets" in the form of SBIR topics within DoD means the absolute concentration is very low relative to the private sector markets where we typically use HHI.

among prime contractors in the larger acquisitions program documented in Section 2.2.

2.3.2 SBIR Process at the Air Force

This section describes aspects of the Air Force SBIR process that are common to the Conventional and the reform programs. 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 are disqualified.[15] In the second step, three government evaluators with expertise in the topic area independently evaluate the application. Each evaluator produces a sub-score on one of three criteria: Technology, Team, and Commercialization.[16] The commercialization sub-score reflects potential to sell any derived product or service within and outside government. 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 below, 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, because each evaluator produces an independent sub-score, no single evaluator can manipulate a firm's position around the cutoff.

In the third step, a contracting officer makes a final decision to award the contract and administers the award. This step does not disqualify applicants on the basis of technical merit[17], but does occasionally disqualify applicants for a business reason, such as a cost that is found to be ineligible. 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

[15]This might reflect a failure to satisfy U.S. government-wide requirements for SBIR awards (such as having fewer than 500 employees), or a failure to satisfy a basic requirement of the solicitation, such as submitting more than the maximum pages of material.

[16]The official description for the conventional program of these criteria are: "(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." See e.g. https://www.afsbirsttr.af.mil/Portals/60/Pages/Phase%20I-II/SBIR%20Phase%20II%20Instructions%200918.pdf.

[17]Note proposals are disqualified by contracting officers if the proposal is not found to be "RDT&E" related, i.e., that the proposal is not relating to research and development, rather related to procuring a service or product.

topic.[18]

Firms' proposed cost is not a primary factor in evaluation as long as the cost is below the 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. Figure A.3 shows clustering of awards, particularly in Phase 1, around the maximum amount ($50,000 for Open topics, and $150,000 for Conventional topics). However, a significant fraction of firms applies for less than the maximum, especially in Phase 2. This is because firms must apply for the amount of money required to do the work they are proposing. Particularly in Phase 2, the firm must provide a detailed accounting of how it plans to use the money. 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.

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 up front, 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 up front. In the context of financially constrained startups, this may present a challenge.

The Phase 1 deliverable is a white paper, or report describing the outcomes of research. The Phase 2 deliverable is typically a prototype, sample product, software, or dataset. Phase 2 contracts are much more detailed, bespoke, and their amounts vary more than Phase 1 (see Figure A.3). In Phase 2, the firm proposes multiple milestones in its application, tied to payment amounts.

2.3.3 SBIR Reforms: Open vs. Conventional

Overview The SBIR reforms have taken place within a new organization called Air Force Ventures (i.e., AFVentures), a business division of AFWERX.[19] AFVenture's stated goals are

[18]Included in the disqualified category are a small number of firms that decline awards. DoD does not observe the reason for decline, but it seems that some firms submit multiple applications to the government for the same work. For example, a project might be relevant to multiple SBIR topics at DoD or another agency. If the firm wins multiple awards, it can accept only one, as it is illegal to take government money twice for the same work.

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

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 2.2. 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.[20] 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 acquisition. 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."[21]

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, to high-skill human capital. Militaries around the world are therefore focusing energies on funding and working with high-tech, small businesses that possess "dual-use" technologies with commercial as well as defense applications.[22]

[20] 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.

[21] 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.

[22] For example, France's RAPID program is quite similar to the Open topic approach, 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. France especially emphasizes this agenda, spending large portions of its defense R&D budget on small businesses.

Open vs. Conventional Topics First conducted in May 2018, Open topics are the centerpiece of AFWERX's reformed SBIR program. Open topics are "bottom-up" in that the solicitation contains no direction regarding the technology – including software – that the applicant may propose. With an explicit 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."[23]

By contrast, Conventional topics are sourced primarily from the Air Force Research Laboratory. They are highly specific; two examples of topics are "Safe, Large-Format Lithium-ion (Li-ion) Batteries for ICBMs" and "Develop Capability to Measure the Health of High Impedance Resistive Materials."

Each year, there are usually three solicitations, each of which has many Conventional topics but, since 2018, only one Open topic. For example, in the second solicitation of 2019, there was one Open topic and 61 Conventional topics. It is important to emphasize that 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 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 than for Conventional.

The Open topics aimed to increase the pace of contracting to more closely match startup financing cycles, as firms had previously complained that the time between application and award was too long for cash-constrained startups.[24] Also, Open topic awards are smaller and have shorter time frames. 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). Phase 1 awards of $50,000 last three months. The firm's objective is to demonstrate the feasibility of developing a product or

[23] https://www.sbir.gov/node/1605931

[24] The mean (median) time between application and award is 33 (33) days for Open, and 178 (176) days for Conventional.

service with an identified Air Force "customer." That is, a successful Phase 1 project identifies an Air Force partner interested in potentially procuring the firm's technology. The white paper delivered at the conclusion of a successful Open Phase 1 describes the technological feasibility of integrating the firm's technology into Air Force operations and may include a statement of interest from the partner.[25]

Conventional Phase 1 awards aim to support basic R&D that would lead to prototyping in Phase 2; they are \$150,000 and last nine months. The Open topics are aimed at firms already developing a technology aimed at commercial use, even if it is in the very early stages, while Conventional topics tend to fund more basic R&D projects, where a prototype or "beta version" does not exist yet. This paper focuses on Phase 1, so we minimize discussion of further awards. The Phase 2 awards of \$300,000 to \$2 million are intended to last 12-24 months. For all but the first two of its Open SBIR topics, AFWERX sought to encourage Phase 1 winners to access outside funding (both private and government sources) with a matching provision in Phase 2. Below, we evaluate the impact of match availability separately from the impact of "openness."

In sum, this section has documented that while U.S. defense R&D has been a historical powerhouse of innovation and military capability, since the mid 1990s, the innovation investment and knowledge spillovers of prime contractors have declined relative to the rest of the economy. At the same time, there has been consolidation and rapidly rising profits. In light of these trends, the Air Force reformed its SBIR program in an effort to make it more "bottom-up" and to encourage a wider diversity of entrants to their competitions. We turn now to describing data from these reforms and evaluating whether they were successful.

3 Data and Summary Statistics

This section describes our dataset (Section 3.1) and explores whether the Open topics achieved their goal of attracting new entrants to the defense market (Section 3.2).

3.1 Data Sources and Samples

Our starting point is a dataset of applications and awards to the Air Force SBIR program between 2003 and 2019. The Open topics reforms begin in 2018 and we observe complete evaluation data for all topics between 2017 and 2019.[26] For Conventional topics, we have

[25] Table A.1 summarizes the key differences across the programs.

[26] AFWERX began in 2018 and also introduced some other smaller competitions (Pitch Day and NSIN) that we use below to uncover the mechanisms underlying the larger treatment effects for Open than

further evaluation data for select years before 2017: 2003-2007, 2015, and part of 2016 (the remaining years' data were lost in 2016 and, unfortunately, do not exist). 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, so that the relevant economic environment and defense procurement factors are similar across the sample. In 2017, all applicants are Conventional. In 2019, is four-fifths of applicants are Open. Figure A.4 shows the number of awards by program and year, and Table A.2 describes proposal and firm counts for all programs. In the 2017-19 sample, there are 7,229 Phase 1 proposals from 3,170 unique firms.

Table 1 describes competition and applicant characteristics at the proposal level. Conventional topics average 18 applicants and 3 winners (i.e., awardees). As explained above, Open topics have a very different model, leading to many applicants and winners per topic (on average, 380 and 213, respectively). The same summary statistics for Phase 2 are in Table A.3.

The two main outcomes of interest are subsequent venture capital (VC) investment and DoD non-SBIR contracts, which correspond to the two key metrics of success from AFWERX's perspective. 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 private financing deals from Pitchbook, CB Insights, SDC VentureXpert, and Crunchbase (we eliminate duplicate deals that appear in multiple databases). The majority of deals come from Pitchbook, which we observe through October 2020. The second outcome is non-SBIR DoD contracts, which represents defense procurement success; in the DoD jargon often termed "transition to programs of record." The DoD values this because it indicates that the research has led to a practical application for the military. To construct this outcome, we use complete data on DoD contracts from the Federal Procurement Data System through July 2020.

We also consider two ancillary outcomes that help us understand innovation and lock-in dynamics, respectively. First, we consider patents to assess technical innovation with potential commercial application.[27] Second, we consider subsequent DoD SBIR awards, using data from the Small Business Administration. We examine whether winning one SBIR award increases the probability of winning a future one, to assess lock-in to the SBIR program.

Conventional.

[27] We obtain patent data from the USPTO via https://www.patentsview.org/download/. We obtain patent applications from AI Patents, courtesy of Liat Belinson.

3.2 Selection into the Open Programs

A central aim of the Open reform was to attract new types of firms to the defense market. We assess whether it succeeded in Table 1, which describes baseline company characteristics. As Panel A shows, Open applicant firms are younger (9.8 vs. 19.2 years old) and smaller (24.7 vs. 52.5 employees) than Conventional applicants. They are more likely to be in the VC hubs of the San Francisco Bay area, greater Boston, and New York City (19.6% vs. 13.7%) and less likely to be in a county where there is an Air Force base (20.4% vs. 25.9%). A lower fraction are female owned (11.1% vs. 15.5%) and about the same fraction are minority owned (12%).[28]

To describe their geographic diversity, we map the location of applicants in Figure A.5, with larger bubbles indicating more firms. We overlay the locations with the intensity of VC activity in 2018. There is clearly a greater concentration of Open topic applicants in Silicon Valley. Some of the otherwise improbable locations for both programs reflect defense spending hubs such as Washington DC and Ohio, where the Air Force Research Lab (AFRL) is located. AFRL is the major historical sponsor of Air Force SBIR topics. The same set of maps for awardees is in Figure A.6, and documents similar patterns.

We explore selection on our outcome variables in Table 2, focusing here on Panel A, which reports statistics for the main analysis sample (2017-19) across the Conventional and Open programs. Open applicants are almost twice as likely to have previous VC financing, at 11.5% relative to 6.0%. After the award decision, 7.9% of Open topic applicants subsequently raise VC, compared to 1.6% of Conventional applicants.

This relationship is reversed for patents; Conventional applicants are twice as likely to have any patent before the award (46% vs. 23%), and more than ten times more likely after the award. Their patents are also more highly cited. Consistent with Conventional topics primarily coming from AFRL and being more basic-research oriented, these patent statistics suggests that Conventional applicants are more often doing scientific research, that might more often lead to patents, and less IT research.[29] Consistent with this, the three most frequent patent classes for Open applicants are engines (10.6%), data processing (7.1%), and transmission of digital innovation (6.5%), while the three most frequent classes for Conventional applicants (in the 2017-19 period) are semiconductors (10.4%), optical systems (5.8%), and materials analysis (3.8%).[30]

[28]The SBA defines "minority-owned" as being at least 51% owned and run on a daily basis by one or more members of the following groups: African Americans, Asian Americans, Hispanic Americans, and Native Americans. To qualify as a member of the group, an individual must be at least one-quarter that group. For example, if one of the owner's four grandparents is Asian American, the individual would qualify as a minority.

[29]The same statistics for the all years for the Conventional program are in Table ??.

[30]These classes are, in order of mention, F01D, G06F, H04L, H01L, G02B, and G01N.

Open applicants also have fewer government contracts: before the award, 23% of Open applicants had a previous DoD SBIR, compared to 63% of Conventional applicants. Open applicants are also about half as likely to have non-SBIR DoD contracts, though the difference narrows after the award.[31] When we split subsequent contracts by R&D vs. procurement contracts, where the latter is the best measure of transition to operational programs of record. There is a larger disparity in the probability of procurement and R&D contracts for Conventional than open applicants both prior to and after SBIR award decision.[32]

In sum, it is clear that firms applying to Open rather than Conventional topics are younger, smaller, and much more likely to have previous VC investment, be located in a VC hub, and have no experience with the DoD or SBIR markets. Thus, the Open Topic program seems to have attracted a good deal of new entry into defense R&D procurement.

4 Empirical Design

The application and scoring processes for Open and Conventional topics are very similar (see Section 2.3.2). These institutional features allow us to use the same regression discontinuity design (RDD) for both programs. The RDD approximates the ideal experiment of randomly allocating awards among applicants. It is relevant in settings where assignment to treatment is based on an applicant's location around a cutoff in a rating variable and is widely used for program evaluation. The intuition of the RDD is conceived either as a discontinuity at the cutoff (Hahn et al. 2001) or local randomization around the cutoff (Lee 2008). Regardless of this intuition, there are two implementations: sharp, in which the rating variable perfectly identifies treatment status, and fuzzy, in which there are crossover observations on one or both sides of the cutoff. Our setting permits a sharp RDD.

A valid sharp RDD has four conditions (Hahn et al. 2001, 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. Second, assignment to treatment must be based solely on the combination of the rating variable and the cutoff. This is true for all the topics. As

[31] We restrict to contracts worth at least $50,000, so that we do not capture very small add-on type awards or minor purchases. Our results are similar using all contracts.

[32] A representative example of a successful Open applicant from the perspective of "transitioning" to an Air Force PEO is Alabama-based Aevum, which is designing 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. A representative example of a Conventional applicant with a subsequent Air Force non-SBIR contract is Cornerstone Research, which was contracted to do other work for the AFRL.

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.

Third, the cutoff must be independent from 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 3, we graph the density of the rating variable around the cutoff. There is no bunching, consistent with no manipulation. The second test is to assess continuity of observable baseline covariates around the cutoff. Figures A.7-A.9 show six baseline covariates observed at the time of application. There are no discontinuities around the cutoff in any of the variables, consistent with an absence of manipulation. We similarly find no discontinuities in pre-award outcome variables, shown in the Figures A.10 and A.11. We use raw means to highlight the differences across groups.

We conduct a third test for manipulation, reflecting the concern in our setting that evaluators might manipulate sub-scores based on an ex-ante preference for which firms should win, potentially leading to scores that are not actually 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 would point to little scope for manipulation. Figure A.12 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 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 the data and controls for separate linear functions of 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 $Kernel_{i,j} = 1 - \frac{|Rank_{i,j}|}{\max_j |Rank_{i,j}| + (0.01)}$.[33] This kernel weighting

[33] We add .01 so that the observations with the maximum absolute rank don't end up with a weight of 0

approach weakens the parallel trends assumption for awardees and non-awardees. We also 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. We also show robustness to controlling for rank quadratically, but we do not use higher order polynomials, following Gelman and Imbens (2018).

The primary model that we estimate within either the Open or Conventional topic samples is Equation 1:

$$\begin{aligned} Y_{it} = \alpha + \alpha_T + \beta\left[1 \mid Rank_{iT} > 0\right] + \gamma_1\left[Rank_{iT} \mid Rank_{iT} > 0\right] \\ + \gamma_2\left[Rank_{iT} \mid Rank_{iT} < 0\right] + \delta PSBIR_{iT} + \varepsilon_{iT}. \end{aligned} \tag{1}$$

Here, the dependent variable Y_{it} is typically an indicator for the firm experiencing some event ever after the award, such as VC funding. We also show that the results are robust to limiting the outcome to within one or two years after the award decision, in case there is bias from Conventional topics having one extra year. $[1 \mid Rank_{iT} > 0]$ is an indicator for having a positive rank and thus receiving an SBIR award. We control for whether the applicant has won a previous DoD SBIR award $PSBIR_{iT}$.[34] The coefficient of interest is β. Our baseline regression model includes all ranks.

Our primary models include only a firm's first proposal between 2017-19. We report one model using all applications during this time frame, which sheds light on the effect of winning in the program overall given that firms may submit multiple applications. The main model uses outcomes ever-after, which will bias towards finding a stronger effect in Conventional as it existed in 2017, while Open began in 2018. Last, for the Conventional topics, we report models with all years of data to test for a long-term effect of the standard program. We also show a number of alternative models in robustness tests, including a narrow bandwidth around the cutoff, adding controls for pre-award outcome variables and other characteristics, omitting all controls, adjusting the functional form, and restricting outcomes to 24 months after the award date.

In a supplemental analysis, we compare program effects to one another using Equation 2:

$$\begin{aligned} Y_{it} = \alpha + \alpha_T + \beta\left[1 \mid Rank_{iT} > 0\right] \cdot \mathbf{Program_T'} + \gamma\left[Rank_{iT} \mid Rank_{iT} > 0\right] \\ + \gamma\left[Rank_{iT} \mid Rank_{iT} < 0\right] + \delta PSBIR_{iT} + \varepsilon_{iT}. \end{aligned} \tag{2}$$

All variables are defined as above, except that $\mathbf{Program_T'}$ is a vector of the four program types:

(which would cause them to drop out of the regression).

[34] These could be from the Air Force before 2017 or from another DoD service anytime before the award date.

Conventional, Open, NSIN, and Pitch Day. The Conventional program is the omitted base group. The fixed effects for the topic (α_T) control for the independent effect of program type and the date of award. We cluster standard errors by firm in our baseline models of Equation 1. As an alternative we cluster by topic when we pool Conventional and Open together to test whether their effects are significantly different in Equation 2.[35]

Our main analysis comparing Open and Conventional topics assesses the Phase 1 award. We do not focus on Phase 2 because these awards are more recent (so there is little subsequent time to observe outcomes) and because the sample for Open topics is very small. However, we do evaluate Phase 2 in extensions as we are interested in its effects over the entire Conventional program, where we can observe long term outcomes. In the Phase 1 analysis, we do not consider the award amount because it is co-linear with winning. In the Phase 2 analysis, we do consider the award amount separately from winning, as there is substantial variation in Phase 2 award amounts.

5 Results

This section first describes the causal impact of winning Open and Conventional competitions on VC investment (Section 5.1), non-SBIR DoD contracts (Section 5.2), and the ancillary outcomes of patenting and SBIR contracts (Section 5.3). We discuss robustness tests in Section 5.4. We study the Phase 2 matching program in Section 5.5. Finally, we assess the role of selection in Section 5.6. The effects of winning a Phase 2 award are in Section A.3.

5.1 Effect on VC Investment

We first examine the role of VC investment, using an indicator for the probability of receiving any VC after the award decision.[36] Figure 4 shows the topic-effect adjusted mean by rank around the cutoff, using a firm's first application in the 2017-19 period. 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. Panel A shows that subsequent VC investment rises just to the right of the cutoff. By contrast, we see no relationship for Conventional topics in Panel B.[37] Table 3 examines these results in regression format using Equation 1. Here and

[35]All results are similar if we cluster by topic for Conventional, but we cannot cluster by topic when estimating 1 and 2, just for Open, as there are too few topics.

[36]Table A.4 shows the same models using the log amount of VC funding as the outcome variable, with qualitatively similar results.

[37]Note that the probability of VC before the award decision increases in rank for the Open program (Figure A.10 Panel A), suggesting that evaluators rate this factor highly, and pointing to the need to control for rank in analysis. By contrast, there is no relationship for Conventional in Figure A.10 Panel B.

in all subsequent tables, the dependent variable mean calculated in the post-award period is reported at the bottom of the table. The first three columns contain only a firm's first Open (Panel A) or Conventional (Panel B) proposal within the 2017-19 time frame. First, column (1) of Panel A shows that winning an Open award increases the probability of VC by 5.7 percentage points, which is 71% of the mean (8%) among Open applicants. This compares to an insignificant effect of -0.1 percentage points for Conventional in Panel B column (1).

Next, we interact winning with a dummy for being a new entrant as indicated by having any previous DoD SBIR awards. The positive effect of Open is clearly driven by firms *without* previous SBIR awards; the effect is 6.7 percentage points for this group (column (2)) whereas there is a significantly negative interaction between the treatment indicator and having a previous SBIR award, suggesting a zero effect for the "incumbent" group. As an alternative measure of entrants we use a dummy for whether a firm started up in the last 5 years (the median age) in column (3). Again, there is a negative and significant interaction between old firms and winning an award. Young firms are 8.5 percentage points more likely to obtain future VC funding, whereas there is an insignificantly negative effect for old firms. Columns (2) and (3) of Panel B show no heterogeneity in the treatment effect for Conventional awards. This is true regardless of how we define age. This suggests that the effort to attract entrants to apply for Open is well-placed: the positive treatment effects are driven by this type of firms. Although our results are robust to selection as they are identified from the discontinuity, attracting a wide range of new firms is likely to be beneficial to overall program success.

In column (4) we include all applications even if there were multiple ones from the same firm. In Panel A, although the treatment effect remains significant, we observe a slightly lower effect of Open (5.3% instead of 5.7%) because the positive effect of Open is driven by firms that are new to the program, as shown by column (2). Since the Open program cannot screen out previous winners, it is useful to know the treatment effect remains positive, even on this more policy-relevant sample. As expected, the treatment effect remains insignificant in Panel B for Conventional. The sample sizes are noteworthy: of all Open applications, only 17% are submitted by firms that previously applied to Open, while the comparable statistic over the same period is 52% for Conventional, consistent with greater lock-in and recurring SBIR-winner presence in the Conventional program.

We extend the sample in the last four columns of Panel B of Table 3, as we have data from 2003 onwards for Conventional topics, repeating the specifications of the first four columns. The results are broadly similar, with zero average treatment effect in columns (5) and (8). However, for firms new to the DoD SBIR market in column (6) we do see a significant positive effect of 4.6 percentage points, about half the size of column (3) in Panel A. These results demonstrate that new entrants to Conventional experience positive effects, but this was only true for earlier program years, as there is no effect in the recent period. The absence of a result in the recent period does not seem to reflect crowding out of Open because we do not find any effect when we restrict to the 2016-17 period, when Open did not exist. This hints at the idea that entrants were more successful for Conventional topics, at least in earlier years.

In sum, Table 3 shows that winning the Open program has a strong positive causal effect on subsequent VC investment, while winning Conventional does not except for new entrants to the SBIR program in earlier years. This positive effect of an Open topic SBIR contract on VC serves as an early-stage proxy for success, indicates private sector interest in the firm, and shows that government money does not crowd out but rather crowds in, or "leverages," private investment. Why would small procurement contracts have such a large effect? One reason is that the Phase 1 SBIRs at AFWERX may be 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, while the goal of the Conventional program is to build the particular widget described in the specific topic. Startups with a successful Open Phase 1 process can bring the evidence of large potential defense customers to VCs, which appears to improve their odds of raising funds.

5.2 Effect on non-SBIR Defense Contracts

Non-SBIR defense contracts are the second primary outcome. One goal of the SBIR reforms is to enable more firms to "transition" out of the SBIR program towards operational programs of record (i.e. beyond only R&D awards). Therefore, in Table 4 and Figure 5, we consider the effect of winning on an indicator for subsequent DoD contracts. In column (1) of Panel A, we see a positive and significant effect of winning in an Open topic of 6.6 percentage points, or 45% of the mean of 14.8%. By contrast, in Panel B, we see no significant effect in Conventional topics. The visual results are in Figure 5. While noisier than Figure 4 for VC, there clearly is a level shift up on the right side of the cutoff, consistent with the effect we see in the Table 4. There is no such jump for Conventional topics.

In columns (2) and (3) we include interactions between the treatment indicator and the incumbent dummies. As with VC in Table 3 these interactions are negative, but they are not significant for the contracts outcome. In column (4) we include all proposals, which does not change the qualitative results. There is a significant causal impact of winning an Open topic of 8.1 percentage points, whereas there is an insignificant (negative) effect of winning a Conventional topic.

Finally, we look at the longer sample from 2003 in the last four columns of Panel B of Table 4. As with VC, we do identify a significant positive treatment effect for the new entrants who win the Conventional program in column (6). By contrast, incumbents are actually *less* likely to obtain future non-SBIR DoD contracts. Column (6) indicates previous SBIR contract holders are 4.4 percentage points less likely and column (8) on all contracts (a sample with firms that applied many times), finds a negative average effect of -2.7 percentage points. It is notable that the mean rate of contracts is much higher for Conventional. As reported in Table 2, the vast majority Conventional applicant contracts have R&D product codes, while only about half of Open contracts are for R&D.[38]

These results demonstrate that consistent with the results for VC, winning an Open topic has a positive causal effect on a firm subsequently creating something of practical value for the DoD, as indicated by a contract.

5.3 Additional Outcomes: Patents and Future SBIR contracts

To further evaluate the Open program, we consider two ancillary outcomes in order to understand the type of innovation that firms are engaged in (patenting) as well as the degree to which winning creates lock-in within the program.

Column (1) of Table 5 suggests that, within the sample of first proposals to the Open program, winning significantly increases the probability of a patent by 2 percentage points, which is over twice the mean of 0.7%. Similar to VC, the effect is stronger among entrant firms (columns (2) and (3)). Panel B shows that there are no significant effects of winning in the Conventional program. Although the coefficients are positive during the 2017-19 period, they are smaller in proportionate terms compared to Panel A. Furthermore, using the post 2003 sample, the coefficients remain insignificant, are smaller and actually become significantly negative in column (8). The visual analysis is in Figure 6. As only a small number of Open applicants have any patents, the figure is very noisy; it does suggest, however, that there may be an effect of winning in Open.

We also examine several other patent-related variables. The first is the number of applications, which has the benefit of data through June 2020, reducing the censoring problem due to long lags between patent application and approval that affects the granted patent data. 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.

The second outcome is originality, which increases in the number of classes a patent cites. A more original patent is less siloed in a particular field and is more basic (Jaffe and Trajtenberg 2002). Given that our data are so recent, this measure has the advantage of being backward-

[38] In unreported analysis, we find that the effects in Open are not different across R&D and non-R&D contracts. They are, however, driven by two contract types: definitive contracts and blanket purchase agreements, and there is no effect for delivery and purchase orders.

looking. Table A.5 shows that winning Open has a positive effect on producing an above-median originality patent (defined among all the applicants in our sample), while winning Conventional has no effect. The third outcome is the number of patent citations, which reflect patent quality. For the 2003-19 period in Conventional, there is sufficient time for citations to accrue (we have no citation data for Open applicant patents). Table A.6 shows that there are no effects on the log number of citations. This contrasts with Howell (2017), where there is a large effect of DOE SBIR grants on patent citations. Above, we showed 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 granted patents though it is too soon to identify effects on patent quality.

Our final outcome variable is the probability of subsequent DoD SBIR contracts. This is akin to looking at the impact of the lagged dependent variable, though it includes SBIR awards from the other services such as the Navy. The RDD helps us to overcome the usual difficulty of separating state dependence (the causal impact of the lagged dependent variable) compared to unobserved heterogeneity. Interestingly, the effect on this outcome appears rather different than the other three. Table 6 Panel A shows that there is no effect of winning Open competitions on winning future SBIR contracts. By contrast, Panel B shows that there is a positive effect of winning Conventional in most of our specifications (Panel B), especially for new entrants. For example, over the full time period in column (4), there is a large and highly significant effect of 14.5 percentage points, which is about half the mean (27.7%). The effect by rank is in Figure 7, which departs from the earlier figures by including first proposals from the whole period in Panel B, to highlight the large lock-in effect.

In sum, it appears that there is a strong dynamic towards persistent dominance in Conventional topics. Whether through reputation, dedicated staff, or some other channel, the traditional SBIR contract gives birth to the recurring SBIR-winners. By contrast, Open Topics seems to have thus far avoided this lock-in effect.

5.4 Robustness Tests

We conducted many robustness tests of the results, some of which are shown in Table 7. For each outcome variable, the first column shows the effect in the Open program and the second column shows the effect in the Conventional program.

First, we add a vector of control variables in Table 7 Panel A, including pre-award outcome variables.[39] Consistent with a valid RD design, the coefficients are very similar to the main results and do not lose any significance. Second, in Panel B we omit all controls and continue to find similar results. Third, in Panel C we estimate the main model for all outcomes using a narrow bandwidth of with the "just winners" of two ranks above and below the threshold ($\pm$1,$\pm$2). We include both ranks on either side of the threshold to keep the sample size reasonably large. The results remain robust.

Fourth, we show that the results are robust to controlling for rank quadratically rather than linearly (Panel D). Fifth, we omit the kernel weighting from the regression model and again find very similar results, albeit more statistically significant for VC and patents, as ranks farther away from the cutoff where the effect is more pronounced are now weighted more heavily (Panel E). Finally, in Panel F we find very similar effects when we restrict the outcomes to 24 months after the award to minimize the difference between Conventional and Open programs in time.

5.5 The Role of the Matching Program in the VC results

In Section 5.1 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 2.3.3, 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 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).

There are several features of the program's implementation that 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.

[39] The controls are whether the firm had any previous patents, previous VC, previous non-SBIR DoD contract, previous DoD SBIR award and whether the firm is located in a VC hub city or in a county with an AF base, as well as a continuous variable for firm age.

Third, we can assess whether the causal effect of Phase 1 on VC is driven by firms that apply for a Phase 2 match. We discuss these factors and the results in detail in Appendix A.2. The main finding is that across all three methods, 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.

5.6 Does the Effect of Open Reflect Only Selection?

Having established different effects in Open and Conventional, we are now interested in whether the strong positive effects of Open on VC investment reflect a different composition of firms – as Open targeted new entrants – or reflect a treatment effect of "openness." The summary statistics and Figure 8 reveal that the Open topics did attract, as was their intention, a very different type of applicant from Conventional topics. Furthermore, as shown in Sections 5.1 and 5.3, the positive effects of winning an Open topic contract on innovation (patents and VC) are concentrated in young firms without previous awards. We use two strategies to probe the role of selection. First, we conduct a comparison with other reform programs and second we examine a "within firm" design.

Other Reforms: Pitch Day and NSIN We compare the effect of Open relative to Conventional with the effect of two other "reform" topics that attracted firms with characteristics more similar to the Open applicants than to the Conventional applicants, but had more specific topics, rather than being entirely open to any idea. These smaller reformed SBIR programs were instituted at roughly the same time as the Open program: "Pitch Days" and "NSIN" (National Security Innovation Network). Air Force Pitch Days were held in VC hubs such as Boston, New York City and Austin starting in mid-2019. They sought to bring mission programs that have large procurement needs directly in contact with promising startups. Senior officers from the programs serve as pitch judges, and contracts are awarded on the spot at the end of the day. The topics are more specific than Open but broader than Conventional topics, such as "Battlefield Air Operations Family of Systems Technologies." The evaluation process has the same structure as all the other topics, but a key difference is that the evaluators are physically present at the pitch, and make their decisions in real time. Winners are immediately notified and are expected to sign a contract at the event.

NSIN topics come from a central DoD office, rather than one of the services. These topics are narrower than Open and Pitch Day, but broader than Conventional. They share with Open topics a focus on dual-use viability; in particular, identifying commercial technologies that can provide immediate solutions in the field for the Air Force (e.g. "Machine Learning for Defense

Applications"). As in the Open program, evaluators favored firms that already had a product and thus had the potential for rapid time to implementation in a defense application. Also like the Open topics, NSIN increased the speed and ease of contracting to be more appealing to young, fast-growing firms. Summary statistics in the pre-award period for these other reform programs are in Table 2 Panel B.

We assess how this compares to the other reform programs in Figure 8. We estimate a multinomial logistic model of the probability of firms applying to a specific program with the indicators discussed in the previous subsection.[40] The figure shows that firms applying to the reformed programs have markedly different characteristics relative to firms applying to the Conventional topics (the baseline group, denoted in the horizontal red line). For example, firms located in VC hub cities are about twice as likely to apply to Open and NSIN, and 50% more likely to apply to Pitch Day, than they are to apply to Conventional topics. In contrast, firms that have received previous SBIR awards are much less likely to apply to reformed programs. In sum, Pitch Day applicants are quite similar to Open applicants, and NSIN applicants are very similar on certain variables but less so on others (such as age). These differences relative to the Conventional program make the other reform topics useful for exploring the role of selection in any causal effects.

The results are in Table 8. A caveat is that the samples for the other two topics are small. However, it should be noted that we observe a significant effect in Open topics on VC even with a narrow bandwidth, which has a similar sample size as the other reform topics. In column (1) of Table 8, we confirm that winning an Open topic has a significantly larger positive effect on future VC investment in Open than Conventional (about five percentage points higher). This model includes first proposals only from the Open and Conventional programs. In this model we can cluster standard errors by topic, which shows that the result is robust to this assumption.

Next, we expand the sample to also include NSIN proposals (column (2)). The interaction between Award and NSIN indicates that relative to Conventional Topics, there is no significant effect of winning an NSIN topic. Third, we include Pitch Day topics in column (3) along with Open and Conventional topics. Again, there is no differential effect of winning in Pitch Day, although the standard errors are large enough that we cannot rule out an effect. However, when we consider Pitch Day topics alone in column (4) the coefficient is negative, suggesting that column (3) simply reflects noise. We also find a negative, insignificant effect within the NSIN topics (column (5)). Note that the magnitude in column (3) is relative to the effect in

[40] In particular, we use indicators for whether a firm has previous federal (non-SBIR) contracts, previous SBIR contracts, previous patents, previous VC investment, whether a firm is located in a VC hub and in a county with an Air Force base, and whether a firm is in the top 25% of the distribution of age and number of employees. We exclude firms that have applied to both open and conventional programs.

Conventional, so we expect a different magnitude than the independent effect.[41]

A Within Firm Design As a second strategy to investigate selection, we assess whether there is a different treatment effect of Open conditional on a firm applying to both types of topics. If the treatment of "openness" rather than selection is the sole reason for different effects in Open, we would expect to see a significant effect of Open relative to Conventional. In Table A.7, we restrict the sample to a first application to each program, and include firm fixed effects. The sample consists of firms that apply to multiple topics – and therefore apply multiple times – rather than those that are new to the SBIR program. Within this group, these regressions assess whether Open and Conventional topics have different effects. There are no effects on any outcome, indicating that the large additional effect of Open is coming not from applicants that apply to both, but rather those that apply only to Open. This is consistent with selection into applying for many awards yielding smaller effects and indicates that the firms which are particularly attracted to Open but not Conventional topics are relevant to the successful impact of the Open program.

In sum, these two exercises are consistent with the hypothesis that the "bottom-up" nature of Open topics is relevant to the success of Open. The first exercise suggests that rather than simply reflecting selection of firms with more startup-like characteristics, there is something about the openness itself that also affects outcomes. At the same time, among a subset of firms that decide to apply to both programs, there are no effects, indicating that selection into Open is also an important part of its recipe.

6 Conclusion

U.S. defense R&D is often held up as an example to the world of how to stimulate aggregate innovation through mission-driven research. This paper shows that the luster has faded somewhat in recent decades, with the prime defense contractors becoming less innovative than the rest of the U.S. economy on a number of dimensions, such as cite-weighted patents. One response of the U.S. Air Force to the concern that procurement has become dominated by incumbents with weakening innovation is to introduce Open SBIR solicitations, which seek to stimulate "bottom-up" innovation from new entrants. Though the SBIR program differs from mainline procurement acquisitions, it faces parallel problems of stale innovation and lock-in of repeat contractors. 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

[41] We find no effects of these additional reform programs on other outcomes.

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 topic reforms.

We show that the Open program successfully attracted a cohort of high-tech startups to the defense market. Our two primary outcomes are innovation benefits for civilian use (VC funding) and winning future DoD contracts to develop the new technologies (a benefit for the military). Using a RDD we find that winning an Open topic has positive effects on both these outcomes, whereas the Conventional topic programs do not. This implies that the Open reform was successful both in terms of military and non-military outcomes. The treatment effects are much stronger for new entrants than for incumbents. Part of this comes from attracting new entrants with stronger treatment effects. But a comparison with other reformed competitions suggests that part of the effect reflects the bottom-up nature of the program design.

We also show that winning an Open award boosts patenting, especially among younger firms. By contrast, winning a Conventional award for the first time strongly increases the chances of a subsequent SBIR contract, whereas winning an Open contract does not. This creates a lock-in effect for incumbents, contributing to the persistent dominance of the repeat SBIR-winners.

While our context is specific, it is important because the U.S. DoD funds more R&D than any other single entity in the world. Our results suggest that a more bottom-up approach to innovation that encourages new entrants to compete for R&D contracts rather than just incumbents can have significant payoffs to firms, the military, and ultimately consumer welfare through enhanced innovation. Beyond defense, our findings relate to other efforts at bottom-up or open innovation, ranging from the large pharmaceutical companies outsourcing innovation to biotech startups (Schuhmacher et al. 2013), to LEGO Ideas, which has led to 30 LEGO model kits based on externally submitted ideas.[42] An important avenue for future work is whether causal evaluations of bottom-up non-military R&D programs reveal similar patterns.

[42] See https://hbr.org/2020/01/turn-your-customers-into-your-community.

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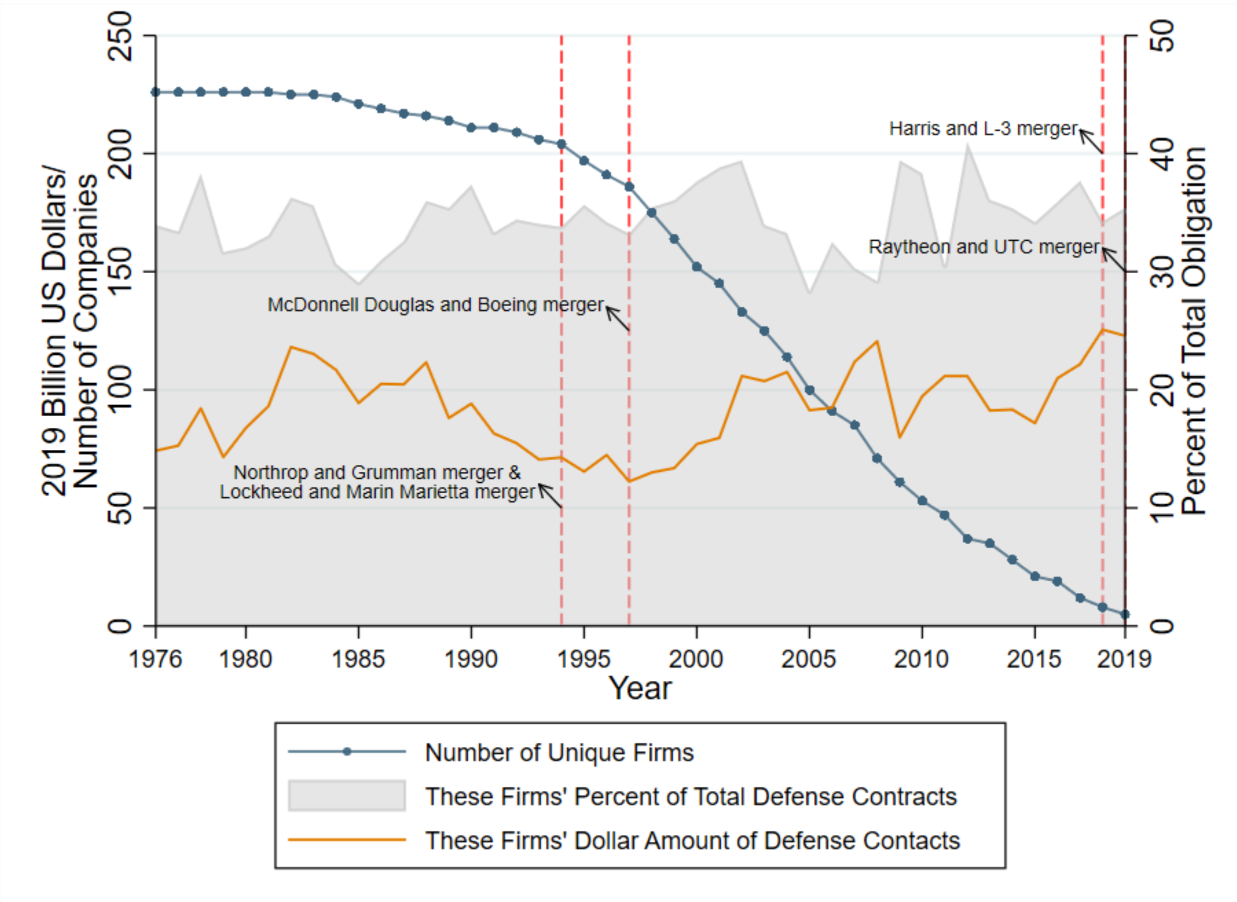
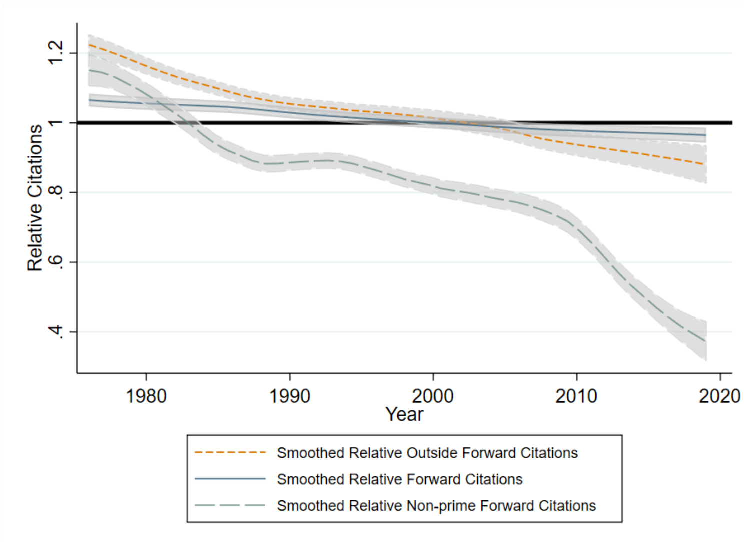
Figure 1: Innovation Dynamics and Consolidation of Prime Defense Contractors



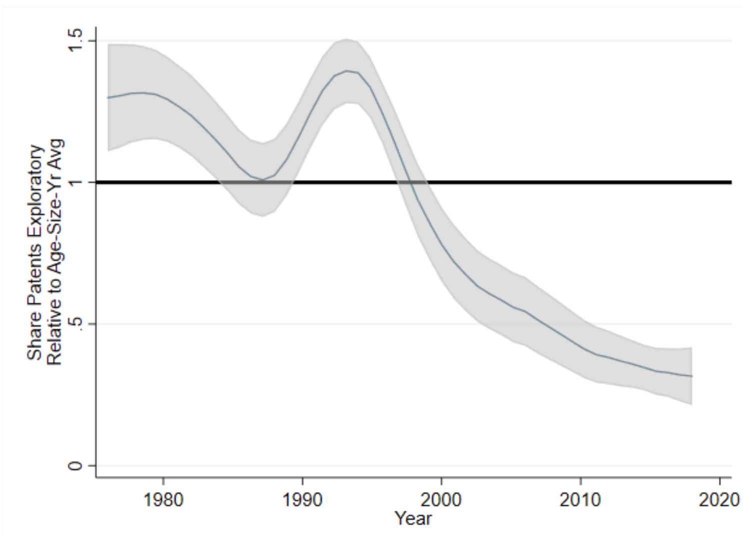
Note: This figure shows the trend of defense contractors' consolidation since the 1980s. We first define prime defense contractors as the top contractors between 2000 and 2020: Boeing, Raytheon, Lockheed Martin, Northrop Grumman, General Dynamics, United Technologies Corp, Harris, and L-3. We then identify 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 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 total defense contract value. Data are sourced from Federal Procurement Data System (FPDS) and Defense Contract Action Data System (DCADS).

Figure 2: Innovation Dynamics and Consolidation of Prime Defense Contractors

(a) Prime Patent Citations

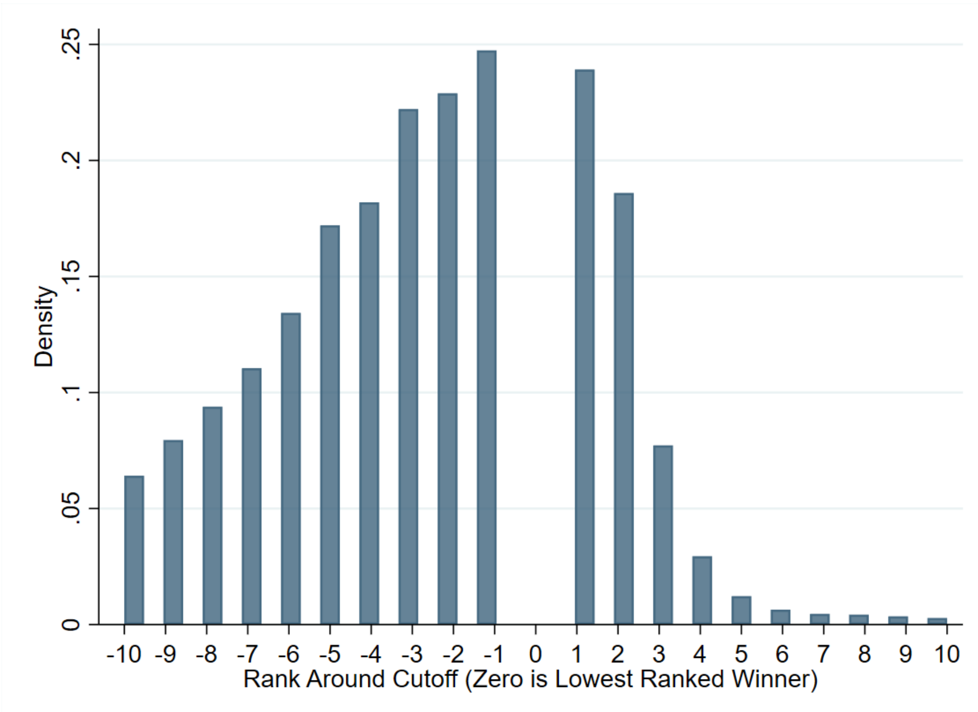


(b) Prime Patent Exploration



Note: These graphs describe patent quality for the prime defense contractors and their acquisition targets from Figure 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 average number of forward citations per patent (solid blue line), outside forward citations (orange line), and outside non-prime forward citations (dashed green 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. Outside citations exclude self-citations, where the company cites one of its own previous patents. Non-prime citations exclude 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. Also 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 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.

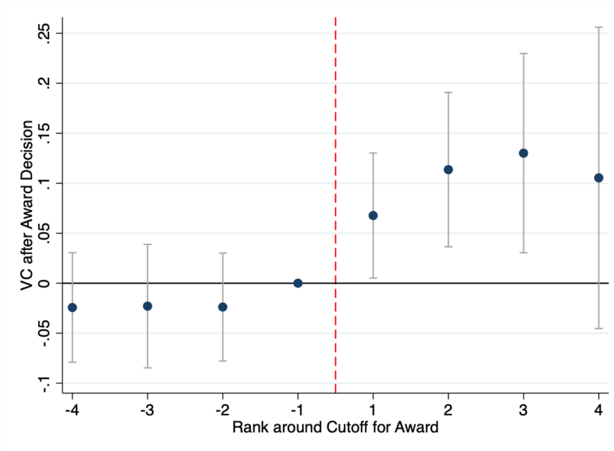
Figure 3: Regression Discontinuity Density Manipulation Test



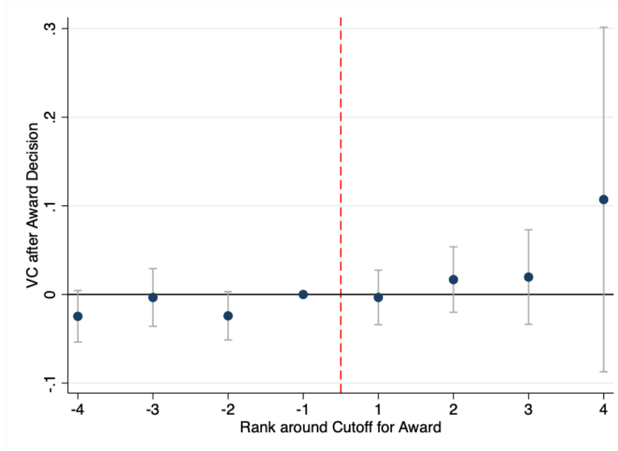
Note: These figures plot the density of applicants by rank around the cutoff using Phase 1 applicants. The formal test yields no evidence of manipulation, consistent with the figures (p-value of manipulation test is 0.62). Note that there is by construction more density overall to the left of the cutoff, as there are many more losers than winners. The point of this graph is to assess evidence of bunching near the cutoff.

Figure 4: Probability of Venture Capital by Rank Around Cutoff

(a) Open



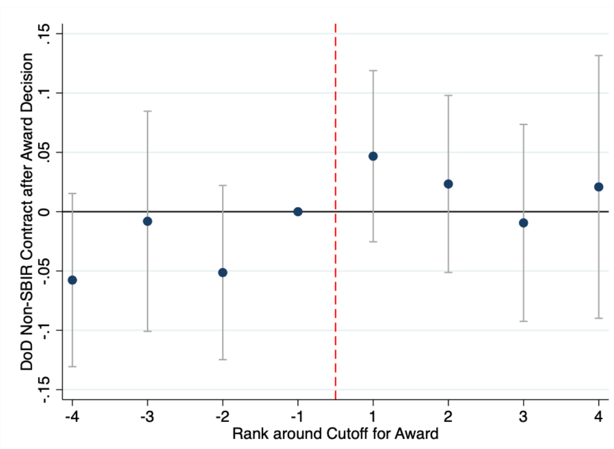
(b) Conventional (2017-19)



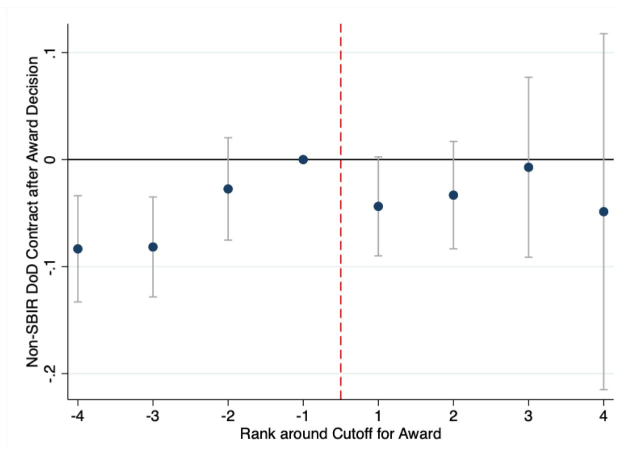
Note: These figures show the probability that an applicant firm raised venture capital investment (VC). In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that 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.

Figure 5: Probability of DoD non-SBIR Contract by Rank Around Cutoff

(a) Open



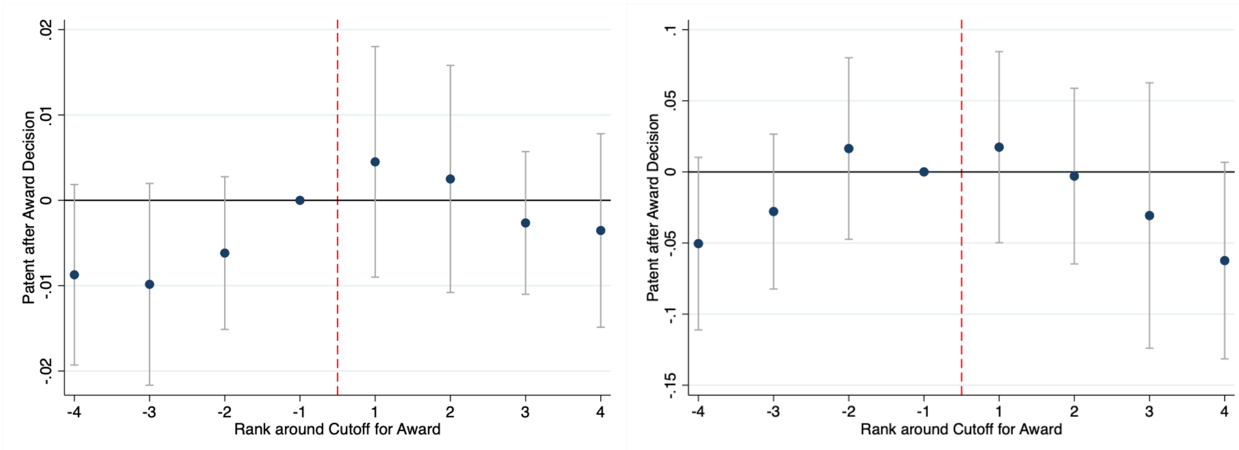
(b) Conventional (2017-19)



Note: These figures show the probability that an applicant firm he probability the applicant had any non-SBIR DoD contracts valued at more than $50,000 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.

Figure 6: Probability of Patents by Rank Around Cutoff

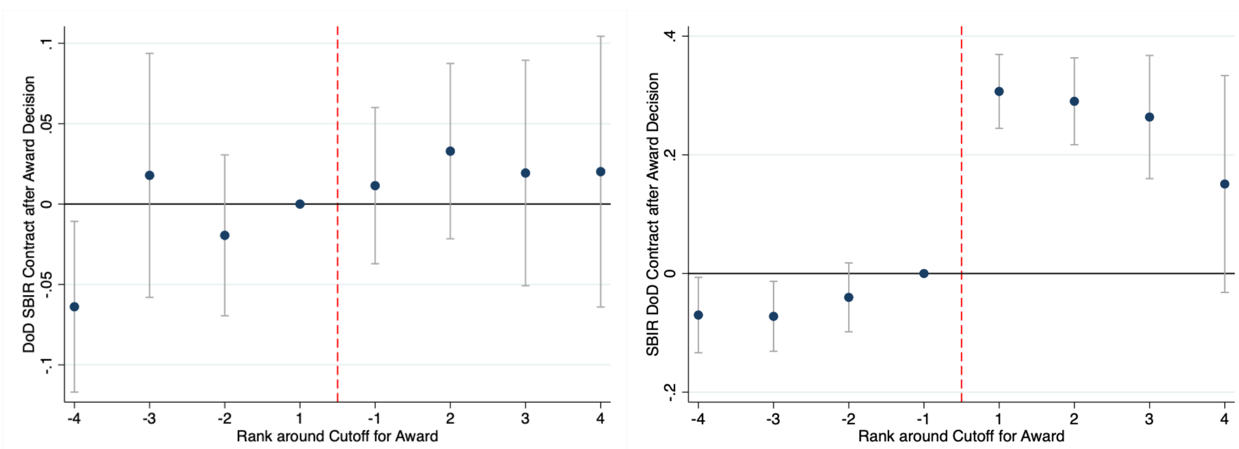
(a) Open (b) Conventional (2017-19)



Note: These figures show the probability that an applicant firm had any patents 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.

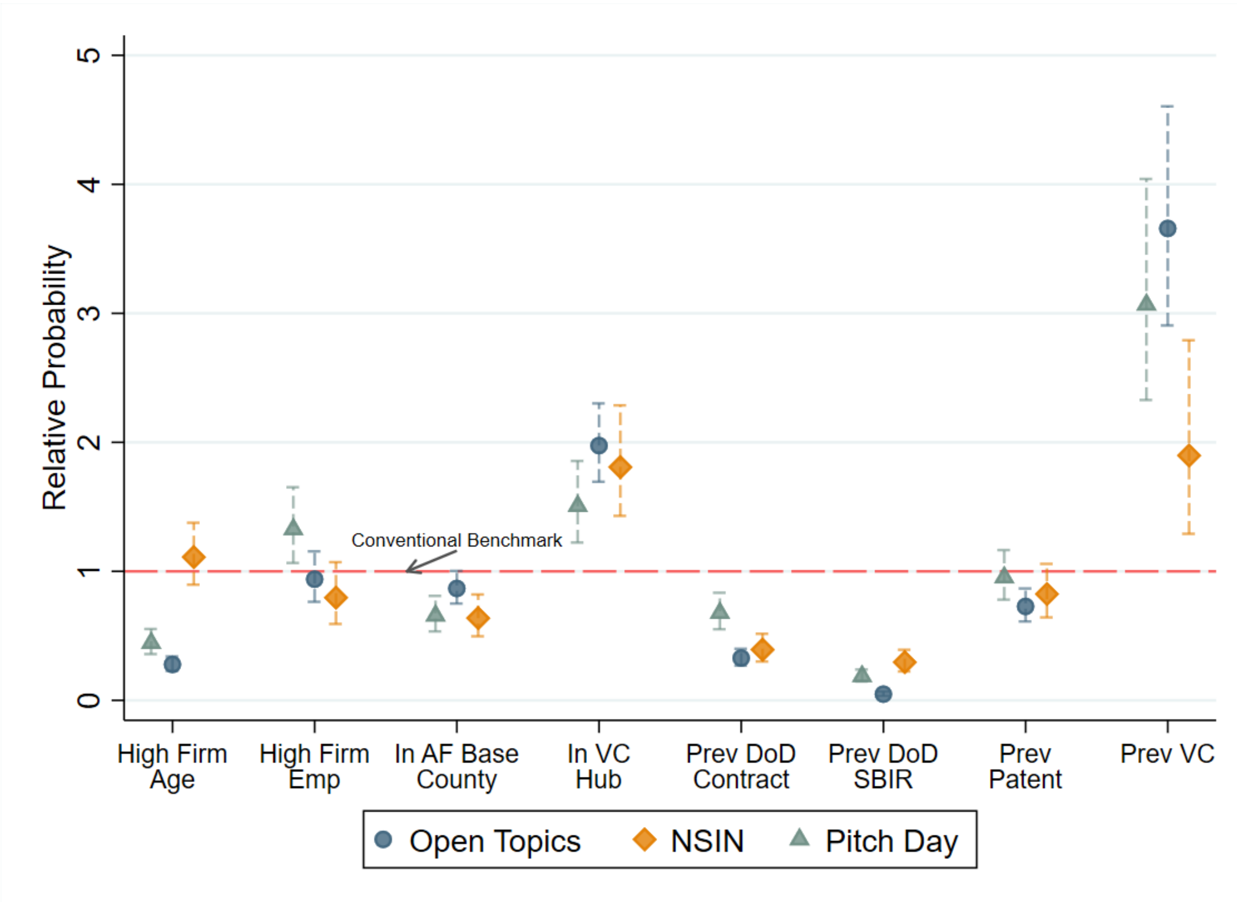
Figure 7: Probability of DoD SBIR Contract by Rank Around Cutoff

(a) Open (b) Conventional



Note: These figures show the probability that an applicant firm he probability the applicant had any DoD SBIR contracts 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 rather than only 2017-19 because the effect is only observed in the whole sample, as the sample in 2017-19 is overwhelmingly repeat-firms.

Figure 8: Selection into Programs



Note: This figure shows the relative probability of a firm selecting into a certain program (compared to conventional topics) by various firm characteristics, using firms from 2017-2019 proposals. The dashed lines indicate the 90% confidence intervals.

Table 1: Summary Statistics on Competition and Applicant Firm Characteristics

Panel A: 2017–2019 Sample

	Open Topic				Conventional				
	N	Mean	Median	SD	N	Mean	Median	SD	*p-value* (diff of means)
Competition Summary									
Num Proposals per Topic	1656	380	375	156	5573	18.7	14	16.3	0.000
Num Winners per Topic	1656	213	297	115	5573	2.99	2	3.4	0.000
Award Amount	269	49569	50000	14636	876	147235	152718	25296	0.000
Company Characteristics									
Age	1656	9.8	5	11	5573	19.2	17	13.3	0.000
Number of Employees	1656	24.7	7	53.9	5527	52.5	18	78.2	0.000
$\mathbb{1}$(in VC Hub)	1656	.196		.397	5573	.137		.344	0.000
$\mathbb{1}$(in County with AF Base)	1656	.204		.403	5573	.259		.438	0.000
$\mathbb{1}$(Minority Owned)	1656	.121		.326	5527	.128		.334	0.443
$\mathbb{1}$(Woman owned)	1656	.111		.314	5527	.155		.362	0.000

Panel B: NSIN and Pitch Day

	NSIN				Pitch Day				
	N	Mean	Median	SD	N	Mean	Median	SD	*p-value* (diff of means)
Competition Summary									
Num Proposals per Topic	423	56.4	57	12.5	324	108	106	5.16	0.000
Num Winners per Topic	423	10.8	9	4.5	324	18.4	19	1.69	0.000
Award Amount	32	69788	76252	11185	51	150601	157744	15011	0.000
Company Characteristics									
Age	423	14.1	8	13.7	324	11.2	6	11.5	0.002
Number of Employees	422	30.5	7	69.5	324	34.6	8	82.1	0.456
$\mathbb{1}$(in VC Hub)	423	.199		.399	324	.179		.384	0.500
$\mathbb{1}$(in County with AF Base)	423	.182		.386	324	.185		.389	0.912
$\mathbb{1}$(Minority Owned)	423	.151		.359	324	.167		.373	0.569
$\mathbb{1}$(Woman owned)	423	.116		.32	324	.133		.34	0.487

Note: This table shows summary statistics about the Phase 1 competitions, as well as select company characteristics as of the application date. The minority- and woman-owned variables are not available before 2017.

Table 2: Summary Statistics on Pre-Award Outcome Variables

Panel A: Open and Conventional, 2017-19

	Open Topic				Conventional			
	N	Mean	Median	SD	N	Mean	Median	SD
$\mathbb{1}$(Private Financing)	1656	.287		.452	5573	.195		.396
$\mathbb{1}$(VC)	1656	.115		.319	5573	.0603		.238
$\mathbb{1}$(DoD Non-SBIR Contract)	1656	.254		.435	5573	.611		.487
# DoD Non-SBIR Contract if Any	420	12.3	4	33.3	3407	19.9	9	29.2
Avg DoD Non-SBIR Contract Amt if Any	420	1929	896	3173	3407	2014	1026	5052
$\mathbb{1}$(Patent)	1656	.231		.421	5573	.46		.498
# Patents if Any	382	12.1	3	39.2	2563	26.4	11	44.4
# Patent Application if Any	506	10.5	3	34.7	2889	24.7	9	43.3
# Patent Cites if Any	382	140	8.5	577	2563	470	56	1122
Avg Patent Originality if Any	382	.3	.314	.216	2563	.317	.322	.181
$\mathbb{1}$(DoD SBIR Contract)	1656	.23	0	.421	5573	.628	1	.483
# DoD SBIRs if Any	381	53.8	14	122	3498	142	36	252
$\mathbb{1}$(Never Awarded SBIR)	1656	.691		.462	5573	.326		.469

Panel B: Full Sample Conventional and Other Reform Programs

	Conventional, 2003-19				NSIN & Pitch Day			
	N	Mean	Median	SD	N	Mean	Median	SD
$\mathbb{1}$(Private Financing)	17790	.127		.333	747	.242		.429
$\mathbb{1}$(VC)	17790	.0583		.234	747	.0736		.261
$\mathbb{1}$(DoD Non-SBIR Contract)	17790	.423		.494	747	.301		.459
# DoD Non-SBIR Contract if Any	7523	13.4	4	23	225	18.3	5	33.3
Avg DoD Non-SBIR Contract Amt if Any	7523	2476	850	7925	225	2312	1129	3503
$\mathbb{1}$(Patent)	17790	.434		.496	747	.245		.43
# Patents if Any	7722	20.4	7	35.9	183	13.2	4	26
# Patent Application if Any	8097	19.9	7	35.7	234	11.9	3	25.9
# Patent Cites if Any	7722	577	85	1337	183	187	15	619
Avg Patent Originality if Any	7722	.327	.341	.193	183	.264	.256	.192
$\mathbb{1}$(DoD SBIR Contract)	17790	.59	1	.492	747	.268	0	.443
# DoD SBIRs if Any	10502	98.9	26	192	200	95.2	15.5	199
$\mathbb{1}$(Never Awarded SBIR)	17790	.365		.481	747	.66		.474

Note: This table shows summary statistics of variables used as outcomes in the analysis, all calculated for the period before the award decision to facilitate evaluating selection into applying for the different programs. Panel A includes data on our main analysis sample (the Open and Conventional programs from 2017-19). The left side of Panel B reports data that includes the whole sample for the Conventional program. The right side of Panel B reports data for the other Air Force SBIR reform programs that we consider in Section 5.6.

Table 3: Effect of Winning on Any Subsequent Venture Capital

Panel A: Open Topics

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Award)	0.057**	0.067**	0.085***	0.053**
	(0.025)	(0.027)	(0.028)	(0.024)
$\mathbb{1}$(Award) × $\mathbb{1}$(Prev. SBIR)		-0.070***		
		(0.026)		
$\mathbb{1}$(Award) × $\mathbb{1}$(High Age)			-0.104***	
			(0.026)	
$\mathbb{1}$(Prev. SBIR)	-0.082***	-0.050***	-0.044***	-0.078***
	(0.014)	(0.015)	(0.016)	(0.014)
$\mathbb{1}$(High Age)			-0.019	
			(0.019)	
Observations	1382	1382	1382	1656
Outcome Mean	0.080	0.080	0.080	0.079
Proposals	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19

Panel B: Conventional Topics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	-0.010	-0.013	0.009	0.002	0.026*	0.046**	0.025	0.004
	(0.023)	(0.031)	(0.028)	(0.010)	(0.015)	(0.020)	(0.018)	(0.005)
$\mathbb{1}$(Award) × $\mathbb{1}$(Prev. SBIR)		0.004				-0.041*		
		(0.022)				(0.023)		
$\mathbb{1}$(Award) × $\mathbb{1}$(High Age)			-0.031				0.001	
			(0.023)				(0.022)	
$\mathbb{1}$(Prev. SBIR)	-0.036***	-0.037***	-0.027**	-0.035***	-0.017	-0.006	-0.011	-0.025***
	(0.011)	(0.011)	(0.011)	(0.008)	(0.011)	(0.011)	(0.012)	(0.006)
$\mathbb{1}$(High Age)			-0.018*				-0.029***	
			(0.010)				(0.010)	
Observations	2704	2704	2704	5573	6670	6670	6670	17790
Outcome Mean	0.024	0.024	0.024	0.016	0.043	0.043	0.043	0.027
Proposals	First	First	First	All	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19	2003-19	2003-19	2003-19	2003-19

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on the probability of any venture capital investment after the award decision, for Open topics (Panel A) and Conventional topics (Panel B). Rank within the topic (competition) is controlled for separately as a linear function on either side of the cutoff. The sample is restricted to first-time applicants only except in Panel A column 4, and Panel B column 7; in these two columns, all applications are included so a firm may appear more than once. In columns 2 and 5 of both panels, we interact winning an award with having won a previous DoD SBIR award and age, respectively. In columns 3 and 6 of both panels we interact winning an award with an indicator for an old firm defined as firm's age above the median of the distribution of firm age. In Panel B, columns 1-3 restrict the sample to the award years 2017-19 to facilitate comparison with the Open topics. Columns 4-7 include all years 2003-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Effect of Winning on Any Subsequent Non-SBIR DoD Contracts

Panel A: Open Topics

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Award)	0.066*	0.070**	0.064*	0.081**
	(0.035)	(0.035)	(0.035)	(0.033)
$\mathbb{1}$(Award) × $\mathbb{1}$(Prev. SBIR)		-0.028		
		(0.065)		
$\mathbb{1}$(Award) × $\mathbb{1}$(High Age)			-0.010	
			(0.048)	
$\mathbb{1}$(Prev. SBIR)	0.369***	0.382***	0.323***	0.370***
	(0.037)	(0.046)	(0.041)	(0.036)
$\mathbb{1}$(High Age)			0.087**	
			(0.040)	
Observations	1382	1382	1382	1656
Outcome Mean	0.148	0.148	0.148	0.160
Proposals	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19

Panel B: Conventional Topics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.038	0.040	0.050	-0.041	0.024	0.093**	0.031	-0.027**
	(0.048)	(0.058)	(0.057)	(0.031)	(0.029)	(0.038)	(0.032)	(0.014)
$\mathbb{1}$(Award) × $\mathbb{1}$(Prev. SBIR)		-0.002				-0.137***		
		(0.050)				(0.042)		
$\mathbb{1}$(Award) × $\mathbb{1}$(High Age)			-0.010				-0.015	
			(0.050)				(0.042)	
$\mathbb{1}$(Prev. SBIR)	0.372***	0.372***	0.331***	0.466***	0.327***	0.363***	0.306***	0.443***
	(0.028)	(0.031)	(0.031)	(0.026)	(0.021)	(0.023)	(0.022)	(0.021)
$\mathbb{1}$(High Age)			0.115***				0.105***	
			(0.031)				(0.023)	
Observations	2704	2704	2704	5573	6670	6670	6670	17790
Outcome Mean	0.330	0.330	0.330	0.439	0.374	0.374	0.374	0.544
Proposals	First	First	First	All	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19	2003-19	2003-19	2003-19	2003-19

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on the probability the firm won a subsequent non-SBIR DoD contract after the award decision, for Open topics (Panel A) and Conventional topics (Panel B). The dependent variable is an indicator for winning any non-SBIR DoD contracts valued at $50,000 or more after the award decision. Rank within the topic (competition) is controlled for separately as a linear function on either side of the cutoff. The sample is restricted to first-time applicants only except in Panel A column 4, and Panel B column 7; in these two columns, all applications are included so a firm may appear more than once. In columns 2 and 5 of both panels, we interact winning an award with having won a previous DoD SBIR award and age, respectively. In columns 3 and 6 of both panels we interact winning an award with an indicator for a young firm defined as firm's age below the median of the distribution of firm age. In Panel B, columns 1-3 restrict the sample to the award years 2017-19 to facilitate comparison with the Open topics. Columns 4-7 include all years 2003-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Effect of Winning on Any Subsequent Patenting

Panel A: Open Topics

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Award)	0.020**	0.024**	0.027**	0.017**
	(0.009)	(0.010)	(0.011)	(0.008)
$\mathbb{1}$(Award) × $\mathbb{1}$(Prev. SBIR)		-0.030*		
		(0.018)		
$\mathbb{1}$(Award) × $\mathbb{1}$(High Age)			-0.029***	
			(0.011)	
$\mathbb{1}$(Prev. SBIR)	0.018*	0.032**	0.020	0.012
	(0.010)	(0.015)	(0.013)	(0.007)
$\mathbb{1}$(High Age)			0.010	
			(0.011)	
Observations	1382	1382	1382	1656
Outcome Mean	0.007	0.007	0.007	0.006
Proposals	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19

Panel B: Conventional Topics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.055	0.040	0.057	0.034*	0.008	0.016	0.029	-0.029**
	(0.036)	(0.032)	(0.036)	(0.019)	(0.025)	(0.030)	(0.029)	(0.014)
$\mathbb{1}$(Award) × $\mathbb{1}$(Prev. SBIR)		0.020				-0.016		
		(0.036)				(0.041)		
$\mathbb{1}$(Award) × $\mathbb{1}$(High Age)			-0.002				-0.061	
			(0.042)				(0.039)	
$\mathbb{1}$(Prev. SBIR)	0.118***	0.113***	0.108***	0.090***	0.203***	0.208***	0.193***	0.230***
	(0.023)	(0.025)	(0.023)	(0.017)	(0.025)	(0.028)	(0.025)	(0.026)
$\mathbb{1}$(High Age)			0.027				0.065***	
			(0.028)				(0.024)	
Observations	2704	2704	2704	5573	6670	6670	6670	17790
Outcome Mean	0.083	0.083	0.083	0.068	0.220	0.220	0.220	0.284
Proposals	First	First	First	All	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19	2003-19	2003-19	2003-19	2003-19

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on any subsequent granted patent after the award decision, for Open topics (Panel A) and Conventional topics (Panel B). Rank within the topic (competition) is controlled for separately as a linear function on either side of the cutoff. The sample is restricted to first-time applicants only except in Panel A column 4, and Panel B column 7; in these two columns, all applications are included so a firm may appear more than once. In columns 2 and 5 of both panels, we interact winning an award with having won a previous DoD SBIR award and age, respectively. In columns 3 and 6 of both panels we interact winning an award with an indicator for a young firm defined as firm's age below the median of the distribution of firm age. In Panel B, columns 1-3 restrict the sample to the award years 2017-19 to facilitate comparison with the Open topics. Columns 4-7 include all years 2003-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Effect of Winning on Any Subsequent DoD SBIR Contracts

Panel A: Open Topics

	(1)	(2)	(3)	(4)
𝟙(Award)	0.006	0.033	0.021	0.005
	(0.026)	(0.025)	(0.025)	(0.025)
𝟙(Award) × 𝟙(Prev. SBIR)		-0.180***		
		(0.056)		
𝟙(Award) × 𝟙(High Age)			-0.062	
			(0.038)	
𝟙(Prev. SBIR)	0.328***	0.411***	0.336***	0.321***
	(0.032)	(0.042)	(0.035)	(0.029)
𝟙(High Age)			0.015	
			(0.032)	
Observations	1382	1382	1382	1656
Outcome Mean	0.096	0.096	0.096	0.107
Proposals	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19

Panel B: Conventional Topics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Award)	0.065	0.174***	0.136**	-0.033	0.145***	0.244***	0.183***	0.009
	(0.043)	(0.054)	(0.053)	(0.028)	(0.026)	(0.034)	(0.029)	(0.010)
𝟙(Award) × 𝟙(Prev. SBIR)		-0.150***				-0.199***		
		(0.046)				(0.036)		
𝟙(Award) × 𝟙(High Age)			-0.111**				-0.116***	
			(0.047)				(0.032)	
𝟙(Prev. SBIR)	0.572***	0.607***	0.575***	0.619***	0.685***	0.737***	0.697***	0.756***
	(0.025)	(0.026)	(0.025)	(0.019)	(0.017)	(0.019)	(0.017)	(0.011)
𝟙(High Age)			0.013				-0.026*	
			(0.024)				(0.015)	
Observations	2704	2704	2704	5573	6670	6670	6670	17790
Outcome Mean	0.359	0.359	0.359	0.485	0.277	0.277	0.277	0.539
Proposals	First	First	First	All	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19	2003-19	2003-19	2003-19	2003-19

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on the probability the firm won a subsequent SBIR contract after the award decision, for Open topics (Panel A) and Conventional topics (Panel B). Rank within the topic (competition) is controlled for separately as a linear function on either side of the cutoff. The sample is restricted to first-time applicants only except in Panel A column 4, and Panel B column 7; in these two columns, all applications are included so a firm may appear more than once. In columns 2 and 5 of both panels, we interact winning an award with having won a previous DoD SBIR award and age, respectively. In columns 3 and 6 of both panels we interact winning an award with an indicator for a young firm defined as firm's age below the median of the distribution of firm age. In Panel B, columns 1-3 restrict the sample to the award years 2017-19 to facilitate comparison with the Open topics. Columns 4-7 include all years 2003-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Robustness Tests

Panel A: Controls

Dep Var:	Any VC		Any Patents		Any DoD Contracts		Any DoD SBIR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.057**	-0.015	0.021**	0.041	0.060*	0.044	0.007	0.056
	(0.026)	(0.022)	(0.009)	(0.037)	(0.035)	(0.049)	(0.026)	(0.043)
Observations	1382	2704	1382	2704	1382	2704	1382	2704
Outcome Mean	0.080	0.024	0.007	0.083	0.148	0.330	0.096	0.359
Topic	Open	Conv	Open	Conv	Open	Conv	Open	Conv

Panel B: No Controls

Dep Var:	Any VC		Any Patents		Any DoD Contracts		Any DoD SBIR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.061**	-0.011	0.019**	0.059	0.046	0.052	-0.012	0.088*
	(0.025)	(0.023)	(0.009)	(0.037)	(0.037)	(0.053)	(0.029)	(0.050)
Observations	1382	2704	1382	2704	1382	2704	1382	2704
Outcome Mean	0.080	0.024	0.007	0.083	0.148	0.330	0.096	0.359
Topic	Open	Conv	Open	Conv	Open	Conv	Open	Conv

Panel C: Narrow Bandwidth

Dep Var:	Any VC		Any Patents		Any DoD Contracts		Any DoD SBIR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.064***	0.014	0.012*	0.007	0.068**	0.039	0.019	0.013
	(0.021)	(0.013)	(0.007)	(0.028)	(0.028)	(0.034)	(0.020)	(0.030)
Observations	668	943	668	943	668	943	668	943
Outcome Mean	0.060	0.020	0.002	0.124	0.154	0.445	0.090	0.513
Topic	Open	Conv	Open	Conv	Open	Conv	Open	Conv

Panel D: Quadratic Rank Control

Dep Var:	Any VC		Any Patents		Any DoD Contracts		Any DoD SBIR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.073***	0.009	0.014***	0.030	0.063**	0.051*	0.031*	0.047*
	(0.019)	(0.013)	(0.005)	(0.023)	(0.025)	(0.030)	(0.018)	(0.026)
Observations	1382	2704	1382	2704	1382	2704	1382	2704
Outcome Mean	0.080	0.024	0.007	0.083	0.148	0.330	0.096	0.359
Topic	Open	Conv	Open	Conv	Open	Conv	Open	Conv

Table 7: Robustness Checks (cont.)

Panel E: No Kernel Weighting

Dep Var:	Any VC		Any Patents		Any DoD Contracts		Any DoD SBIR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.065***	-0.008	0.020***	0.049	0.062*	0.053	0.005	0.069*
	(0.023)	(0.020)	(0.008)	(0.034)	(0.032)	(0.047)	(0.024)	(0.041)
Observations	1382	2704	1382	2704	1382	2704	1382	2704
Outcome Mean	0.080	0.024	0.007	0.083	0.148	0.330	0.096	0.359
Topic	Open	Conv	Open	Conv	Open	Conv	Open	Conv

Panel F: Truncated Two-Year Outcomes

Dep Var:	Any VC		Any Patents		Any DoD Contracts		Any DoD SBIR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Award)	0.066***	-0.002	0.020***	0.052	0.062*	0.053	0.005	0.082**
	(0.023)	(0.017)	(0.008)	(0.034)	(0.032)	(0.047)	(0.024)	(0.042)
Observations	1382	2704	1382	2704	1382	2704	1382	2704
Outcome Mean	0.079	0.018	0.007	0.082	0.148	0.330	0.096	0.352
Topic	Open	Conv	Open	Conv	Open	Conv	Open	Conv

This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on the probability of any venture capital investment (columns 1-2), any subsequent granted patent, (columns 3-4), any subsequent DoD non-SBIR contract over $50,000 (column 5-6), and any subsequent DoD SBIR contract (columns 7-8) after the award decision for Open and Conventional Topics. In Panel A, we add a full suite of controls for whether the firm had any previous patents, previous VC, previous non-SBIR DoD contract, and whether the firm is located in a VC hub city or in a county with an AF base, as well as a continuous variable for firm age, in addition to any previous DoD SBIR award. In Panel B, we do not include any controls. In Panel C, we restrict the bandwidth to include only 2 applicants on each side of the cutoff. In Panel D, we control for rank quadratically on each side of the cutoff. In Panel E, we control for rank linearly on each side of the cutoff and do not weight observations close to the cutoff more heavily. In Panel F, we limit the outcome variables to within two years of application. In all panels, the sample is restricted to first-time applicants only and award years 2017-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Effect of Open, NSIN and Pitch Day Topics Relative to Effect of Conventional Topics

Sample:	Open & Conv	Open, Conv & NSIN	Open, Conv & Pitch Day	Pitch Day Topics	NSIN Topics
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topics)	0.054***	0.051***	0.053***		
	(0.015)	(0.016)	(0.015)		
$\mathbb{1}$(Award) × $\mathbb{1}$(NSIN)		0.016			
		(0.042)			
$\mathbb{1}$(Award) × $\mathbb{1}$(Pitch Day)			0.041		
			(0.024)		
$\mathbb{1}$(Award)	0.003	0.002	0.001	-0.016	-0.112
	(0.021)	(0.021)	(0.022)	(0.063)	(0.071)
Observations	4086	4509	4410	423	324
Outcome Mean	0.043	0.045	0.044	0.071	0.062

Note: This table compares the effect of winning an award on subsequent VC after the award decision for Open Topic and two other "reform" topics, relative to conventional topics. The other reform topics are Pitch Day and NSIN (discussed in the text). A wide bandwidth model with controls for rank on either side of the cutoff is used throughout. In columns 1-3, the base group is conventional proposals. Column 1 interacts winning an award with an indicator for the topic being open, so that the independent coefficient on award represents the effect of winning a conventional topic award. In columns 2 and 3, we add the NSIN and Pitch Day topics, and also interact award with indicators for the topic being one of those. Note the topic FE control for the independent effects of Open, NSIN, and Pitch Day. In columns 4-5, we consider as separate samples the effect of winning within Pitch Day and NSIN topics, respectively. As elsewhere, we include only first-time proposals. Standard errors are clustered by topic, except in columns 4 and 5 where they are robust. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

(For Online Publication)

A.1 Slowing Innovation in the US Defense Industry

Despite widespread concern over several decades among policymakers, we know of no studies of the evolution of prime defense contractors' innovation.[43] 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.

Figure 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%.[44] 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 2 shows patent activity for the firms in Figure 1, weighted by future citations. Patent activity is only one proxy for innovativeness, but it is relevant to

[43] 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.

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

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 IPC3 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.[45] 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. This measure omits self-citations, which occur when a company cites one of its own previous patents. Outside citations offer a proxy for knowledge spillovers to the broader economy.[46] On this measure, presented in the dashed orange line, defense contractor patents exhibit a steeper downward trend, from having 22% more outside citations than the average patent in 1976 to 11% fewer in 2019.[47] Finally, we restrict outside citations to patents from firms that are not featured in the graph, that is, from firms outside the prime contractor universe. These citations are 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" patent 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. Panel B shows the average share of exploratory patents relative to other firms with similar in age, size, and year. As above, all firms from Figure 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

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

[46] Self citation is calculated by matching the USPTO assignees of cited and citing patents. For example, if Boeing cited a McDonnell Douglas patent in 2000, it would not be counted as a self citation. If McDonnell Douglas and Boeing file for patents solely under "Boeing" as the assignee after the merger, then those citations will be counted as self citations.

[47] 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. Also 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 A.1 Panel A).

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, 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 similar age since first patent.

Figure A.1 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 after this we see a divergence, with defense contractors patenting at a lower rate.[48] The subsequent three panels use Compustat data and compare primes to other firms in the same three-digit NAICS industry.[49] 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.

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 continuing into the period of higher spending following 9/11 and the Iraq War.

A.2 Details on the Role of the Matching Program in the VC results

In Section 5.1 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 2.3.3, an additional reform in the Open topics was to offer matching in Phase 2.

[48] 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 Marin Marietta.

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

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 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).

There are several features of the program's implementation that 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 match is 7.2%. The fraction that raised VC and also obtained a private match from the Phase 2 program is 1.2%. Table A.8 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.[50] Among Phase 2 applicants, 20.3% applied for a private match and 12.4% 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. About 30% of the private matches are from VC.

We are interested in whether the matching program was successful in driving subsequent 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 A.9, we repeat the main specification from Table 3 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 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 4.4 percentage points, significant at the .1 level. This is 61% of the mean. Comparing it with the main result from Table 3 of 5.7 percentage points (71% 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

[50] It is also possible to have an outside government match (as the table shows, 24% of Phase 2 applicants had matching government funds). We find no relationship between the government match and VC.

VC but had no private match. As we would expect, the effect is larger relative to the mean, at 1.3 percentage points relative to a mean of 1.2%.

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 offers VC matching (Column 3) and topics that do not offer VC matching (column 4). There is not a statistically significant effect in column 3, while the effect in column 4, topics with no matching offered, sees a large and statistically significant effect of 7.1 percentage points (104% of 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.

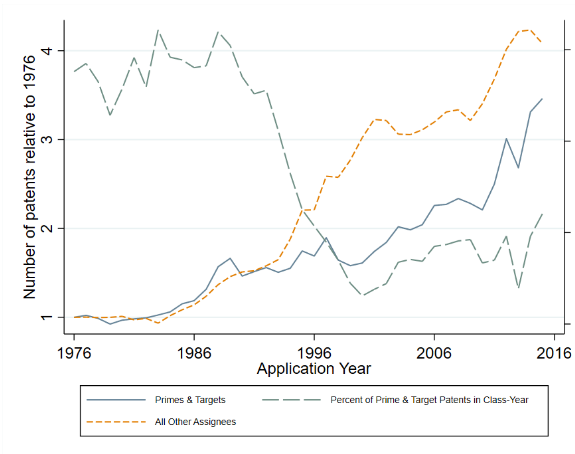
A.3 Phase 2 Analysis

In this analysis, we consider the effect of Phase 2 awards. However, we are cautious in interpreting them 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. An interesting aspect of Phase 2 is that it enables considering the amount of award, as there is substantial variation in the Phase 2 award amount (Figure A.3).

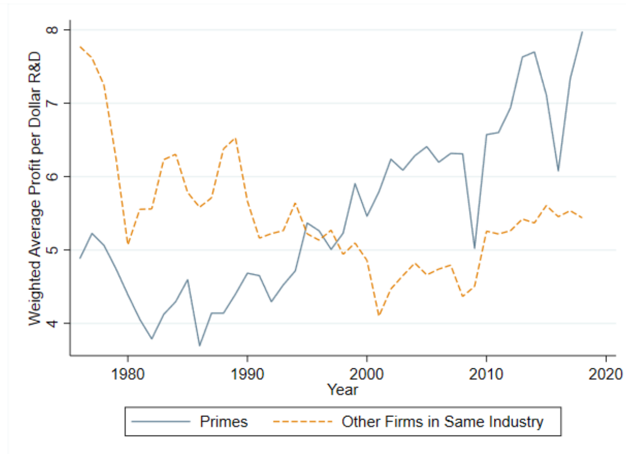
Tables A.10 and A.11 show RDD estimates of the effect of winning a Phase 2 award on all four outcomes of interest. For Open topics, we find a positive, significant effect of award amount on VC (Table A.10 Panel A), suggesting that the amount of an award and not the extensive margin matters for Phase 2. We find no effects of the Conventional topic Phase 2 on any outcome, even over the long term (column (5) 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.

Figure A.1: Historical Dynamics of Prime Defense Contractors

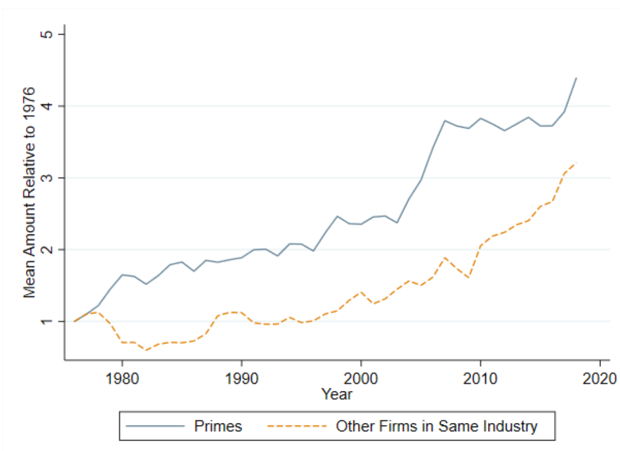
(a) Number of Patents



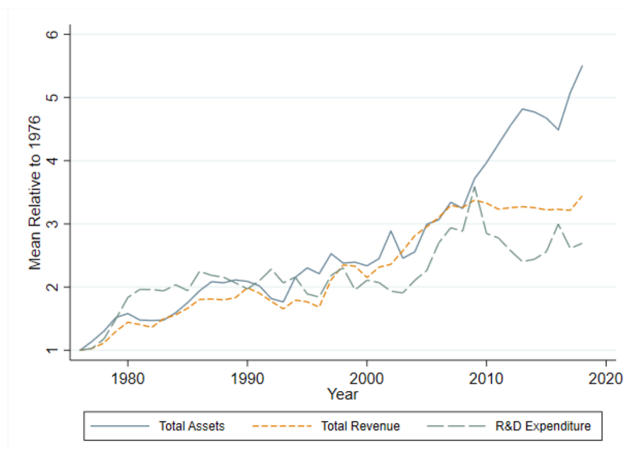
(b) Profit per Dollar R&D



(c) Profits



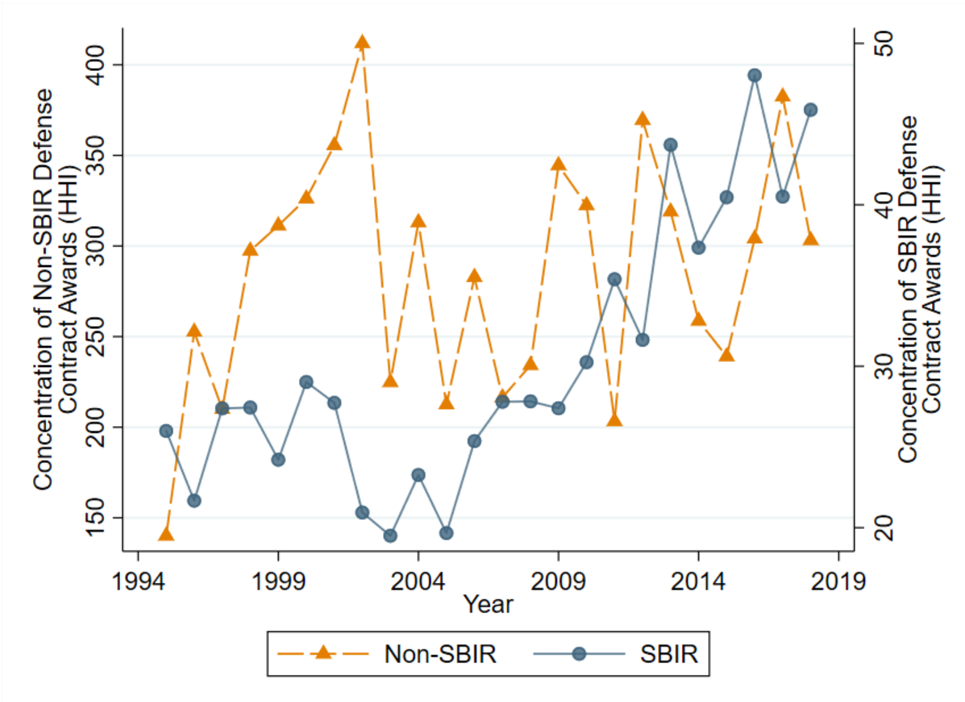
(d) Total Assets, Revenue, and R&D Expenditure



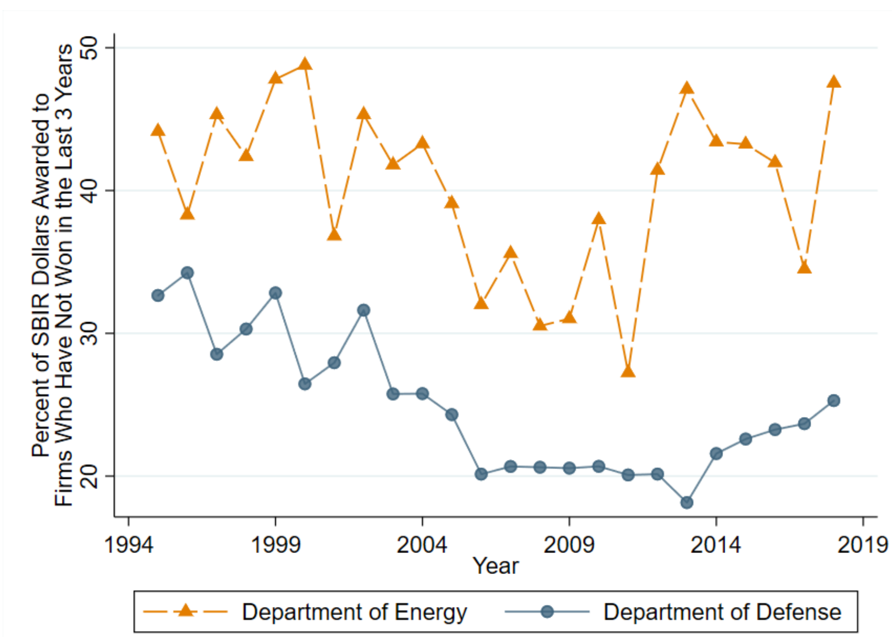
Note: This figure shows the dynamics of prime defense contractors. Panel A shows growth in the number of granted patents for prime defense contractors and their acquisition targets (blue line) and the number of granted patents for all other assignees (orange line) from 1976 - 2016, using data from the 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.

Figure A.2: Concentration of Federal Contracts

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

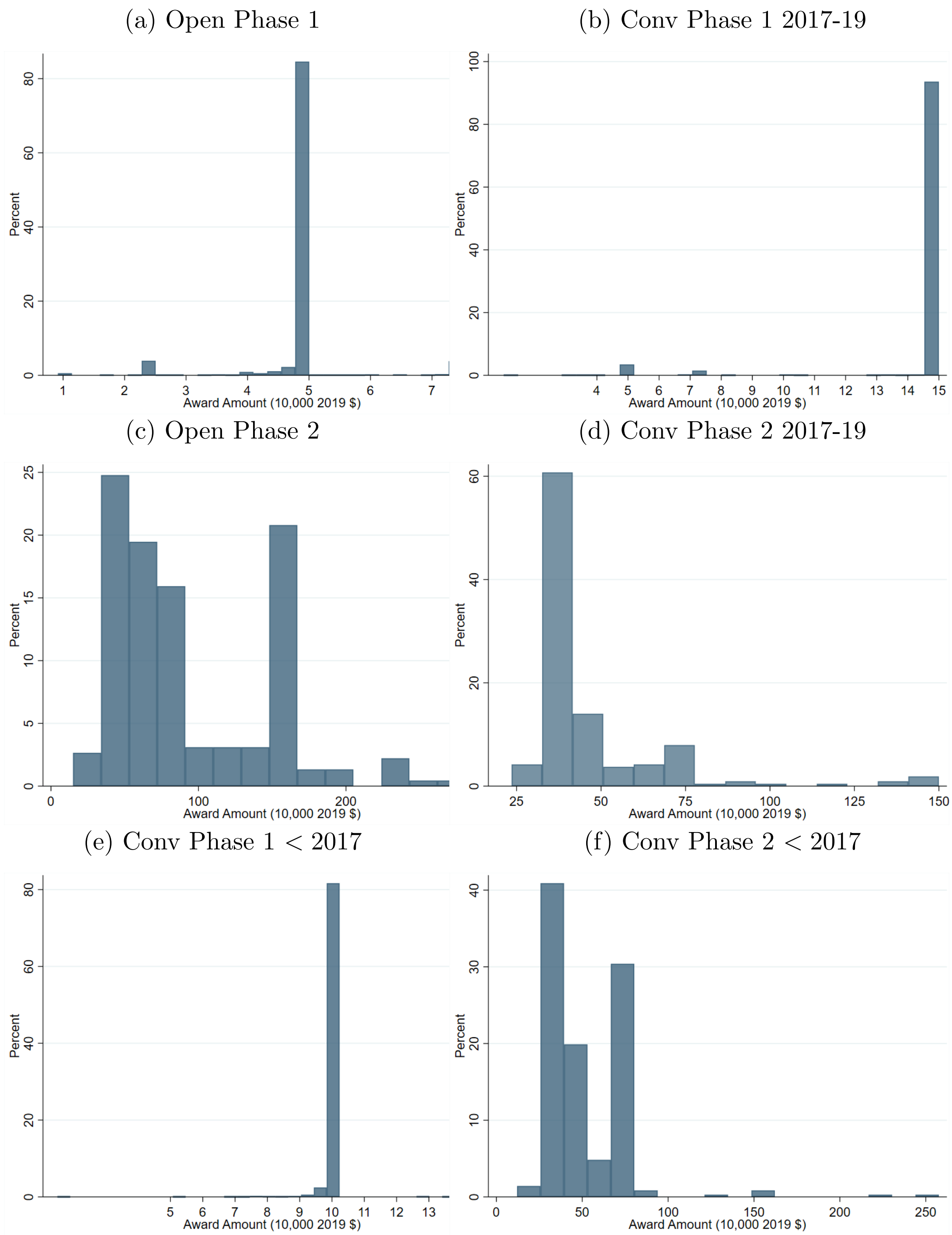


(b) Share of Firms without Recent Repeat Contracts in Two SBIR Programs



Note: Panel A in this figure shows the Herfindahl–Hirschman Index (0-10,000) for SBIR and Non-SBIR Department of Defense contracts from 1990 to 2018. In general, non-SBIR contracts are more concentrated than SBIR contracts. 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% 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.

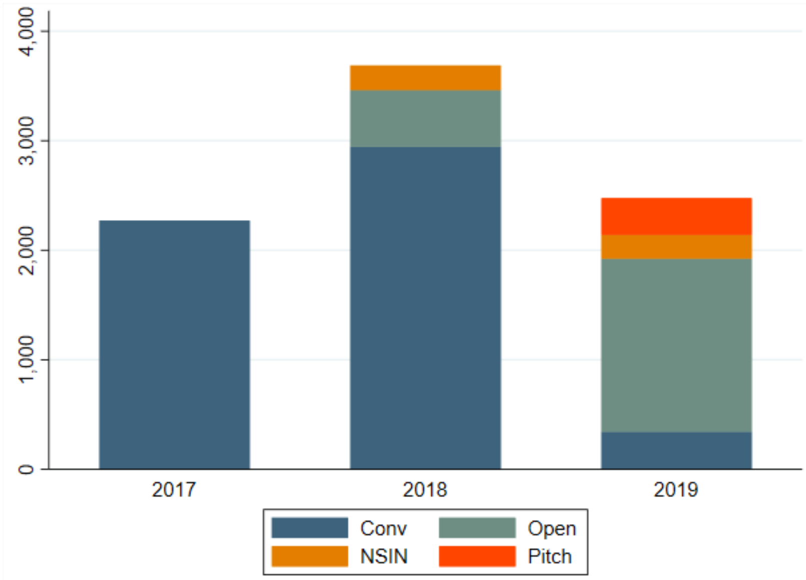
Figure A.3: Histograms of Award Amounts by Topic Type and Phase



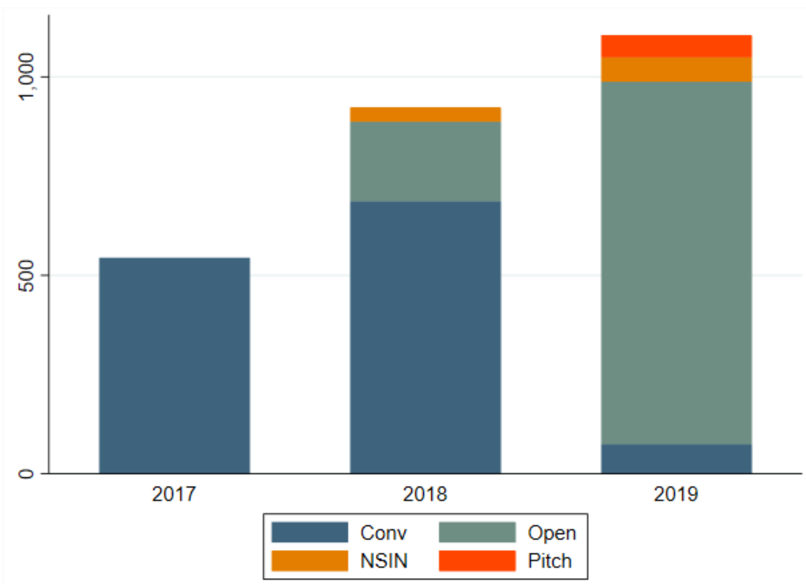
Note: These histograms show the share of awards by amount, in real 2019 dollars. For the bottom right graph (Phase 2 <2017), we omit one outlier $12 mill contract.

Figure A.4: Number of Applications and Awards Over Time by Topic Type (Analysis Sample)

(a) Applications



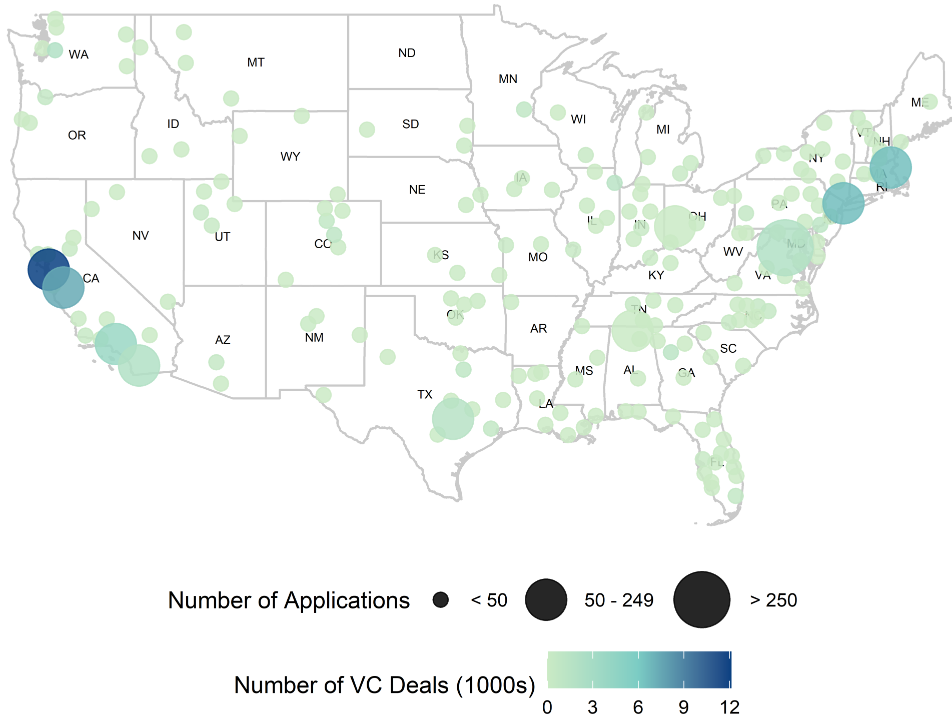
(b) Awards



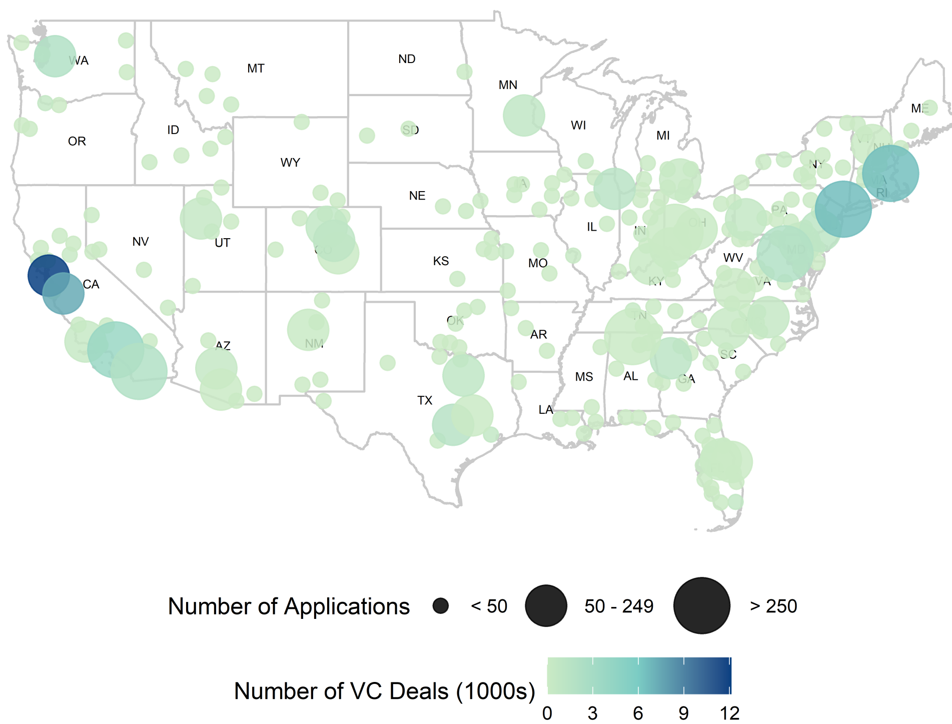
Note: These figures show the number of applications (top) and awards (bottom) in our "analysis sample" of data from 2017-2019 by topic type.

Figure A.5: Geographic Dispersion of Applications (2017-19)

(a) Open Topic Applications and VC Deals



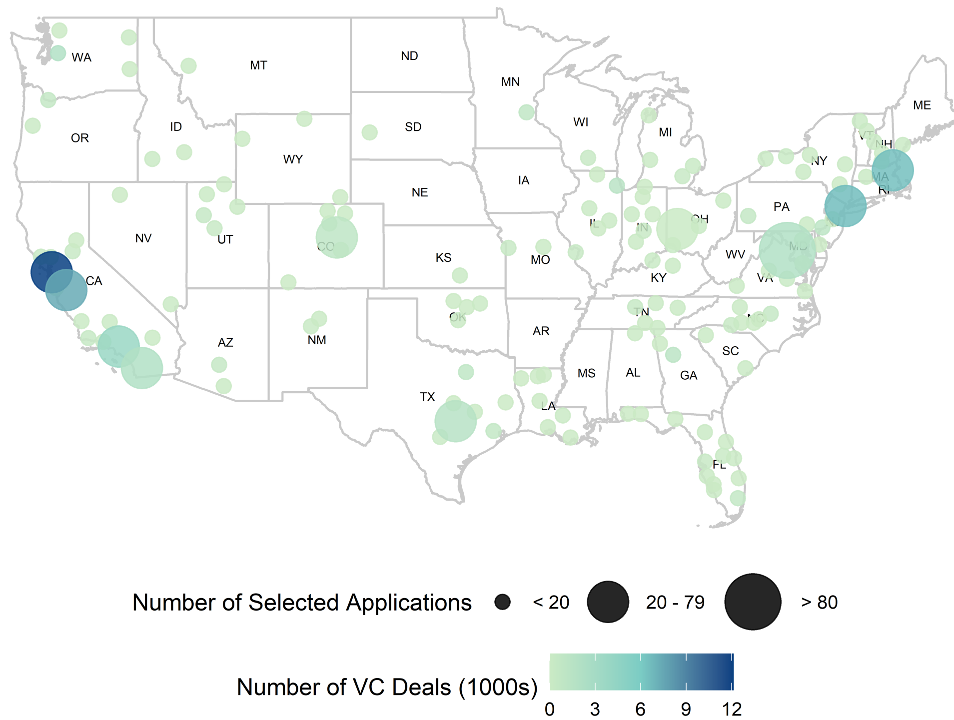
(b) Conventional Topic Applications and VC Deals



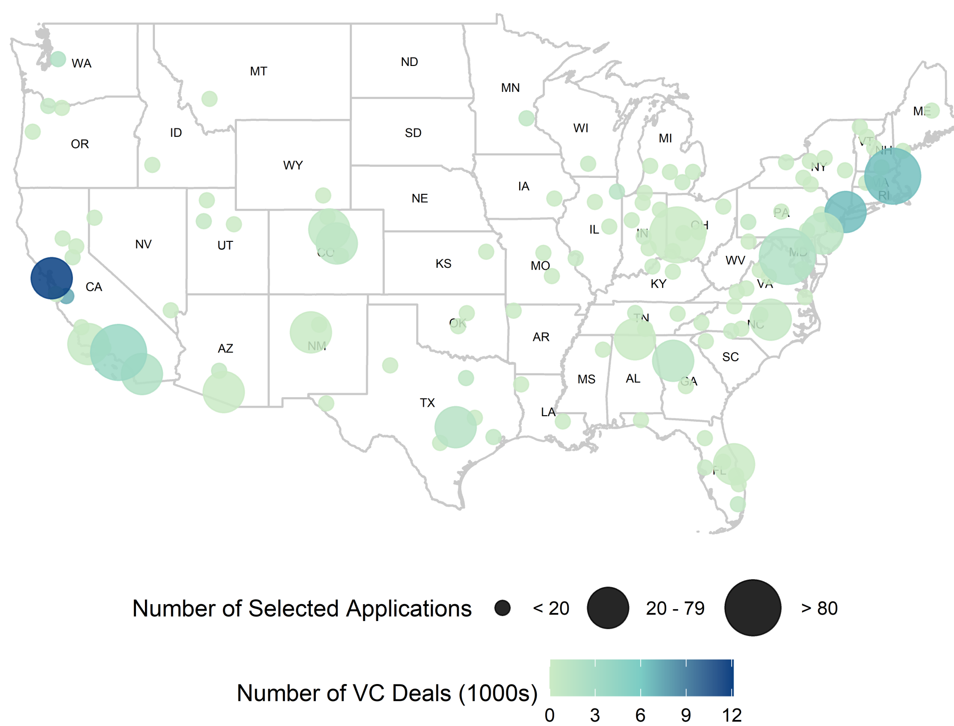
Note: These maps show the number applications to open (Panel A) and conventional SBIR topics (Panel B) by MSA from 2017 to 2019. The size of the bubble represents the relative number of applications. Both maps also shows VC activity by MSA.

Figure A.6: Geographic Dispersion of Awards (2017-19)

(a) Open Topic Awards and VC Deals



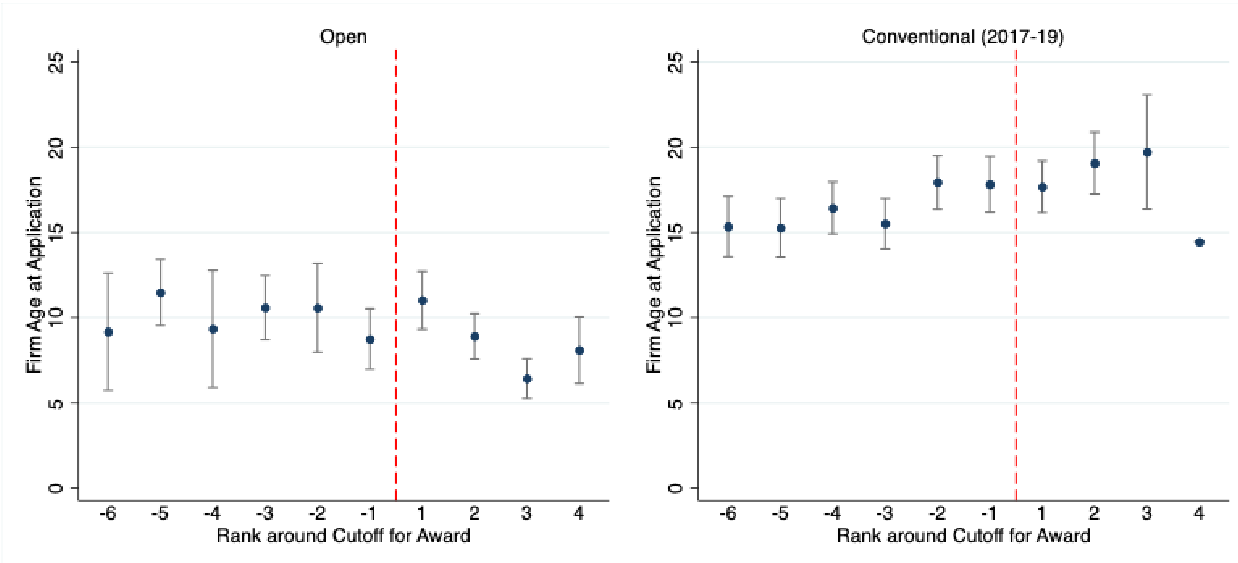
(b) Conventional Topic Awards and VC Deals



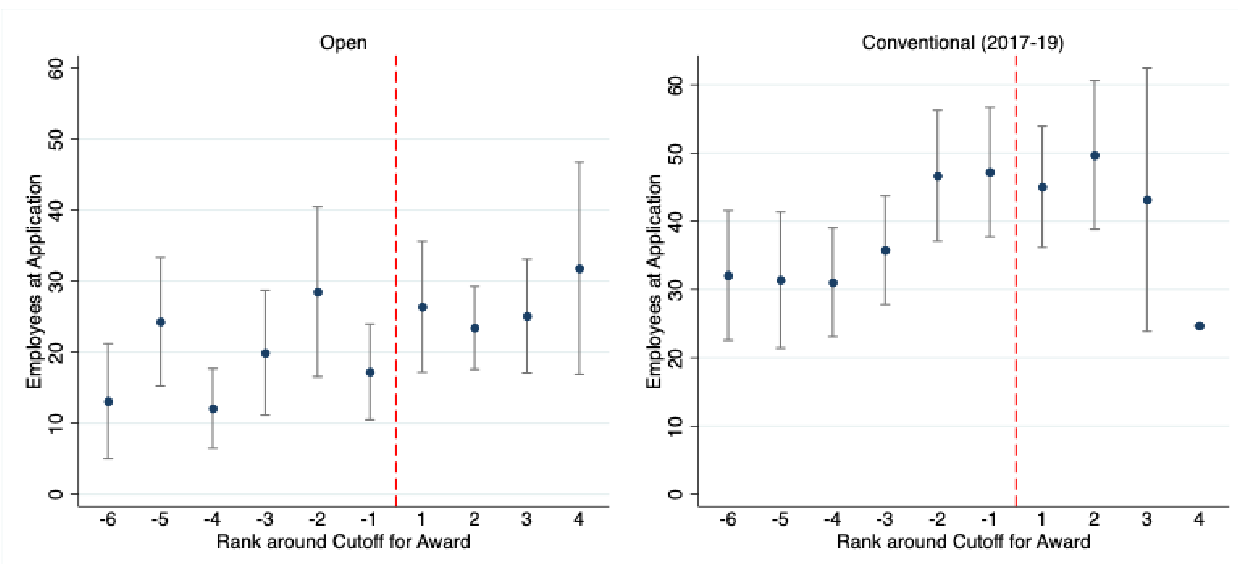
Note: These maps show the number awards (i.e. contracts) for open (Panel A) and conventional SBIR topics (Panel B) by MSA from 2017 to 2019. The size of the bubble represents the relative number of applications. Both maps also shows VC activity by MSA.

Figure A.7: Continuity of Baseline Characteristics by Rank around Cutoff (Part 1 of 3)

(a) Firm Age at Application



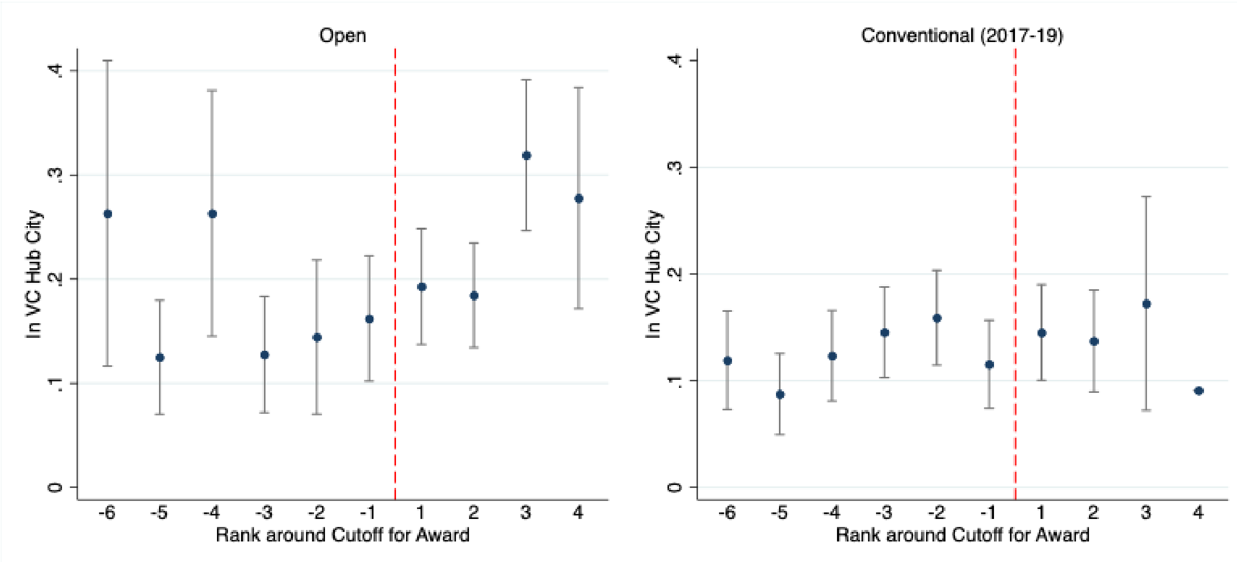
(b) Firm Employment at Application



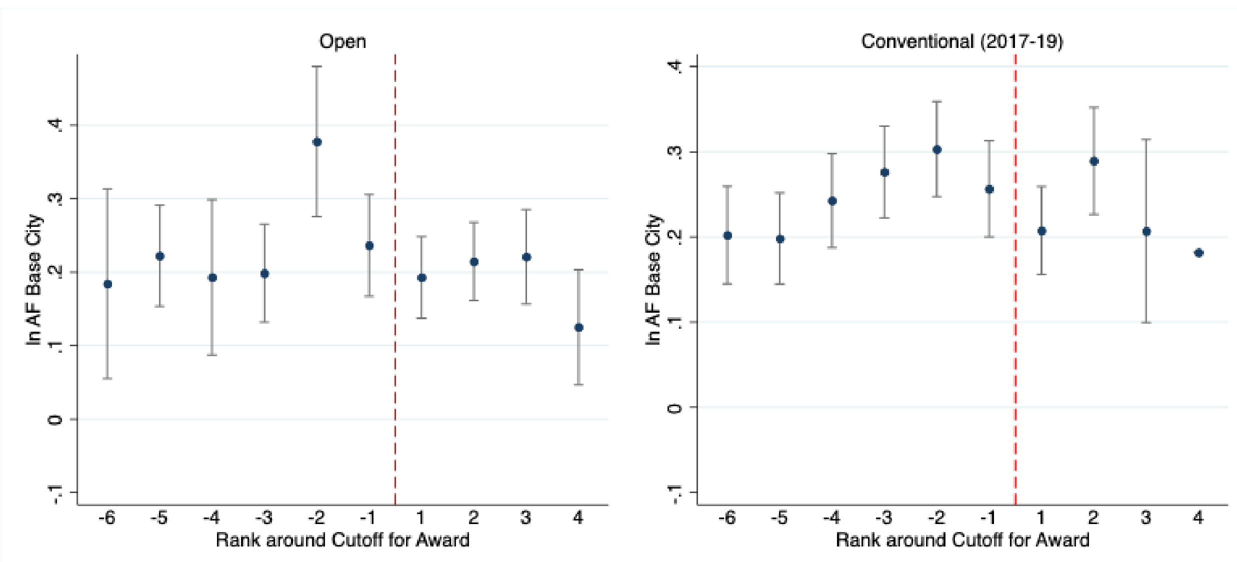
Note: These figures show applicant firm age (top figures) and employment (bottom figures) at the time of the application. In all cases, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1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

Figure A.8: Continuity of Baseline Characteristics by Rank around Cutoff (Part 2 of 3)

(a) Probability Firm Located in VC Hub City



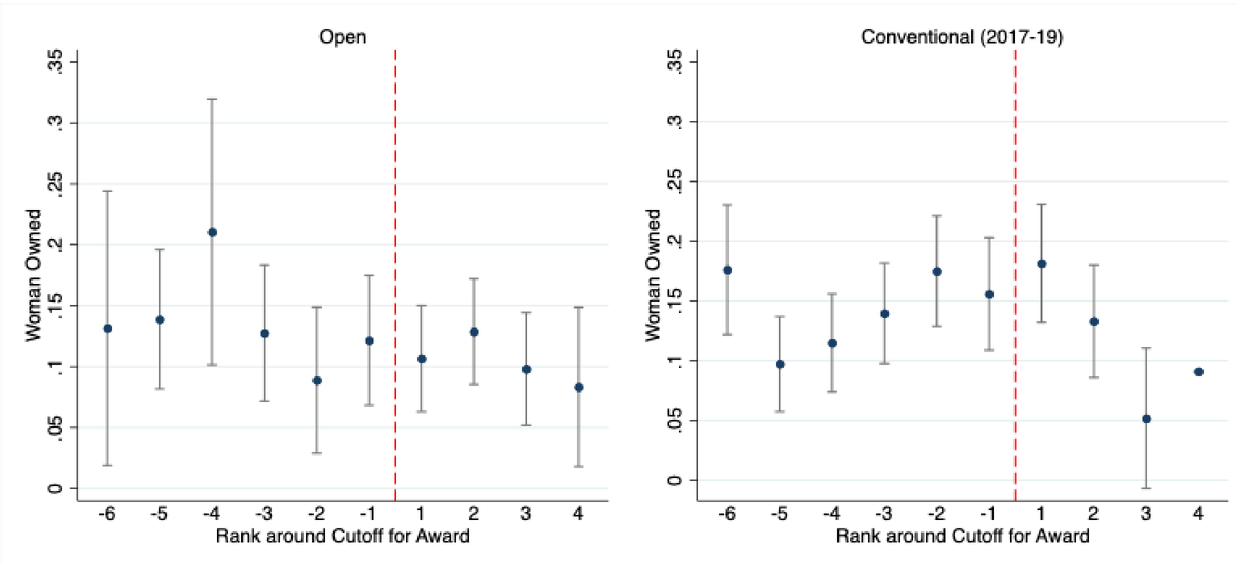
(b) Probability Firm Located in a County with an Air Force Base



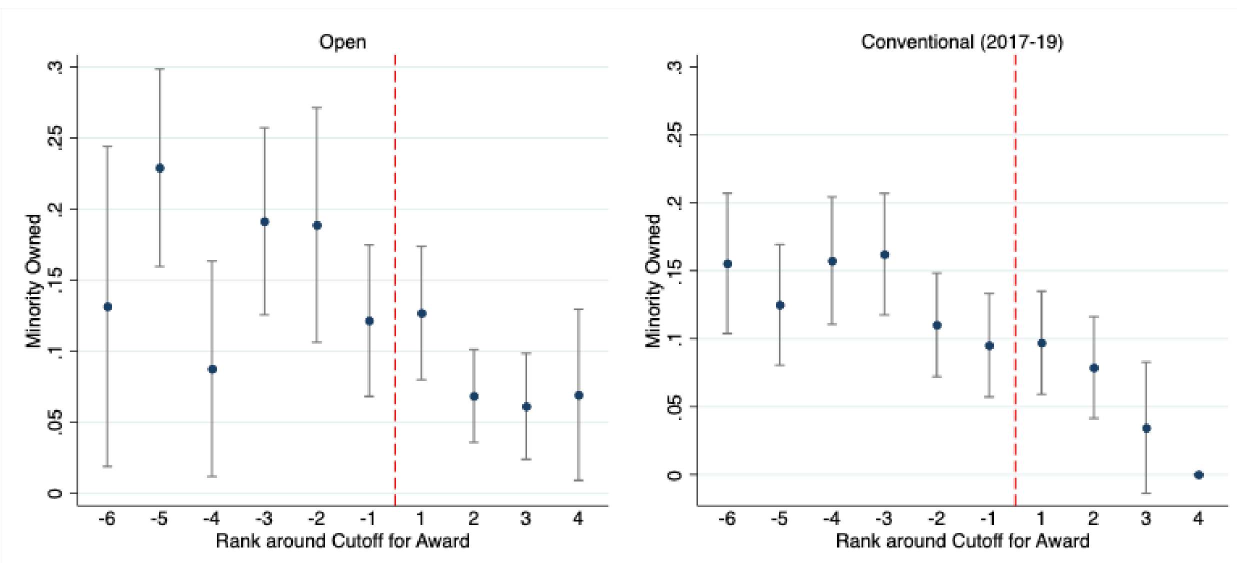
Note: These figures show the probability that an applicant firm is located in either San Francisco/San Jose, Boston, or New York City (top figures) and the probability the firm is located in a county with a U.S. Air Force base (bottom figures) at the time of the application. In all cases, the x-axis 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.

Figure A.9: Continuity of Baseline Characteristics by Rank around Cutoff (Part 3 of 3)

(a) Probability Firm Woman-Owned at Application



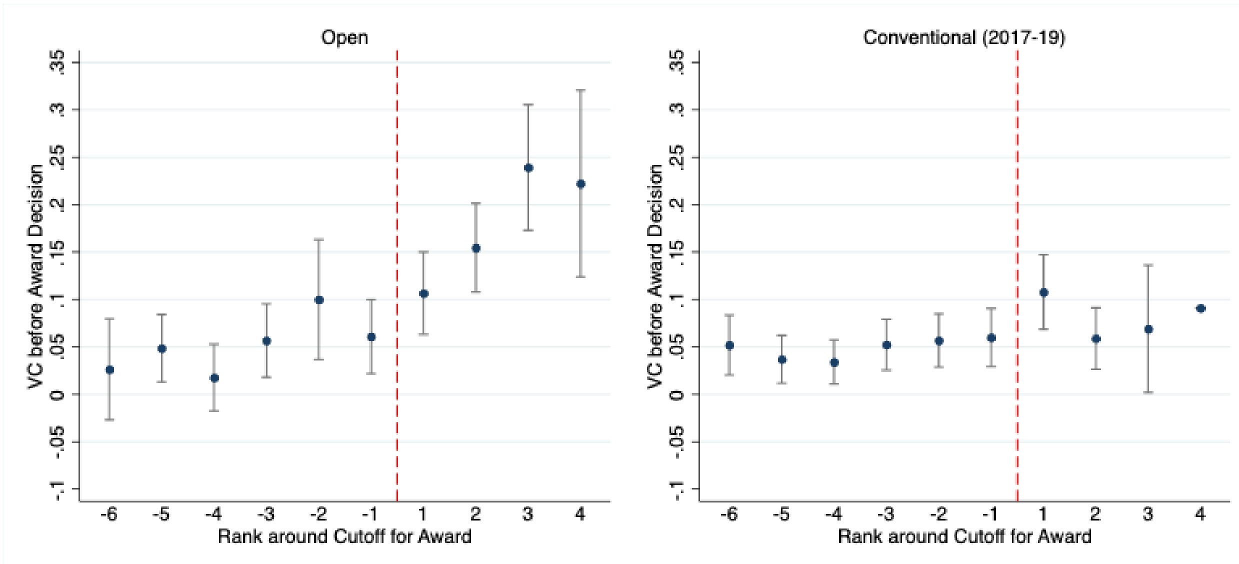
(b) Probability Firm Minority-Owned at Application



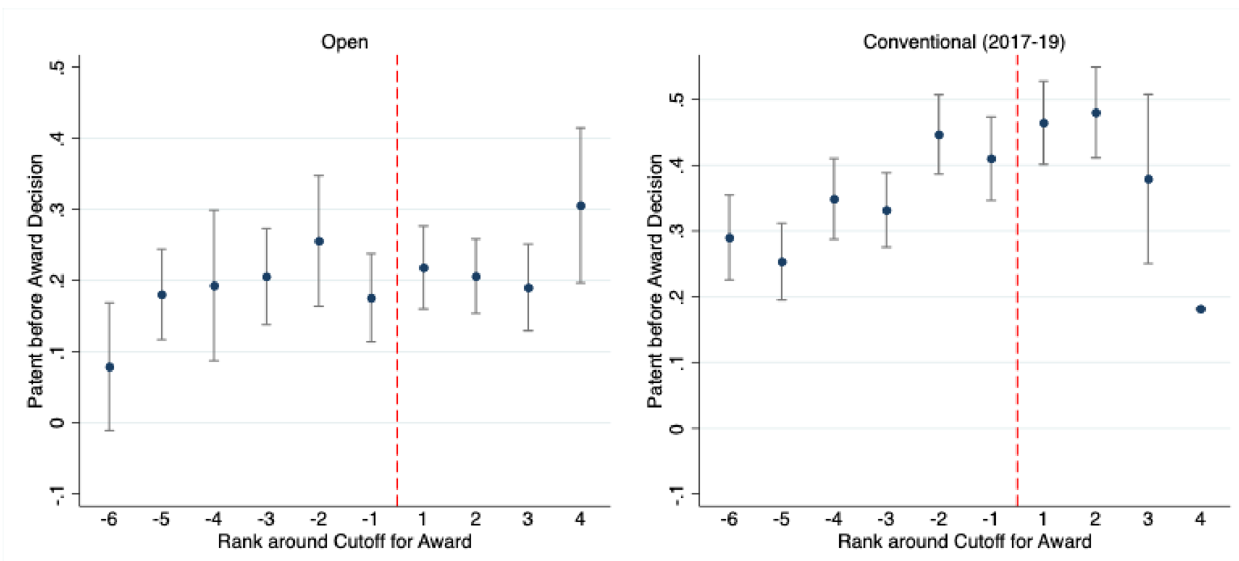
Note: These figures show the probability that an applicant firm is woman-owned (top figures) and minority-owned (bottom figures) at the time of application. In all cases, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score 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.

Figure A.10: Continuity of Baseline Innovation Outcome Variables by Rank around Cutoff

(a) Probability of Venture Capital Before Award Decision



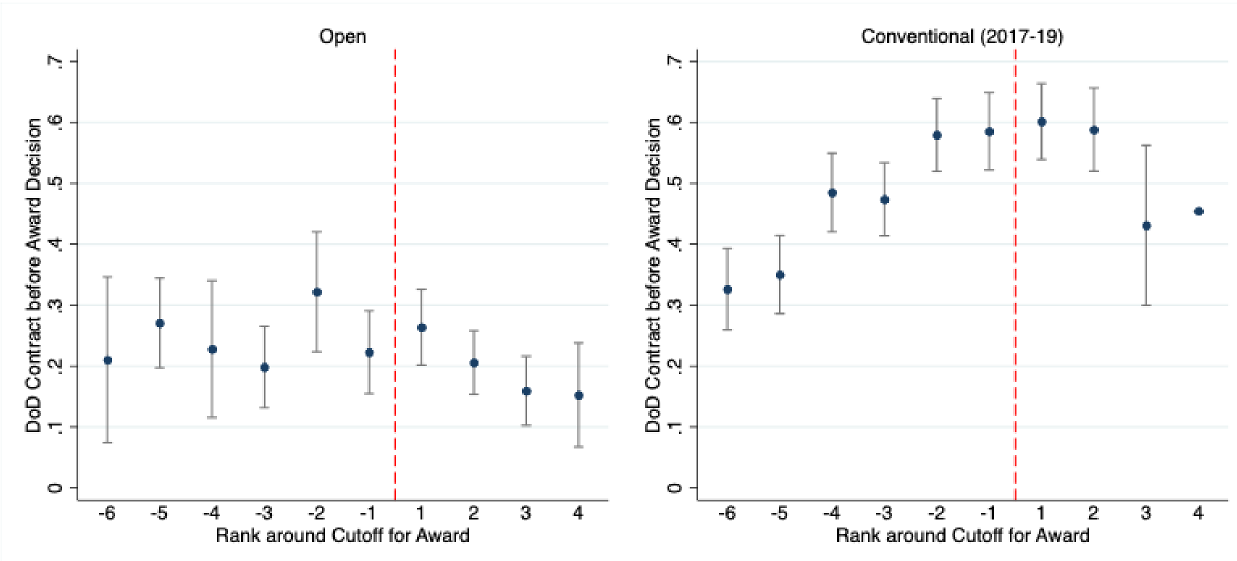
(b) Probability of Patent Before Award Decision



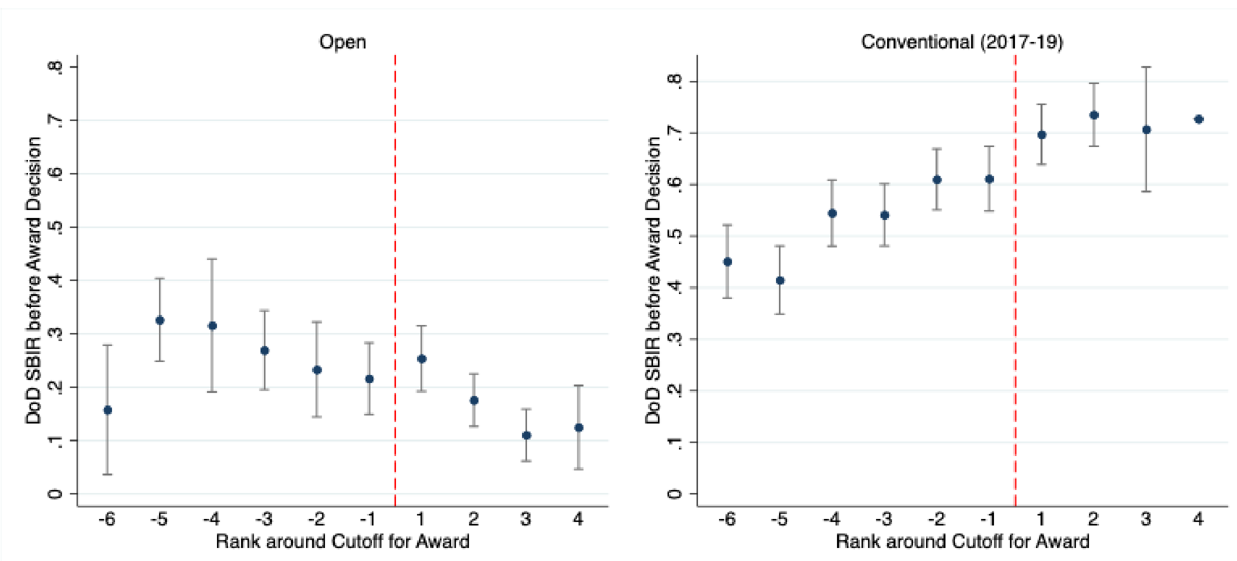
Note: These figures show the probability that an applicant firm raised venture capital investment (VC, top figures) and had any patents after the award decision (bottom figures). In all cases, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant 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.

Figure A.11: Continuity of Baseline DoD Contract Variables by Rank around Cutoff

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



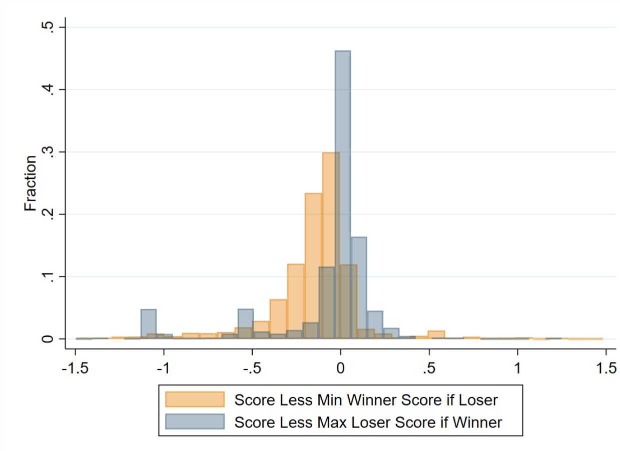
(b) Probability of DoD SBIR Before Award Decision



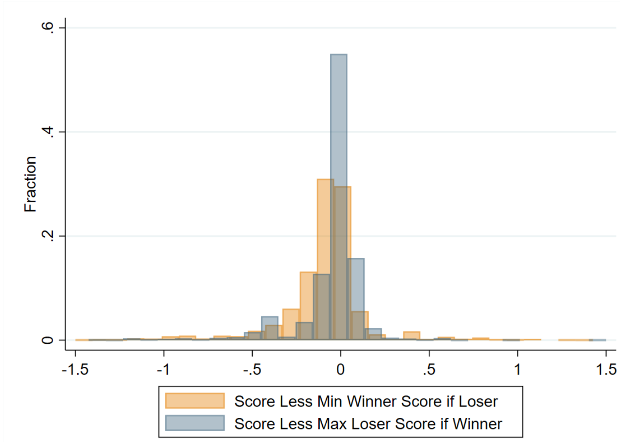
Note: These figures show the probability that an applicant firm he probability the applicant had any DoD SBIR contracts after the award decision (top figures) and had any non-SBIR DoD contracts valued at more than $50,000 after the award decision (bottom figures). A rank of 1 indicates that the applicant 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.

Figure A.12: Prevalence of Crossover Sub-scores

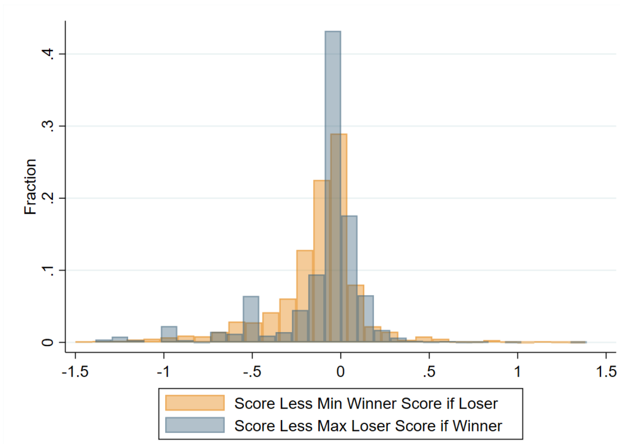
(a) Tech Score



(b) Team Score



(c) Commercialization Score



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" (shown in these graphs). All topics 2017-19 are included.

Table A.1: Key Features of Conventional, Pitch Day, and Open Air Force SBIR Topics

Panel A: Phase 1

	Conventional	Open (AFWERX)	Pitch Day (AFWERX)	Special (NSIN)
Eligible technologies	Specific requests	Any with possible military application	IT/digital area	Commercial sector with possible military application
Maximum Amount	\$150,000	\$50,000	\$158,000	\$75,000
Contract Type	Fixed-price	Fixed-price	Fixed-price	Fixed-price
Contract Length	9 months	3 months	5 months	3 months
Technical Application	$\leq$ 15 pages	$\leq$ 5 pages	$\leq$ 5 pages	$\leq$ 5 pages
Pitch Deck in Application	None	$\leq$ 15 slides	$\leq$ 15 slides	$\leq$ 15 slides

Panel B: Phase 2

	Conventional	Open (AFWERX)	Pitch Day (AFWERX)	Special (NSIN)
Eligible proposals	Successful Phase 1 award	Successful Phase 1 award	Successful Phase 1 award	Successful Phase 1 award
Maximum Amount	\$750,000	\$1,500,000	\$750,000	\$750,000
VC (or Govt) Match	None	Up to \$1,500,000	None	None
Contract Type	Cost-plus	Fixed-price	Fixed-price	Fixed-price
Contract Length	27 months	15-27 months	15-27 months	15-27 months
Technical Proposal in Application	$\leq$ 50 pages	$\leq$ 15 pages	$\leq$ 15 pages	$\leq$ 15 pages
Pitch Deck in Application	None	$\leq$ 15 slides	$\leq$ 15 slides	$\leq$ 15 slides

Note: This table summarizes the key features of Air Force SBIR awards, focusing on the elements that were reformed in the AFWERX program. Conventional topics are usually, but not always, proposed by the Air Force Research Lab, and are administered by the Air Force SBIR office. In a VC or government match, the Air Force matches up to \$1.5 million of money raised from VC or a different government program office (this is in addition to the Phase 2 award). Examples of conventional topic titles are: "Safe, Large-Format Lithium-ion (Li-ion) Batteries for ICBMs" or "Develop Capability to Measure the Health of High Impedance Resistive Materials." The Open topic titles are: "Open Call for Innovative Defense-Related Dual-Purpose Technologies/Solutions with a Clear Air Force Stakeholder Need." Examples of Pitch Day topic titles are "Battlefield Air Operations Family of Systems Technologies" or "Command, Control, Communications, Intelligence, and Network (C3I&N)." Examples of NSIN topic titles are "Medical Monitoring, Diagnostics, and Triage" and "Machine Learning for Defense Applications."

Table A.2: Proposal and Firm Counts

Panel A: Open & Conventional (2017-19)

	Both	Open Topic	Conventional
Number of Topics:			
Phase I	512	6	506
Phase II	180	5	175
Number of Proposals:			
Phase I	7229	1656	5573
Phase II	865	444	421
Number of Firms:			
Applied to Type	3170	1408	2409
Exclusively Applied to Type	647	761	1762

Panel B: Full Sample (2003–2019)

	Both	Open Topic	Conventional
Number of Topics:			
Phase I	1796	6	1790
Phase II	661	5	656
Number of Proposals:			
Phase I	19446	1656	17790
Phase II	1684	444	1240
Number of Firms:			
Applied to Type	6485	1419	5724
Exclusively Applied to Type	658	761	5066

Panel C: NSIN and Pitch Day

	Both	NSIN	Pitch Day
Number of Topics:			
Phase I	11	8	3
Phase II	2	1	1
Number of Proposals:			
Phase I	747	423	324
Phase II	28	18	10
Number of Firms:			
Applied to Type	606	361	286
Exclusively Applied to Type	41	320	245

Note: This table shows the counts of topics, proposals (i.e. applications), and unique firms in the full sample and in the 2017-19 period, which we focus on to compare the effects of conventional and open topics. For example, there are 1,408 unique firms that have applied to the open topics, of which 761 applied exclusively to open topics. There are 7,229 proposals (note firms can apply multiple times), of which 1,656 are in open topics.

Table A.3: Phase 2 Competition Summary Statistics

Panel A: 2017–2019 Sample

	Open Topic				Conventional				
	N	Mean	Median	SD	N	Mean	Median	SD	*p-value* (diff of means)
Competition Summary									
Num Proposals per Topic	444	107	91	44.5	421	4.36	2	4.94	0.000
Num Winners per Topic	444	54.4	45	25.9	421	1.95	1	1.94	0.000
Award Amount	63	820422	749801	457851	81	850104	763550	275214	0.630
Company Characteristics									
Age	444	9.19	5	10.3	421	21.6	21	13.7	0.000
Number of Employees	444	28.8	10	58.4	403	76.8	37	92.3	0.000
$\mathbb{1}$(in VC Hub)	444	.236		.425	421	.15		.357	0.001
$\mathbb{1}$(in County with AF Base)	444	.155		.363	421	.273		.446	0.000
$\mathbb{1}$(Minority Owned)	91	.11		.314	0	.		.	.
$\mathbb{1}$(Woman owned)	444	.115		.319	403	.0695		.255	0.023

Panel B: Full Sample

	Open Topic				Conventional				
	N	Mean	Median	SD	N	Mean	Median	SD	*p-value* (diff of means)
Competition Summary									
Num Proposals per Topic	444	107	91	44.5	1240	2.85	2	3.18	0.000
Num Winners per Topic	444	54.4	45	25.9	1240	1.28	1	1.42	0.000
Award Amount	63	820422	749801	457851	554	1061265	976091	657153	0.005
Company Characteristics									
Age	444	9.19	5	10.3	1240	18.4	16	12.8	0.000
Number of Employees	444	28.8	10	58.4	1159	61.4	26	83	0.000
$\mathbb{1}$(in VC Hub)	444	.236		.425	1240	.164		.37	0.001
$\mathbb{1}$(in County with AF Base)	444	.155		.363	1240	.31		.463	0.000

This table contains summary statistics about the Phase 2 competitions. Only applications from 2017-19 are included in Panel 1, while all years are included in Panel 2.

Table A.4: Effect of Award on Log Amount of VC

Panel A: Open Topics

	(1)	(2)	(3)	(4)
𝟙(Award)	0.350	0.473	0.681*	0.227
	(0.351)	(0.378)	(0.388)	(0.331)
𝟙(Award) × 𝟙(Prev. SBIR)		-0.805**		
		(0.347)		
𝟙(Award) × 𝟙(High Age)			-1.244***	
			(0.360)	
𝟙(Prev. SBIR)	-0.953***	-0.582***	-0.507**	-0.963***
	(0.177)	(0.208)	(0.218)	(0.186)
𝟙(High Age)			-0.209	
			(0.282)	
Observations	1382	1382	1382	1656
Outcome Mean	0.997	0.997	0.997	0.988
Proposals	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19

Panel B: Conventional Topics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Award)	-0.093	-0.092	0.162	0.347	0.634*	0.356	0.022
	(0.325)	(0.486)	(0.394)	(0.235)	(0.324)	(0.283)	(0.072)
𝟙(Award) × 𝟙(Prev. SBIR)		-0.001			-0.576		
		(0.366)			(0.370)		
𝟙(Award) × 𝟙(High Age)			-0.413			-0.046	
			(0.367)			(0.341)	
𝟙(Prev. SBIR)	-0.384**	-0.383**	-0.301*	-0.313**	-0.162	-0.244	-0.335***
	(0.168)	(0.155)	(0.178)	(0.150)	(0.149)	(0.157)	(0.060)
𝟙(High Age)			-0.144			-0.322**	
			(0.157)			(0.132)	
Observations	2704	2704	2704	6670	6670	6670	17790
Outcome Mean	0.298	0.298	0.298	0.526	0.526	0.526	0.314
Proposals	First	First	First	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2003-19	2003-19	2003-19	2003-19

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on the log amount of subsequent venture capital investment (real 2019$) within Open topics (Panel A) and Conventional topics (Panel B). Rank within the topic (competition) is controlled for separately as a linear function on either side of the cutoff. The sample is restricted to first-time applicants only except in Panel A column 4, and Panel B column 7; in these two columns, all applications are included so a firm may appear more than once. In columns 2 and 5 of both panels, we interact winning an award with having won a previous DoD SBIR award and age, respectively. In columns 3 and 6 of both panels we interact winning an award with an indicator for an old firm defined as firm's age above the median of the distribution of firm age. In Panel B, columns 1-3 restrict the sample to the award years 2017-19 to facilitate comparison with the Open topics. Columns 4-7 include all years 2003-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.5: Effect of Winning on Any High-Originality Patenting (originality defined within AF SBIR applicants in year)

Panel A: Open Topics

	(1)	(2)	(3)	(4)
𝟙(Award)	0.012*	0.013*	0.015*	0.011*
	(0.007)	(0.006)	(0.008)	(0.006)
𝟙(Award) × 𝟙(Prev. SBIR)		-0.002		
		(0.012)		
𝟙(Award) × 𝟙(High Age)			-0.009	
			(0.006)	
𝟙(Prev. SBIR)	0.009	0.010	0.013	0.006
	(0.008)	(0.008)	(0.011)	(0.006)
𝟙(High Age)			-0.003	
			(0.008)	
Observations	1382	1382	1382	1656
Outcome Mean	0.004	0.004	0.004	0.003
Proposals	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2017-19

Panel B: Conventional Topics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Award)	0.002	0.008	0.002	-0.009	-0.007	0.001	-0.042***
	(0.029)	(0.021)	(0.026)	(0.026)	(0.029)	(0.029)	(0.013)
𝟙(Award) × 𝟙(Prev. SBIR)		-0.009			-0.004		
		(0.025)			(0.040)		
𝟙(Award) × 𝟙(High Age)			0.002			-0.027	
			(0.029)			(0.041)	
𝟙(Prev. SBIR)	0.053***	0.055***	0.043***	0.156***	0.157***	0.145***	0.200***
	(0.009)	(0.011)	(0.009)	(0.019)	(0.021)	(0.019)	(0.009)
𝟙(High Age)			0.027**			0.061***	
			(0.011)			(0.019)	
Observations	2704	2704	2704	6670	6670	6670	17790
Outcome Mean	0.040	0.040	0.040	0.162	0.162	0.162	0.230
Proposals	First	First	First	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2003-19	2003-19	2003-19	2003-19

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on any subsequent granted high originality patent after the award decision, for Open topics (Panel A) and Conventional topics (Panel B). We define a patent to be highly original if its originality index is above the median in the sample of AF SBIR applicant's granted patents. Rank within the topic (competition) is controlled for separately as a linear function on either side of the cutoff. The sample is restricted to first-time applicants only except in Panel A column 4, and Panel B column 7; in these two columns, all applications are included so a firm may appear more than once. In columns 2 and 5 of both panels, we interact winning an award with having won a previous DoD SBIR award and age, respectively. In columns 3 and 6 of both panels we interact winning an award with an indicator for a young firm defined as firm's age below the median of the distribution of firm age. In Panel B, columns 1-3 restrict the sample to the award years 2017-19 to facilitate comparison with the Open topics. Columns 4-7 include all years 2003-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.6: Effect of Winning on Subsequent Patent Citations in Conventional Topics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$(Award)	0.005	0.008	0.005	-0.044	0.015	-0.002	-0.154***
	(0.020)	(0.016)	(0.015)	(0.104)	(0.116)	(0.106)	(0.053)
$\mathbb{1}$(Award) × $\mathbb{1}$(Prev. SBIR)		-0.004			-0.117		
		(0.016)			(0.164)		
$\mathbb{1}$(Award) × $\mathbb{1}$(High Age)			0.000			-0.108	
			(0.017)			(0.162)	
$\mathbb{1}$(Prev. SBIR)	0.024***	0.025***	0.019***	0.699***	0.730***	0.631***	0.789***
	(0.006)	(0.007)	(0.006)	(0.075)	(0.086)	(0.072)	(0.038)
$\mathbb{1}$(High Age)			0.013			0.361***	
			(0.009)			(0.075)	
Observations	2704	2704	2704	6670	6670	6670	17790
Outcome Mean	0.015	0.015	0.015	0.574	0.574	0.574	0.786
Proposals	First	First	First	First	First	First	All
Time Period	2017-19	2017-19	2017-19	2003-19	2003-19	2003-19	2003-19

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award on the number of subsequent log one plus patent citations within Open topics (Panel A) and Conventional topics (Panel B). Note that the time period of 2017-19 is insufficient for citations to accumulate (and thus the null effects we observe are not very informative). Rank within the topic (competition) is controlled for separately as a linear function on either side of the cutoff. The sample is restricted to first-time applicants only except in Panel A column 4, and Panel B column 7; in these two columns, all applications are included so a firm may appear more than once. In columns 2 and 5 of both panels, we interact winning an award with having won a previous DoD SBIR award and age, respectively. In columns 3 and 6 of both panels we interact winning an award with an indicator for a young firm defined as firm's age below the median of the distribution of firm age. In Panel B, columns 1-3 restrict the sample to the award years 2017-19 to facilitate comparison with the Open topics. Columns 4-7 include all years 2003-19. All columns include topic fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.7: Within-Firm Effect of an Award in Open relative to Conventional Conditional on Applying to Both

Dep Var:	Any VC	Any DoD non-SBIR	Any Patents	Any DoD SBIR
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Award) × $\mathbb{1}$(Open Topic)	-0.003	-0.013	0.003	-0.104
	(0.003)	(0.043)	(0.036)	(0.084)
$\mathbb{1}$(Award)	-0.001	-0.079***	-0.037*	-0.093*
	(0.001)	(0.028)	(0.020)	(0.048)
$\mathbb{1}$(Open Topic)	-0.001	-0.082**	-0.075***	-0.130*
	(0.001)	(0.037)	(0.026)	(0.073)
Observations	1259	1259	1259	1259
Outcome Mean	0.056	0.074	0.072	0.365

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 1 award, with the goal of comparing treatment in Open vs. Conventional topics among firms that apply to both, restricting the sample to the first application to each type from 2003 to 2019, and including firm fixed effects. The sample thus consists of the type of firms that apply to multiple topics, rather than those that are new to the SBIR program. Within this group, these regressions assess whether Open and Conventional topics have different effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.8: Phase 2 VC and Government Matching (Open Topics Only) Summary Statistics

	N	Mean	Median	SD
Share Government Match	444	.131		.337
Share Private Match	444	.124		.33
Confirmed Govt Match Amt	56	702224	479964	883347
Confirmed Private Match Amt	22	1263203	1500000	477235
Share Applied Government Match	444	.191		.394
Share Applied Private Match	444	.203		.402
Applied Govt Match Amt	85	614304	500000	542265
Applied Private Match Amt	90	1365454	1500000	1107699

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

Table A.9: Effect of Winning Phase 1 Interacted with Phase 2 Match

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)	0.044*	0.013	-0.051	0.071*	0.037
	(0.025)	(0.008)	(0.046)	(0.037)	(0.032)
$\mathbb{1}$(Award $\times$ Match Offered in Topic)					0.028
					(0.034)
Observations	1382	1382	706	676	1382
Outcome Mean	0.072	0.012	0.091	0.068	0.080

This table contains regressions showing the effect of winning a Phase 1 award 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 private match. That is, the dependent variable is zero if a firm got VC and also got a private match. 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. Column 3 includes only those topics that offered a match, (19.1 and 19.2), while column 5 includes the remaining topics that did not offer a match. Column 5 shows the interaction. All models include topic fixed effects. The sample is restricted to first-time applicants only. Standard errors are robust (equivalent to clustering by firm in all models). ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.10: Effect of Phase 2 Award and Award Amount on VC and AF Contracts (non-SBIR)

Panel A: Any VC After Award

	Open Topics		Conventional Topics		
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.127	-0.100	-0.041	-0.043	-0.008
	(0.090)	(0.087)	(0.052)	(0.066)	(0.076)
Award Amt	0.001**	0.001**	-0.001	-0.001	0.000
	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	444	444	403	403	1159

Panel B: Any DoD non-SBIR Contract After Award

	Open Topics		Conventional Topics		
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	0.011	0.030	-0.055	-0.053	0.007
	(0.099)	(0.096)	(0.120)	(0.122)	(0.129)
Award Amt	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	444	444	403	403	1159

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 2 award on subsequent venture capital and non-SBIR Air Force contracts. We include both an indicator for award and the award amount in real 2019 dollars. This is possible as the award amount varies, which it does not for Phase 1. The sample is restricted to Open topics in columns 1-2, and conventional topics in columns 3-5. Columns 1-4 use data from 2017-19, while column 5 uses all years of conventional topics. We use all proposals to maximize the sample size, but the results are similar with first proposals only. Controls are indicators for whether the firm had any previous patents, private financing, non-SBIR Air Force contract, SBIR award, and whether the firm is located in a VC hub city, in a county with an AF base, as well as a continuous variable for firm age. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.11: Effect of Phase 2 Award and Award Amount on Patents and AF SBIR Contracts

Panel A: Any Patent After Award

	Open Topics		Conventional Topics		
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.007	-0.007	-0.033	-0.038	0.023
	(0.007)	(0.007)	(0.099)	(0.106)	(0.116)
Award Amt	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.002)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	444	444	403	403	1159

Panel B: Any DoD SBIR Contract After Award

	Open Topics		Conventional Topics		
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Award)	-0.135**	-0.116*	-0.018	-0.010	0.006
	(0.067)	(0.068)	(0.103)	(0.104)	(0.104)
Award Amt	0.000	-0.000	0.001	0.001	0.001
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	444	444	403	403	1159

Note: This table shows regression discontinuity (RD) estimates of the effect of winning a Phase 2 award on subsequent patenting and Air Force SBIR contracts. We include both an indicator for award and the award amount in real 2019 dollars. This is possible as the award amount varies, which it does not for Phase 1. The sample is restricted to Open topics in columns 1-2, and conventional topics in columns 3-5. Columns 1-4 use data from 2017-19, while column 5 uses all years of conventional topics. We use all proposals to maximize the sample size, but the results are similar with first proposals only. Controls are indicators for whether the firm had any previous patents, private financing, non-SBIR Air Force contract, SBIR award, and whether the firm is located in a VC hub city, in a county with an AF base, as well as a continuous variable for firm age. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.