Procuring innovation: evidence from the SBIR program *

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Abstract

Economists have been long debating about the effectiveness of policies aimed at inducing directed technical change. Policymakers can use several tools, such as military-driven public investment, research grants, or public procurement. I examine a unique amalgamation of such tools in a US context, where small businesses winning federal research grants (SBIR) can also secure procurement contracts from the Department of Defense. Employing a Difference-in-Differences framework and three comprehensive datasets - SBIR grants, DoD procurement contracts (USAspending.gov), and Patstat - I find that while procurement contract winners do not patent more than other SBIR participants, they get 1 million dollars more in government contracts every year.

Keywords: Technology policy, Military Procurement, Innovation

JEL Codes: O31, O33, O38

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1 Introduction

Fostering innovation is one of the primary objectives of economists and policymakers. Since Arrow (1962) researchers have studied the role economic actors have in directing technical change (Acemoglu et al., 2012; Slavtchev and Wiederhold, 2016). A central actor is arguably the state, which can set technological priorities and allocate resources to achieve them. However, how to best achieve them is still at the heart of the debate. Some economists have shown that big technological projects, such as the Manhattan project (Gross and Sampat, 2020), the Apollo program (Kantor and Whalley, 2022), or military spending (Moretti et al., 2019) can generate spillovers and crowd in private innovation. Others have shown the efficacy of smaller and more targeted tools, such as research grants (Howell, 2017; Santoleri et al., 2022; Myers and Lanahan, 2022) or public procurement (Belenzon and Cioaca, 2022; de Rassenfosse et al., 2019). This paper studies a combination of grants and procurement, in a context in which funding priorities are set by the Department of Defense (DoD).

I focus on the SBIR program, a US federal program that awards research and development grants to small businesses. Originally created in 1982, this program aims to help small businesses conduct research and development. It is federally funded, but it is run separately by governmental agencies (such as the Department of Defense, the Department of Energy, and the National Institute of Health), that award grants according to their needs. Firms can apply to the program, and if they are selected, they receive a research grant to develop a proof of concept. If the proof of concept is successful, the firm can apply for a second research grant to develop a prototype. SBIR funds end there. Then, some agencies - among which the DoD - can award a procurement contract to help the firm commercialize the product.

One of the most famous examples of the program is iRobot, a firm that was awarded a research grant in 1998 by the Department of Defense to develop a robot (called PackBot) that could be used to detect and disarm bombs. The prototype was successful, and the firm was awarded a procurement contract by the DoD itself. At the same time, iRobot used the technology developed for the PackBot to create a commercial product, Roomba, a vacuum cleaner robot. Roomba was a commercial success, and the firm went public in 2005.

In this paper, I try to provide systematic evidence of cases like iRobot. First, I try to understand whether demand from the public sector directs innovation. I find that procurement contract winners do not patent more than other SBIR participants, neither in terms of quantity nor quality. Second, I investigate whether public procurement - on top of research grants - can impact firm performance. I find that procurement contracts help firms strenghten their ties with the DoD, getting around 0.6 more contracts (for a value of $1,000,000$$) per year. However, it is not yet clear whether those firms increase their market value, or they just become preferred suppliers of the DoD.

I combine three datasets: the first one contains all SBIR grants awarded from 1983 to 2023, the second one (USAspending.gov) contains all DoD procurement contracts from 2000 to 2021, and the third one (Patstat) contains all patents granted by the USPTO from 1976 to 2023. I test my hypotheses in a Difference-in-Differences framework, comparing procurement winners (i.e. firms that have been awarded a Phase III contract) to SBIR participants that have received only Phase I and Phase II contracts. My design does not allow me to get neat identification, as there are no public rankings of the firms that apply to the program.

This paper contributes to two strands of literature. First, there is a growing interest in the effect of research grants on innovation, with a particular focus on the SBIR program. Since the early 2000s, many economists (Lerner, 2000; Audretsch, 2003; Gans and Stern, 2003; Link and Scott, 2010; Keller and Block, 2013) have described the program as an effective policy instrument for the US government. However, only recently the availability of micro-data has allowed researchers to provide a quantitative assessment of the program.

Howell (2017) cleanly shows that landing early stage SBIR financing (i.e. Phase I) makes firms more likely to access venture capital financing, patent and increase revenues. She also shows that this effect is stronger for liquidity constrained firms. Myers and Lanahan (2022) document that SBIR funding crowds in private investment, as for every patent produced by grant recipients, there are three more produced by other firms.

Recent work has tried to understand if the program was effective in directing technical change. Howell et al. (2021) show that an "open innovation" approach, that was introduced in the Air Force in 2018, has crowded in applicants and increased the quality of the projects. Firms that were awarded a grant under the new approach become more likely to be awarded a procurement contract. Bhattacharya (2021) tries to give a welfare assessment of the program. He focuses on procurement contracts of a specific DoD branch (the Navy) and shows that there is a substantial trade off between the aggregate social welfare (i.e. more innovation) and the DoD's objective (i.e. procurement of goods that are useful for military purposes).

I contribute to this literature by arguing that procurement contracts - on top of research grants - apparently do not direct innovation.

A second strand of literature studies the effect of procurement contracts on firm performance. Belenzon and Cioaca (2022) argue that changes in the content of DoD procurement contracts can affect the direction of innovation. They show that when awarded federal contracts, firms produce more publications, and tend not to protect their knowledge with patents. Hvide and Meling (2022) focus on a narrow set of procurement contracts, regarding road construction in Norway. They show that start-ups winning a procurement auction increase their sales and employment by 20% and become more profitable, compared to narrow losers. These effects seem to persist for several years. In Italy, construction firms that win a procurement contract are 70% more likely than losers to survive after 3 years, but they do not increase their productivity (Cappelletti and Giuffrida, 2021). Furthermore, their earnings become much more dependent on public sector contracts, generating a potentially vicious cycle. Two papers focus on firm behavior after receiving a SBIR grant. Howell and Brown (2022) show that SBIR funds are also used to raise compensations for incumbent workers. Lanahan et al. (2021) complement this evidence, showing that SBIR recipients create less jobs than losers, and even within the group of winners, receiving more money does not translate into creating more jobs. I complement this literature by focusing on a different industry (military procurement), which is more technology-intensive than construction, and more strictly linked to government priorities. As in Cappelletti and Giuffrida (2021), I find that procurement contracts help firms strengthen their ties with the public sector, but I do not find evidence of direct impact on firm performance.

The remainder of the paper proceeds as follows. Section 2 describes the SBIR program and the data I use. Section 3 presents the preliminary results. Section 4 concludes.

2 Context

2.1 The SBIR program at the Department of Defense

SBIR is a US federal program that aims to help small businesses conduct research and development. It was created in 1982 by the Reagan administration, but all US governments since then have supported it with increased funding.[1] The program is federally funded, but it is run separately by 12 governmental agencies (such as the Department of Defense, the Department of Energy or the National Institute of Health).[2] It is open to all small businesses that are majority-owned by US citizens and consists of two phases. In Phase I, each agency lists their own priorities (i.e. the problems they want to solve), and firms can apply to the program with their own proposals. There is no need for prototypes. Firms just have to show that their idea is feasible.

If a firm is selected, it receives a research grant to develop a proof of concept. The grant can be up to $200,000, and it lasts for 6 months. If the proof of concept is successful, the firm can apply for a second research grant ("Phase II") to develop a prototype. The grant can be up to $1,500,000, and it lasts for 2 years. After the second phase, SBIR funds end.

Those features are common to all SBIR grants, regardless of the agency that awards them. However, there is vast heterogeneity in the way the program is run by each agency. Indeed, some (such as the National Institute of Health or National Science Fundation) are more similar to traditional grant-awarding agencies. Their work is mostly to establish scientific priorities, and they award grants to firms that can help them achieve those priorities. On the other hand, agencies such as the Department of Defense or NASA are more concerned about their own needs. They use the program to individuate firms that can help them solve their problems. Formally speaking, the Department of Defense does not award grants, but signs contracts with firms, even for Phase I and Phase II.

Furthermore, in recent years some agencies have introduced a third phase, that is financed by their own budget.[3] It aims to help Phase II winners commercialize their product. However, there is even starker heterogeneity in the way this phase is run. Grant-awarding agencies (such as the Department of Energy) are more focused on finding external customers for the product, while agencies that award contracts (such as the Department of Defense) are interested in buying the product themselves. In particular, after winning a Phase III contract at the DoD, firms are entitled to sell their specific product (i.e. the one they developed using Phase I and II funds) to the

[1] See National Research Council (2014), National Research Council (2020) or similar reports for a detailed history of the program.

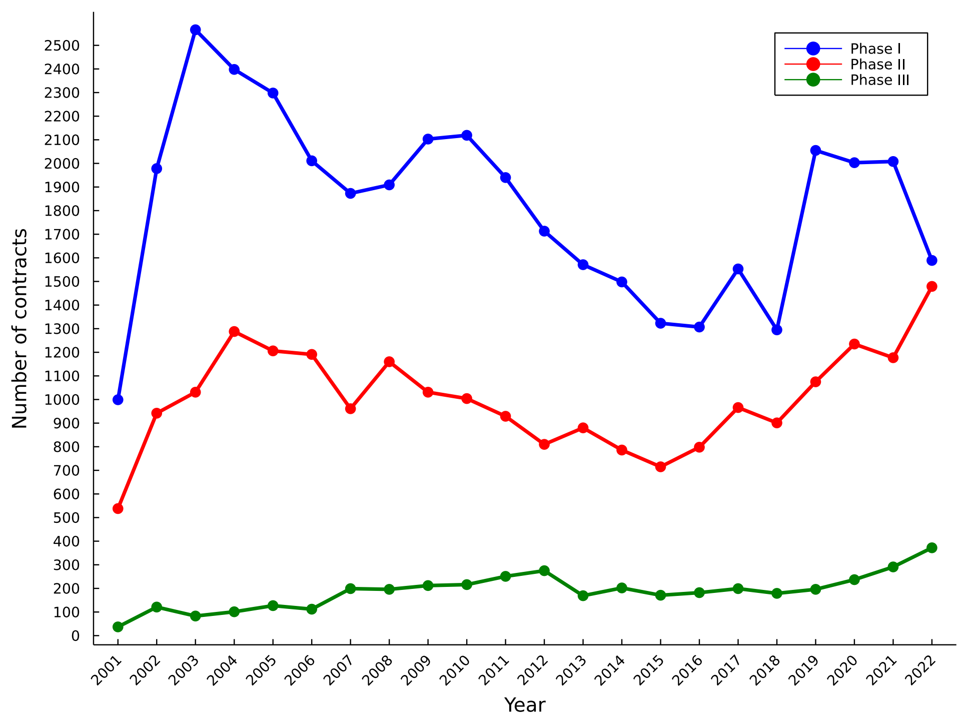
[2] Full list is available at `https://www.sbir.gov/agencies-landing`.

[3] There is no official introduction year, but this type of contracts have been used more and more frequently from the 2000s on. See `https://www.sbir.gov/about` for more information.

DoD without having to face competition from other firms.

Throughout this paper, I will focus on Phase III (also referred to as "procurement") contracts awarded by the Department of Defense. The graph in Figure 1 shows the number of SBIR contracts awarded by the Department of Defense from 2000 to 2022. Phase I and Phase II contracts represent the largest share of the contracts awarded by the DoD, averaging more than 1,000 contracts per year. However, the number of Phase III contracts has increased in the recent years, as almost 300 contracts were awarded in 2022.

Figure 1. Department of Defense, number of contracts



2.2 Data

I use three different datasets, one on SBIR grants, one on DoD procurement contracts, and one on patents. I combine them to create a panel of firms that have been awarded at least a Phase II contract, and observe their activities, on innovation (measured by patents) and government contracts (measured by non-SBIR procurement contracts).

SBIR grants The first dataset contains all SBIR grants awarded by all agencies from 1983 to 2023. It is retrieved from the SBIR website (https://www.sbir.gov/

sbirsearch/award/all). Each contract has a unique identifier, and it contains information on the awarded firm, the agency and branch that awarded the contract, the year, the phase and the amount of money awarded. It also contains the title and the abstract of the proposal, which would allow me to define the technological content of the contract, for further analysis. The dataset contains 197,664 observations (each one corresponding to a grant or contract), 89,134 of whose are contracts awarded by the Department of Defense.

Filtering only post-2000 observations, I obtain 66,609 unique contracts, 45,232 unique Phase I contracts, and unique 23,441 Phase II contracts. Most of the times the contract id changes from Phase I to Phase II. Sometimes it does not, and it creates discrepancies in the numbers above. The total number of firms is 9298 (identified by Dun and Bradstreet number). In the dataset it is quite common to find firms that have been awarded multiple contracts. Among firms that have been awarded at least a Phase I contract, 4658 (equal to 52.27%) have been awarded just one. Similarly, among firms that have been awarded at least a Phase II contract, 2925 (equal to 52.84%) have been awarded just one.

DoD procurement contracts The second dataset contains all DoD procurement contracts awarded from 2000 to 2021. It is retrieved from USAspending.gov, a publicly available database that registers all federal contracts awarded since 2000, broken down by agency. Each entry corresponds to a contract, and it contains several (288) features on the awarded firm, the awarding agencies (and branches), the competition rules that were applied, and the type of contract. I use this dataset for two purposes. First, I filter only SBIR-related contracts, exploiting the fact that not only it contains Phase I and Phase II (already present in the SBIR dataset), but also Phase III contracts. Second, I use it to retrieve non-SBIR contracts awarded to SBIR firms, that are further used to construct the firm panel.

I downloaded all DoD contracts since 2000, and I filtered them by contract type. I kept only contracts that were labeled as "research" contracts, corresponding to any of the three phases of the SBIR program. This procedure results in a dataset of 66,340 contracts, of which 40,206 are Phase I, 22,401 are Phase II, and 4219 are Phase III. There are two possible identifiers for the firm that was awarded the contract: the Duns number and the UEI number. Being consistent with the SBIR dataset, I use the Duns number, and I find 9819 unique firms. An alternative identifier is the UEI number, which identifies a slightly larger number of firms (10,555).

As it was already clear from the SBIR dataset, it is quite common to find firms that have been awarded multiple Phase I or Phase II contracts. 7934 firms have been awarded at least a Phase I contract. Out of those, 4374 (55.13%) have been awarded just one. Similarly, 2738 firms (53.67%) out of the 4431 Phase II winners, have won the contract just once. On the other hand, the vast majority of Phase III winners have been awarded just one contract. Indeed, the dataset contains 1,926 Phase III winners, and 1367 of them (70.98%) have been awarded just one contract.

Patents The third dataset is PATSTAT, which tracks all wordwide patent applications. It is retrieved from the European Patent Office, and it contains several pieces of information on the patent, such as inventor, year of application, title, abstract, follow-on citations, etc. Each patent is assigned to its inventor, that may be an individual or a corporation. However, in the case of firms, there is no identifier such as Duns or UEI. I perform a fuzzy matching algorithm, selecting all patent assignees that have a name that is similar to a SBIR grant winner. I choose a threshold of 0.9, with Levenshtein distance. Practically speaking, it means that I select all assignees whose name is at least 90% similar to a SBIR grant winner. Results are robust to different thresholds (0.8, 0.95).

Matching the datasets In order to create a dataset that can be used in regression analysis, I need to join the three datasets described above. First, I match the SBIR dataset with the DoD dataset, using the contract identifier. I keep only Phase I and Phase II contracts, because Phase III contracts are not stored in the SBIR dataset. The resulting dataset contains 48,266 unique contracts, 31,791 unique Phase I contracts, and unique 16,885 Phase II contracts. The number of unique firms is 7271 (identified by Duns number). A small number of firms have multiple Duns, so that the unique number of firms, identified by name-Duns pairs, is 7089. I use information on those firms to search for their patents in Patstat, as described above.

Firm panel Throughout the regression exercises I will use a panel of firms that have been awarded at least a Phase II contract. I will do it for two reasons. First, it is not possible to directly link Phase III contracts to Phase I and Phase II contracts, because there is no common identifier. It would be possible to impute Phase III contracts to the closest Phase II contract, in terms of technological content, but it would be a very rough approximation, worsened by the fact that the description of Phase III contracts is often very vague in the USAspending.gov dataset. Second, although contracts are awarded for a specific technology, funds are awarded to firms, that have a certain freedom in deciding how to use them. Therefore, a firm-level analysis is more appropriate to properly evaluate the program. Notice also that most of Phase III winners have been awarded just one contract.

The panel is built as follows: I select all 4134 firms that have been awarded at least a Phase II contract, and I observe their activities in the following years. I observe the number of Phase I and Phase II contracts awarded to the firm, the number of patents granted to the firm, and the number of citations received by the firm's patents. I also observe when and whether the firm has been awarded a Phase III contract (which is my treatment variable, in econometric terms), and the number of non-SBIR contracts awarded to the firm.

3 Results

3.1 Empirical strategy

I now empirically test whether getting access to public procurement affects firm outcomes. I focus on two set of outcomes: innovative activities (measured by patents) and further procurement contracts (measured by non-SBIR contracts). In order to do so, I consider all firms that received at least a Phase II contract, and I compare procurement winners (i.e. firms that have been awarded a Phase III contract) with non-procurement winners. I do it in a Difference-in-Differences framework, where the treatment is the award of a Phase III contract. Notice that some (30%) firms have received multiple Phase III contracts, so that they are treated multiple times. I consider as treatment only the first Phase III contract awarded to each firm. Notice also that treatment is staggered throughout time, as firms are awarded Phase III contracts in different years.

More important, the results that I present here do not rely on any identification strategy. Although some policies have been introduced in the recent years, there has been no abrupt change in the way Phase III contracts are awarded. Furthermore, as discussed in Rathje (2019), the decision to award a Phase III is rather subjective, and depends on decisions made by the program managers. Figure A6 in Appendix A shows how the conditional probabilities to get to Phase III have changed over time, and across DoD branches.

My baseline specification is the following:

$$y_{i,t} = \sum_{\tau=-5}^{5} \beta_\tau \text{YearsSinceProcurement}_{i,t+\tau} + \gamma_i + \delta_t + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the number of patents (or non-SBIR contracts) granted to firm i in year t (in alternative specifications I use also the inverse hyperbolic sine, the log or just an indicator), $\text{YearsSinceProcurement}_{i,t}$ is a variable that counts how many years have passed since firm i was awarded a procurement contract (ranging from -5 to 5), γ_i and δ_t are - respectively - firm and year fixed effects. I estimate the equation using OLS, and I cluster the standard errors at the firm level. As described in section 2.2, my panel is made of 4134 firms that have been awarded at least a Phase II contract in the years 2000-2021.

3.2 Innovative activities

On the one hand, getting access to public procurement could provide firms with some source of guaranteed demand (Belenzon and Cioaca, 2022; Arora et al., 2021; Hvide and Meling, 2022), that could ease their financial constraints and help them develop their product, and so produce more innovation. On the other hand, getting access to public procurement could soften the incentive to innovate, as firms could rely on secured profits without having to further sharpen their product. Here I consider a standard - although imperfect - measure of innovation, which is the number of patents granted to the firm. I consider two dimensions of patenting activity: the number of patents granted to the firm, and the number of citations received by the firm's patents. While the former is a measure of quantity, the latter should also capture - at least partially - the quality of the patents.

Conditional on patenting, firms in my dataset file around 0.2 successful patent applications (and 3.8 citations) per year. The average number of patents per firm is 3.9 (73.3 citations).

Figure 2. Procurement does not affect patenting activity

(a) Asinh of patents (b) Asinh of citation-weighted-patents

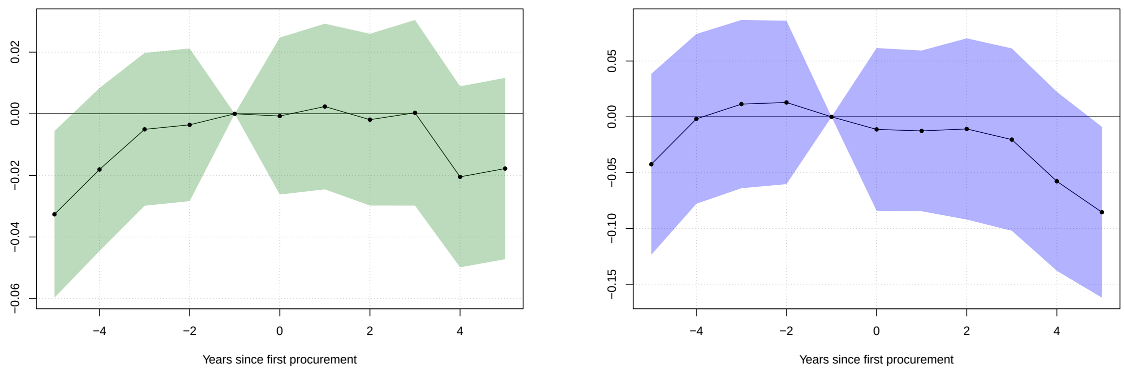


Figure 2 shows the event study plot, where I estimate Equation 1 for the inverse hyperbolic sine of the number of patents (panel a) and citations (panel b). It is not possible to reject the null hypothesis that landing a Phase III contract has no effect on patenting. Some slight form of anticipation seems to be present, as the number of patents slightly increases in the years before the award of the contract. It may signal that as firms approach the timing of the award, their technology is already mature for a patent application. However, the effect is not statistically significant, and it is even more attenuated when considering citations.

Results shown in Figure 2 reinforce the findings of both Howell et al. (2021) and Belenzon and Cioaca (2022). Howell et al. (2021) show that - in the context of traditional SBIR grants in the Air Force - Phase II winners are not more likely to patent than just Phase I winners. The same appears to hold true even comparing Phase III to Phase II winners. More generally, Belenzon and Cioaca (2022) argue that procurement contracts do not have a direct impact on patenting. However, they consider the whole universe of DoD procurement contracts, encompassing also many contracts that are not research-related. In this case, narrowing down the analysis to research-related contracts does not seem to change the results.

Table A1 and A2 in Appendix A shows the Diff-in-Diff results for different specifications, for patents and citation-weighted patents respectively.

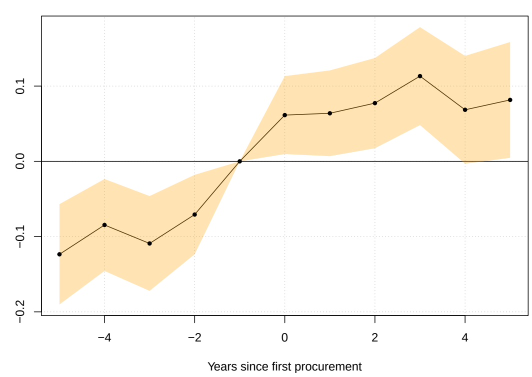
3.3 Non-SBIR contracts

The second outcome I consider is the number of non-SBIR contracts awarded to the firm. As it was explained in Section 2, Phase III at the DoD is meant to be a way to open the gates of the DoD procurement system to SBIR firms. It gives the awarded firm the legal right to sell its product to the DoD, without having to face competition from other firms. However, this right is limited to the product that was developed throughout the previous phases of the SBIR program (National Research Council, 2020). It would be reasonable to expect that firms that have been awarded a Phase III contract are more likely to be awarded further contracts. Results in Figure 3 confirm this intuition.

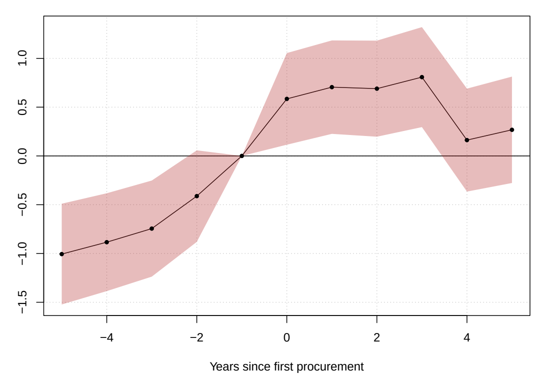
Both the number of contracts (panel a) and the dollar value of contracts (panel b) increase after the award of a Phase III contract. Conditional on being awarded at least a contract in the whole timeframe, firms in my dataset are awarded around 2.2 contracts per year, for a total value of $840,000. The average number of contracts per firm is 38.8, for a total value of $14,976,000.

Figure 3. Non-SBIR contracts increase after Phase III

(a) Asinh of contracts number



(b) Asinh of contracts dollar value

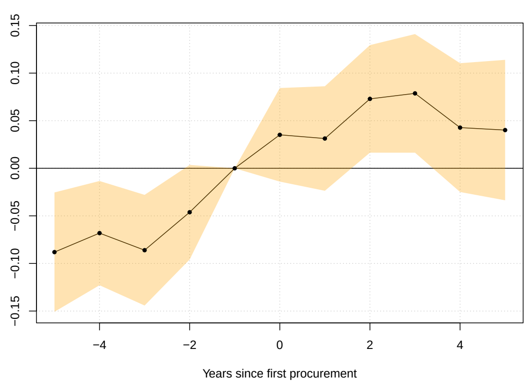


After getting access to public procurement, firms are awarded around 0.6 more contracts per year, for a total value of $1,000,000. These results reinforce the findings of Howell et al. (2021), who show that Phase II winners are more likely to be awarded further procurement contracts. In this case, it appears that - among Phase II winners - those that are awarded a Phase III contract are even more likely to strengthen their ties with the DoD. At the same time, they are also consistent with Hvide and Meling (2022), who analyze public procurement auctions in Norway, and show that firms that are awarded a public procurement contract are more likely to receive further contracts from the same agency.

I then break down the number of contracts into competed and non-competed. Indeed, Phase III winners are allowed to sell the product they developed without having to face competition from other firms. It would be then reasonable to expect that the increase in procurement contracts is mostly due to non-competed contracts, rather than competed ones. Figures 4 and 5 confirm this intuition. The number and the dollar value of competed contracts (figure 4) increases only slightly after the award of a Phase III contract, and the effect seems to fade away after 5 years. On the other hand, the number and the dollar value of non-competed contracts (figure 5) increases more steadily, and the effect is still visible after 5 years. In the latter case, after 5 years firms are awarded around 0.5 more contracts per year, for a yearly value of $730,000.

Figure 4. Competed non-SBIR contracts slightly increase after Phase III

(a) Asinh of contracts number



(b) Asinh of contracts value

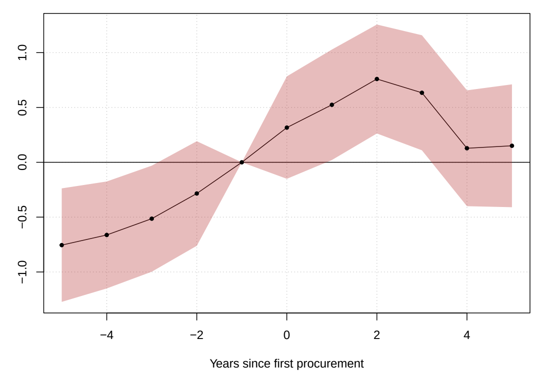
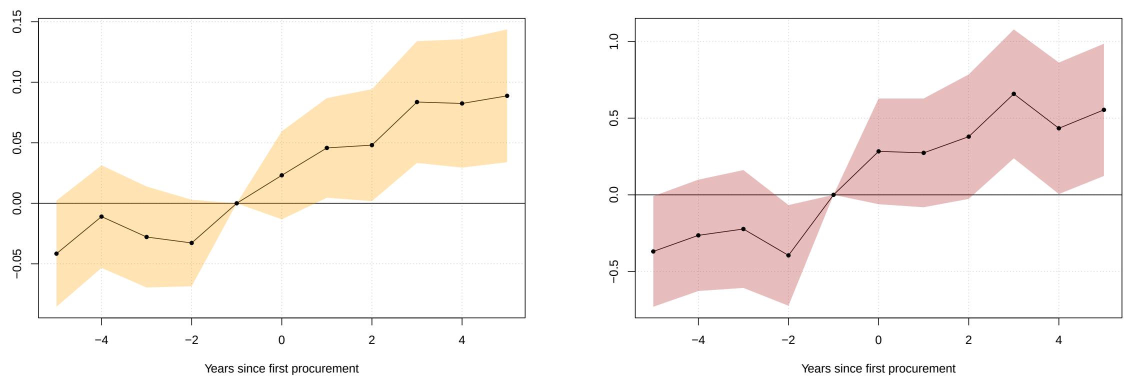


Figure 5. Noncompeted non-SBIR contracts increase more after Phase III

(a) Asinh of contracts number

(b) Asinh of contracts value



It appears, then, that the increase in non-SBIR contracts is mostly driven by the increase in non-competed contracts. Put it differently, Phase III is effective in opening the gates of the DoD procurement system to SBIR firms, but mostly for a specific product. Based on this evidence, it is not possible to assess formally whether the program is welfare improving or not. On the one hand, the SBIR program has the broad purpose of helping small businesses grow and innovate. On the other hand, every agency is free to manage it as it prefers. The DoD is explicitly interested in addressing its own needs. Their goal is to develop technologies that can be used for military purposes, strenghten the ties with the firms that developed them, and add them to the pool of potential contractors. The results that I showed so far suggest that Phase III winners do not become more innovative (at least in terms of patenting). However, they seemingly become more valuable to the DoD, that is more likely to award them further contracts, especially for the product that was developed in the SBIR program. The economic question that arises is whether and how becoming part of the DoD procurement system can benefit small businesses.

3.4 Robustness

Recent evolutions in the debate about the use of Two Way Fixed Effects estimators (TWFE) have shown that when there is heterogeneity in the treatment effect, the standard TWFE estimator is biased (De Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Borusyak and Hull, 2020). In the case of the SBIR program, the treatment (i.e. the award of a Phase III contract) is not awarded a single time, but it is staggered throughout time. In principle, there is no reason to suppose that - as the program developed - firms funded in different years received a similar treatment effect. Lanahan and Feldman (2015, 2018) show that the program might have heterogeneous effects at state level, mainly due to the presence of statal funds (i.e. the State match program) that come on top of SBIR funding. While there is no State match program within the DoD, cohort-specific treatment effects might still be present. Indeed, the program might have gotten more effective over time, or firms might have learned how to better exploit the program. In order to take into account cohort-specific treatment effects, I use the estimator proposed by Sun and Abraham (2021). The estimator is more effective when the sample is divided into a small group of treated units (around 20% of the sample) and a large group of control units, that are never treated. In my sample I have 901 treated units, out of 4134 firms. There are 20 cohorts, from 2001 to 2020. In Appendix B I reproduce Figures 2 - 5 of the main text using the Sun and Abraham (2021) estimator. Results are qualitatively and quantitatively similar to the ones reported in the main text.

However, there is another potential problem with the estimates reported in this paper. It is not possible to observe why some firms have been awarded a Phase III contract, while others have not. Therefore, ex ante, the treatment is not exogenous. While the Sun and Abraham (2021) estimator takes into account cohort-specific treatment effects, it does not address the problem of endogenous selection into treatment, which is still a potential concern in this case. Borusyak and Hull (2020) propose a propensity-score method to assess - at least partially - the problem of non-random exposure to exogenous shocks. However, it would not fit well in my case, for two separate reasons. First, I have not been able to identify an exogenous aggregate shock (e.g. in budget allocation or in Defense priorities) that could have affected the award of Phase III contracts. Second, their method heavily relies on covariates that are not currently available in my database.

4 Conclusion

The effectiveness of public procurement as a catalyst for innovation has been a subject of ongoing discourse among economists (Slavtchev and Wiederhold, 2016). This study delves into a specific subset of procurement beneficiaries – firms already granted research awards – and their potential to engage in military contracts. Interestingly, while winning a procurement contract does not correlate with heightened patenting activity, these firms become integrated into the DoD procurement ecosystem, enjoying increased likelihood of securing subsequent contracts (approximately 0.6 additional contracts per year, with a cumulative value of $1,000,000). The majority (80%) of these contracts are non-competitive, directly awarded by DoD officials, facilitating new contractor retention. From the DoD's perspective, the program is successful in attracting and maintaining new contractors. However, assessing the program's overall welfare impact remains intricate. SBIR participants are primarily small, young businesses. One of the most desirable outcomes for such firms is to be acquired by larger firms, which can provide the resources necessary to grow and innovate. It is crucial to consider the nature of the acquiring firm. If winning a procurement contract increases the value of SBIR participants only for large DoD contractors, which eventually acquire them, the program's intended benefits could be diluted. Instead of fostering competition, it may reduce it. Conversely, acquisitions by non-DoD contractors might offer more favorable welfare implications, facilitating technology transfer to broader sectors. Future research directions involve scrutinizing acquisition frequency among SBIR participants and the nature of the entities involved in such transactions.

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A Appendix Tables and Figures

Appendix Table A1. Patents

	Patents	Asinh Patents	Log Patents	Pat. Indicator
	(1)	(2)	(3)	(4)
Post × *Treat*	0.0177	0.0050	0.0746	0.0016
	(0.0181)	(0.0080)	(0.0834)	(0.0062)
R^2	0.25564	0.25160	0.49454	0.20778
Observations	76,849	76,849	3,118	76,849
Firm F. E.	✓	✓	✓	✓
Year F. E.	✓	✓	✓	✓

Appendix Table A2. Citation-Weighted Patents

	Pat. Citations	Asinh Pat. Citations	Log Pat. Citations
	(1)	(2)	(3)
Post × *Treat*	-0.7231	-0.0278	-0.1082
	(0.4816)	(0.0218)	(0.1878)
R^2	0.11069	0.19127	0.72820
Observations	76,849	76,849	2,424
Firm F. E.	✓	✓	✓
Year F. E.	✓	✓	✓

Appendix Table A3. Non-SBIR Contracts

	N. Contr. (1)	Asinh Contr. (2)	Log Contr. (3)	Contr. Indicator (4)
Post × *Treat*	0.7499	0.1498	-0.0324	0.0826
	(0.4109)	(0.0230)	(0.0428)	(0.0109)
R^2	0.53689	0.65236	0.74121	0.44261
Observations	76,849	76,849	12,585	76,849
Firm F. E.	✓	✓	✓	✓
Year F. E.	✓	✓	✓	✓

Appendix Table A4. Non-SBIR Contracts Dollar Value

	Contract Value (1)	Asinh Contract Value (2)	Log Contract Value (3)
Post × *Treat*	758,060.6	1.119	0.0312
	(200,860.2)	(0.1524)	(0.0829)
R^2	0.59099	0.47856	0.58954
Observations	76,849	76,849	12,235
Firm F. E.	✓	✓	✓
Year F. E.	✓	✓	✓

Appendix Table A5. Cumulative Patents

	Cum. Patents (1)	Asinh Cum. Patents (2)	Log Cum. Patents (3)
Post × *Treat*	0.3818	0.1166	0.1305
	(0.0886)	(0.0169)	(0.0326)
R^2	0.64339	0.74014	0.84709
Observations	76,849	76,849	16,324
Firm F. E.	✓	✓	✓
Year F. E.	✓	✓	✓

Appendix Table A6. Cumulative Citation-Weighted Patents

	Cum. Pat. Cit. (1)	Asinh Cum. Pat. Cit. (2)	Log Cum. Pat. Cit. (3)
Post × *Treat*	5.525	0.2018	0.1022
	(1.652)	(0.0381)	(0.0342)
R^2	0.74147	0.77377	0.96173
Observations	76,849	76,849	13,976
Firm F. E.	✓	✓	✓
Year F. E.	✓	✓	✓

Appendix Table A7. Phase 1 Grants

	N. Grants	Asinh N. Grants	Log N. Grants	Grant Indicator
	(1)	(2)	(3)	(4)
Post × *Treat*	-0.0257	-0.0335	0.0516	-0.0435
	(0.0387)	(0.0157)	(0.0218)	(0.0107)
R^2	0.55115	0.40265	0.57373	0.27400
Observations	76,849	76,849	11,566	76,849
Firm F. E.	✓	✓	✓	✓
Year F. E.	✓	✓	✓	✓

Appendix Table A8. Phase 2 Grants

	N. Grants	Asinh N. Grants	Log N. Grants	Grant Indicator
	(1)	(2)	(3)	(4)
Post × *Treat*	0.0184	-2.57×10^{-6}	0.0431	-0.0145
	(0.0226)	(0.0130)	(0.0213)	(0.0104)
R^2	0.37772	0.28796	0.51435	0.18974
Observations	76,849	76,849	9,124	76,849
Firm F. E.	✓	✓	✓	✓
Year F. E.	✓	✓	✓	✓

Appendix Table A9. Competed Non-SBIR Contracts

	N. Contr.	Asinh Contr.	Log Contr.	Contr. Indicator
	(1)	(2)	(3)	(4)
Post × *Treat*	0.4570	0.1038	-0.0554	0.0622
	(0.3347)	(0.0209)	(0.0492)	(0.0105)
R^2	0.54796	0.62765	0.73207	0.40941
Observations	76,849	76,849	10,184	76,849
Firm F. E.	✓	✓	✓	✓
Year F. E.	✓	✓	✓	✓

Appendix Table A10. Competed Non-SBIR Contracts Dollar Value

	Contract Value	Asinh Contract Value	Log Contract Value
	(1)	(2)	(3)
Post × *Treat*	443,395.2	0.8390	0.0259
	(151,217.0)	(0.1481)	(0.0987)
R^2	0.55387	0.44035	0.56762
Observations	76,849	76,849	9,833
Firm F. E.	✓	✓	✓
Year F. E.	✓	✓	✓

Appendix Table A11. Noncompeted Non-SBIR Contracts

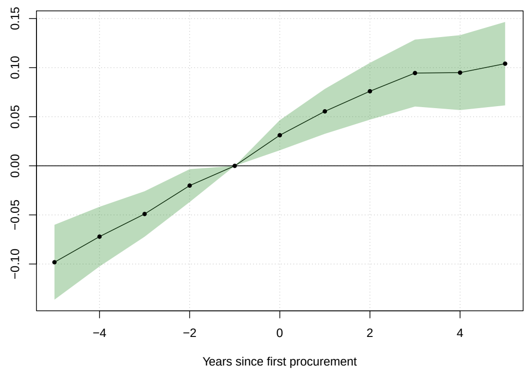
	N. Contr. (1)	Asinh Contr. (2)	Log Contr. (3)	Contr. Indicator (4)
Post × *Treat*	0.2930	0.0808	0.0027	0.0509
	(0.1212)	(0.0161)	(0.0614)	(0.0091)
R^2	0.34564	0.57646	0.69081	0.42283
Observations	76,849	76,849	5,756	76,849
Firm F. E.	✓	✓	✓	✓
Year F. E.	✓	✓	✓	✓

Appendix Table A12. Noncompeted Non-SBIR Contracts Dollar Value

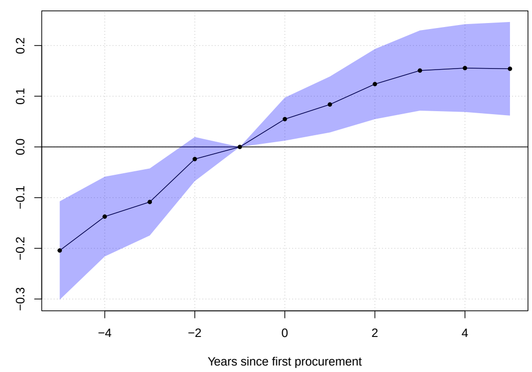
	Contract Value (1)	Asinh Contract Value (2)	Log Contract Value (3)
Post × *Treat*	314,665.4	0.6584	0.0894
	(122,872.5)	(0.1171)	(0.1196)
R^2	0.30352	0.44717	0.64155
Observations	76,849	76,849	5,608
Firm F. E.	✓	✓	✓
Year F. E.	✓	✓	✓

Appendix Figure A1. Cumulative patents increase constantly

(a) Asinh of cumulative patents

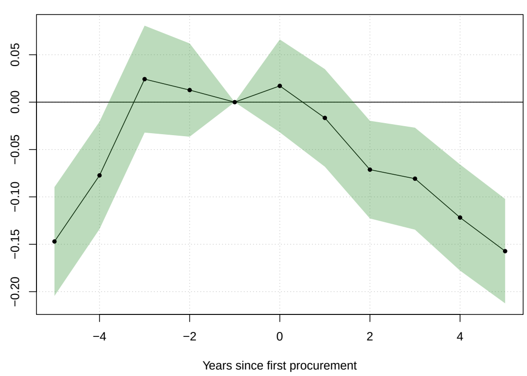


(b) Asinh of cumulative citation-weighted-patents

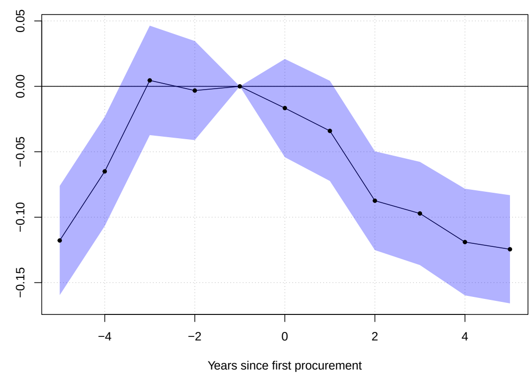


Appendix Figure A2. No more Phase I after Phase III

(a) Asinh of phase I grants number

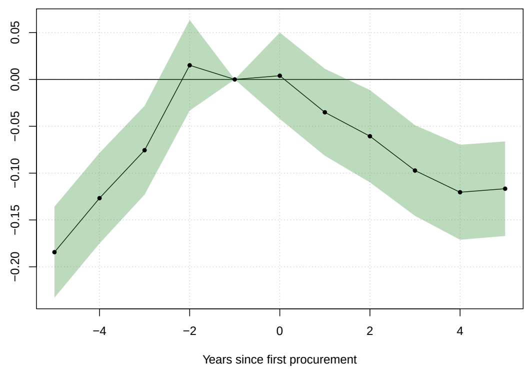


(b) Grants indicator

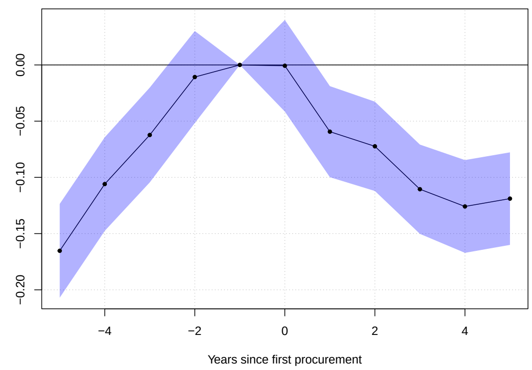


Appendix Figure A3. Phase II grants decrease after Phase III

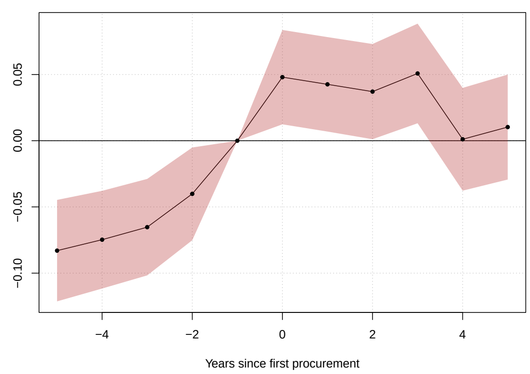
(a) Asinh of phase II grants number



(b) Grants indicator

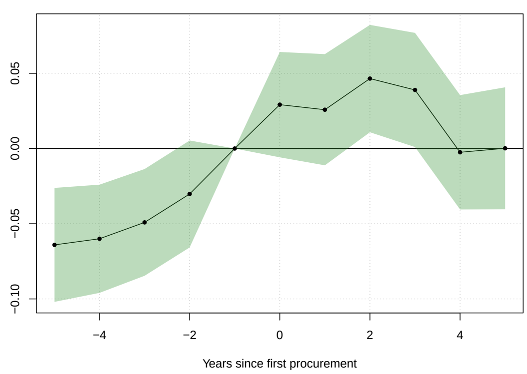


Appendix Figure A4. Effect of procurement on non sbir contracts indicator

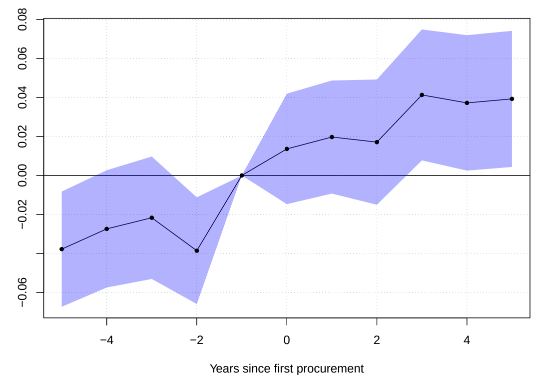


Appendix Figure A5. Competed and noncompeted procurement contracts indicators

(a) Competed contracts indicator

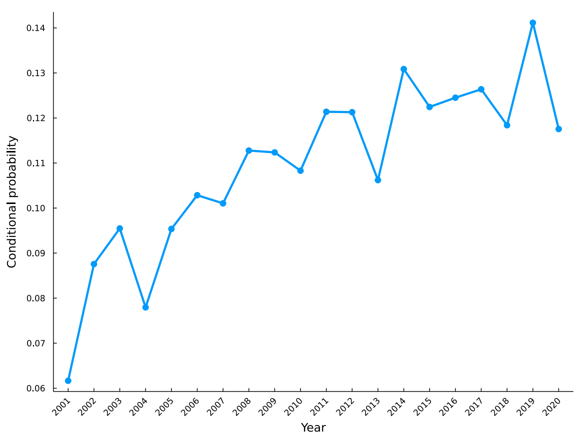


(b) Noncompeted contracts indicator

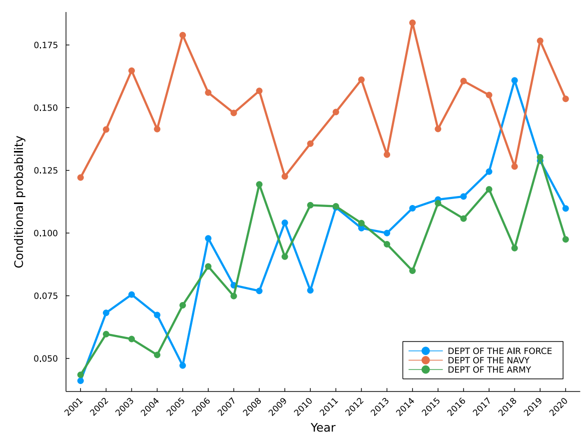


Appendix Figure A6. Conditional probabilities of reaching Phase III

(a) All Agencies



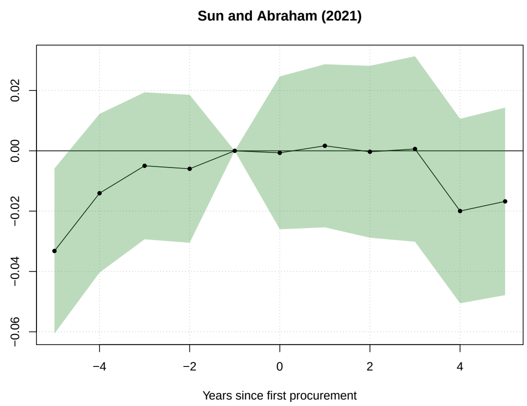
(b) Top 3 Agencies



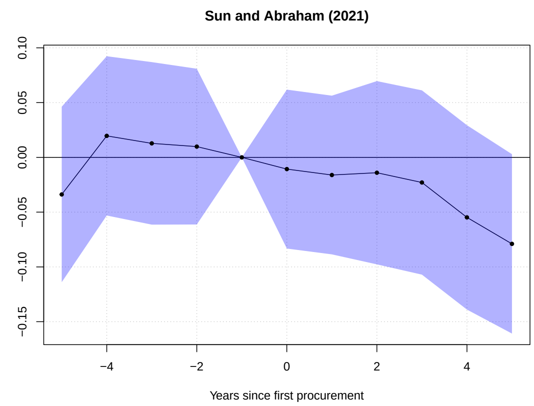
B Robustness checks

Appendix Figure B1. Procurement does not affect patenting activity

(a) Asinh of patents

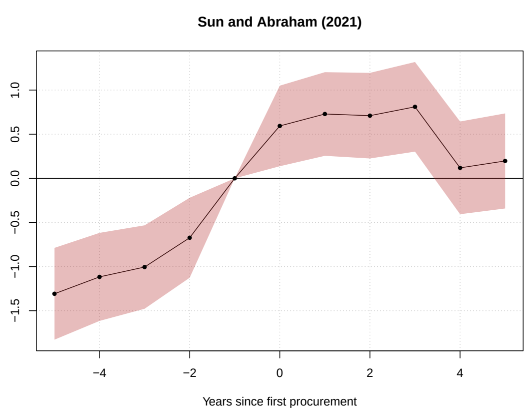


(b) Asinh of citation-weighted-patents

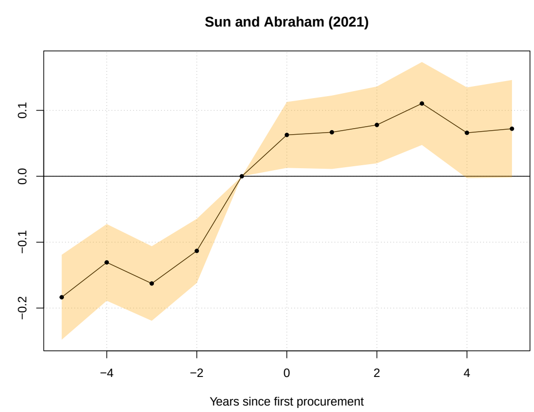


Appendix Figure B2. Non-SBIR contracts increase after Phase III

(a) Asinh of contracts number

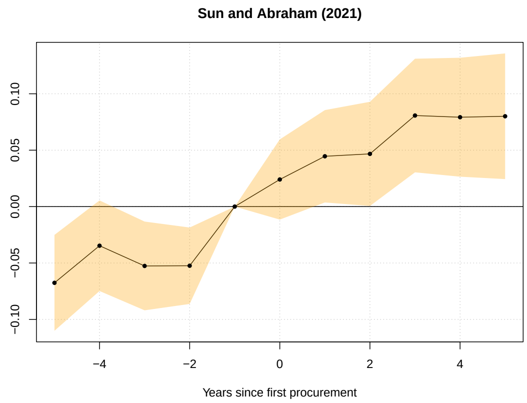


(b) Asinh of contracts dollar value

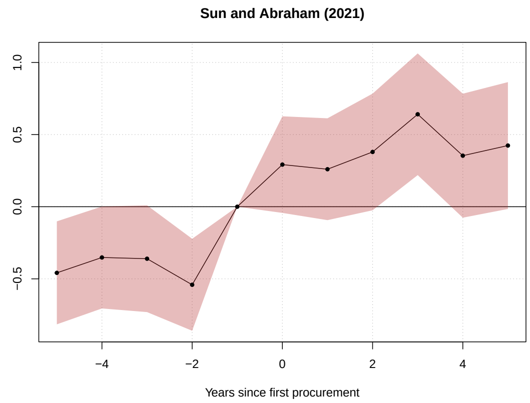


Appendix Figure B3. Noncompeted non-SBIR contracts increase more after Ph. III

(a) Asinh of contracts number

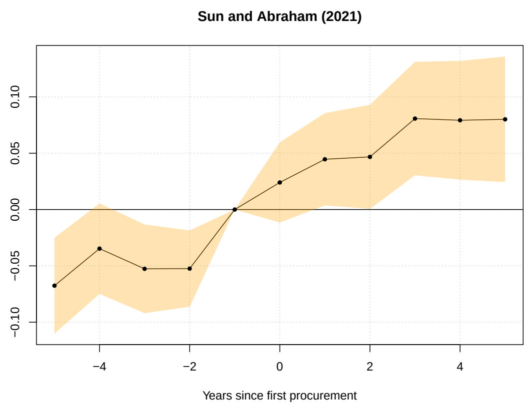


(b) Asinh of contracts value



Appendix Figure B4. Noncompeted non-SBIR contracts increase more after Ph. III

(a) Asinh of contracts number



(b) Asinh of contracts value