The Journal of Technology Transfer
https://doi.org/10.1007/s10961-021-09859-0

Helping the Little Guy: the impact of government awards on small technology firms

Aleksandar Giga[1,5] · Alexandra Graddy-Reed[2] · Andrea Belz[1] · Richard J. Terrile[3] · Fernando Zapatero[4]

Accepted: 18 April 2021

Abstract

The Small Business Innovation Research (SBIR) program provides federally funded research awards to companies with 500 or fewer employees. We explore the differential effects of the National Aeronautics and Space Administration SBIR program on firms of various sizes on their future patenting activity. Using propensity score matching, we construct comparable samples of selected and non-selected Phase II SBIR applicants by firm size. We then estimate the effect of selection for the matched sample on the probability of forward patent activity and conditional on any forward patenting, the count of patents within three years of the proposal. While firms with fewer than 10 employees, are least likely to patent, their probability of patenting is positively affected by receiving a Phase II award. We find sparse evidence of corresponding increase for larger firms. Nor do we find any evidence that a Phase II award impacts the conditional number of forward patents in the three years following the award. These data suggest that the Phase II award serves to advance the smallest teams "over the hump" to creating a potential source of competitive advantage.

Keywords Innovation policy · SBIR · R&D subsidies · Entrepreneurship

JEL Classification O310 · O380

✉ Andrea Belz
abelz@usc.edu

1 Viterbi School of Engineering, University of Southern California, Los Angeles, CA, USA

2 Sol Price School of Public Policy, University of Southern California, Los Angeles, CA, USA

3 Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA

4 Questrom School of Business, Boston University, Boston, MA, USA

5 Present Address: Faculty of Technology, Policy, and Management, Delft University of Technology, Delft, the Netherlands

Published online: 20 May 2021

1 Introduction

The United States Small Business Innovation Research (SBIR) program, one of the pillars of government effort to enhance innovation, has offered research and development (R&D) awards to firms with 500 or fewer employees since 1982. The rationale of the program is straightforward; by providing early-stage financing to small companies that might not attract funding in the market, the program focuses on the population with the highest potential for growth, both in revenue and employment. In fiscal year (FY) 2017, all eleven federal agencies with R&D budgets in excess of $100 million allocated 3.2 percent of their budget to SBIR awards, shown previously in some agencies to be linked to increases in entrepreneurial activity, venture capital, company growth, revenue, and patents. (Cumming & Li, 2013; Howell, 2017; Lerner, 1999).

The National Aeronautics and Space Administration (NASA) SBIR program is one such agency—providing more than $150 million a year in grants to aerospace industry firms (NASA 2016). The aerospace industry is important because of its size, worldwide scope, innovation capacity, and technological complexity (Niosi & Zhegu, 2005, 2010), as well as its importance as a source of patents and invention (Ardito et al., 2016; Mcguire & Islam, 2015), a potentially important outcome of the SBIR program. It therefore presents a rich laboratory to study the interplay of small businesses, innovation, and federal intervention. Using a propensity score matching methodology, we analyze data from the NASA SBIR program to study its effect across different firm sizes within its small-firm universe. We study the second-stage (larger) SBIR award and its impact on the invention performance of so-called "microfirms" of 1–9 employees, comparing it with that of larger small businesses (10–249 employees) and ask: are selected firms more likely to patent after receiving the award and if so, does the number of patents increase with the award?

We find that receiving a Phase II SBIR award positively impacts a microfirm's probability of patenting. Specifically, selected firms show a nearly 8 percent increase in the probability of patenting compared to non-selected firms. This is a sizable effect for microfirms in our sample as only 12 percent of them patent. In contrast, we do not find a similar effect for larger firms. In each subsample, conditional on patenting, we find no impact on the number of patents generated. Thus, the SBIR award helps the smallest companies take some of the first important steps to cross the so-called "Valley of Death" (VOD), a lack of funds needed at the earliest stages of technology development. Clouded in technical risk, the smallest companies are most vulnerable to such financing constraints since they are unlikely to self-finance and often lack a track record (i.e. revenue, stock of intangible assets) that attracts investors.

This paper contributes to the general literature on entrepreneurial finance and so-called "deep technology ventures" by exploring a subset of technologies of great importance to the economy; in parallel, our results have implications for the aerospace industry. We also contribute to the dialogue on the outcomes related to federal interventions and their potential impact on innovation.

2 Literature review

In initial product development, a small technology firm may struggle to attract resources from private capital due to high risk (Gompers & Lerner, 2001), especially in less active investment periods (Nanda & Rhodes-Kropf, 2013). This is problematic because small companies are more innovative than large ones (Belz et al., 2019; Edwards & Gordon, 1984). They are of particular interest on a national level because the newest small firms contribute disproportionately to economic growth, and yet formation is on the decline (Akcigit & Kerr, 2018; Decker et al., 2016; Haltiwanger et al., 2013).

2.1 Subsidies and SBIR

Subsidy programs have developed to remedy market failures (Hall & Lerner, 2010; Zúñiga-Vicente et al., 2014). Although public funding could "crowd-out" private investment (Wallsten, 2000), studies from around the world suggest that this is not the case (Bronzini & Iachini, 2014; Choi & Lee, 2017; Dimos & Pugh, 2016; González & Pazó, 2008; Huergo & Moreno, 2017; Lach, 2002; Smith et al., 2018). Instead, evidence exists that small firms respond to public subsidies by increasing their internal R&D expenditure (Almus & Czarnitzki, 2003; Bronzini & Iachini, 2014; Lach, 2002). Alternatively, the subsidy may enable a firm to pursue research that would be otherwise discontinued (Belz & Giga, 2018; Feldman & Kelley, 2006). Additionally, public subsidy impact depends on the firm's prior R&D experience (Caloffi et al., 2018), and its ties to universities (Siegel & Wessner, 2012). Public support may inhibit growth of academic spinoffs (Ayoub et al., 2017) and combinations of public support may decrease the subsidy's effectiveness (Dumont, 2017; Marino et al., 2016). However, government grants have also been shown to increase a firm's likelihood of subsequent survival (Smith et al., 2018), attracting future funding (Feldman & Kelley, 2006), debt financing (Meuleman & De Maeseneire, 2012), and venture capital (Islam et al., 2018; Toole & Turvey, 2009). Regarding the latter outcome of venture capital, studies are mixed on whether this link results from certification (Lerner, 1999) or directly funding important technology development (Howell, 2017).

In the United States, the SBIR program provides such subsidies under a structure with objectives including: stimulating innovation; using small businesses to meet federal needs; creating access for historically disadvantaged groups; and accelerating commercialization of federally funded research (Wessner, 2008). SBIR awards have been positively linked to increases in entrepreneurial activity, venture capital, company growth, high-tech entrepreneurship, patent generation, externally generated patents, and technological advancement (Belz et al., 2019; Cumming & Li, 2013; Galope, 2016; Howell, 2017; Lerner, 1999; Qian & Haynes, 2014; Toole & Turvey, 2009).

These benefits are especially important because of the decline in research conducted by the largest firms; their share has dropped by about one-quarter between 1985 and 1998 as companies have focused on advanced development more than basic research (Arora et al., 2018), and acquisitions over R&D (Blonigen & Taylor, 2000). Simultaneously, venture capital has migrated dramatically away from hardware-driven technologies (Belz, 2016), necessitating intervention because smaller firms may not have enough internal funds to finance risky but potentially rewarding R&D projects (Ughetto, 2008). These dynamics make federal support of basic research in small companies even more critical.

2.2 Aerospace industry

The aerospace industry is nationally strategic, characterized by complex, advanced technologies linking the defense and civil markets. As a strategic employer of highly skilled engineers, it represents a quintessential industry to anchor regional growth and its evolution has thus been studied extensively (Alberti & Pizzurno, 2015; Cooke & Ehret, 2009; Niosi & Zhegu, 2005, 2010; Sammarra & Biggiero, 2008; Turkina et al., 2016). However, technology infusion is complicated by high development costs, complex products, limited markets with cyclical cash flow, high industrial concentration with few key players, and complex products conforming to strict performance and reliability standards (Corallo et al., 2009). The need for high customization leads to extended product life cycles and a tendency toward launching variants of existing models rather than new products, leading to networked models of knowledge-sharing (Corallo et al., , 2012, 2014; McAdam et al., 2008).

Because development costs increase as a technology advances, it becomes difficult to demonstrate the satisfactory performance of a technology in order to obtain funding (Terrile & Jackson, 2013). This intermediate range of technology advancement—beyond proof of principle and prior to prototype—defines the "Valley of Death," and funding these activities is a critical challenge (Auerswald & Branscomb, 2003; Beard et al., 2009; Frank et al., 1996; Islam, 2017) intensified in space agencies by the limited frequency and number of mission opportunities (Szajnfarber, 2014). New frameworks to manage a space agency early-stage portfolio have been proposed (Szajnfarber & Weigel, 2013; Terrile & Jackson, 2013; Terrile et al., 2014; Wicht & Szajnfarber, 2014). In the context of the SBIR program, these issues are important because the very small firms experience the widest distribution of technical outcomes (Belz et al., 2019).

2.3 Innovation and patents

Over the years, as data-mining techniques have become more accessible and popular, patents have become an important tool in studying innovation. Although patent generation is an incomplete measure (Archibugi & Pianta, 1996; Fontana et al., 2013) and not the only way to protect intellectual property (Strumsky & Lobo, 2015) it is linked to firm value (Hall et al., 2005; Trajtenberg, 1990) and startup growth (Helmers & Rogers, 2011). The importance of patents varies with firm size (Brouwer & Kleinknecht, 1999) and industry (Arora et al., 2008; Fontana et al., 2013; Pérez-Cano & Villén-Altamirano, 2013). In the aerospace industry, patents are tracked as a signal of cluster development (Mcguire & Islam, 2015).

Patents may be an important waypoint between government funding and commercialization. Subsidies show positive effects on patent generation (Bronzini & Piselli, 2016; Jaffe & Le, 2015) and government loans focusing more on commercialization lead to higher patent renewal rates (Svensson, 2013). Patents serve as signals in external financing, but only for small firms (Hottenrott et al., 2016) and in attracting venture capital (Conti et al., 2013); indeed, the impact of patents as a signaling mechanism decreases in later funding rounds when more information is available (Ardito et al., 2016; Hoenen et al., 2014). For very small companies in particular, this form of intellectual property may play an outsized role: venture-backed startups were reported to hold an average of six patents or applications, while those without venture capital generally had none (Graham et al., 2009). For the "deep-technology" companies that are based on the cutting edge of scientific and technological advances, patenting is a natural choice to build competitive advantage, and the patent process may be carefully managed at the strategic level (Zahringer et al., 2018). Furthermore, as they precede sales, patents measure the success of technology development, not ambiguated by the business acumen.

Thus, though imperfect, not only are patent outcomes important as a direct innovation measure, but as an indicator of potential success in the financing marketplace. The complexity of technologies in the aerospace industry conspires to create an even larger challenge in the VOD, enhancing the need for federal intervention. Scholars have previously determined that NASA SBIR award recipients proposed projects with commercial potential (Archibald & Finifter, 2003) and that progress on the technology's development is indeed made in the program (Belz et al., 2019). However, innovation outcomes have not previously been explored thoroughly, nor has the relationship between early-stage technology subsidies and the funding agency's mission (Edler & Fagerberg, 2018; Mazzucato & Semieniuk, 2017).

3 Data

NASA manages its own SBIR program in a highly structured fashion, producing open solicitations for research proposals and selecting the entirety of the coming year's project portfolio at one time. Decisions for the next tranche of investment are similarly made simultaneously for all proposals that seek continued funding. This two-phase structure is pervasive throughout the federal agencies administering the SBIR program. The contract purchases no rights for the agencies; they do not demand equity nor the rights to a selected firm's intellectual property.

In fiscal year 2016, the NASA SBIR budget exceeded $150 million (NASA 2016). It addresses the agency's needs in executing its strategy of earth and space exploration. NASA SBIR funding is awarded in an initial six-month Phase I with a maximum award that has grown from $70,000 to $125,000 in the past decade. Typically, about 24 percent of proposing companies are selected for funding.[1] At the end of the Phase I performance period, awarded firms may submit a Phase II proposal for an estimated $500,000–750,000 and a term of two years.[2] Each Phase I award makes a firm eligible for one subsequent Phase II award. An eligible company (e.g. an American firm with up to 500 employees) may propose up to 10 Phase I proposals in a given year. With that constraint in mind, there is no further limitations to how many Phase II awards a company can win. If a company wins 10 Phase I awards in a given year, it can win up to 10 subsequent Phase II awards. At NASA, over 96 percent of Phase I awardees elect to submit a Phase II proposal, with approximately 41 percent succeeding.[3] Funded technologies span many disciplines of interest to NASA, and each technology topic is managed at one of the twelve NASA Centers.

[1] NASA SBIR/STTR Participation Guide: https://sbir.gsfc.nasa.gov/sites/default/files/012-19-001-010.pdf. (reference last accessed on October 18th, 2019).

[2] The cost information contained in this document is of a budgetary and planning nature and is intended for informational purposes only. It does not constitute a commitment on the part of JPL and/or Caltech.

[3] NASA SBIR/STTR Participation Guide: https://sbir.gsfc.nasa.gov/sites/default/files/012-19-001-010.pdf (accessed on October 18th, 2019).

Table 1 Sample selection

	(1) 1999–2012	(2) 2002–2012
Full Proposal Population	4016	3177
Firms with Multiple Proposals in a Year	− 1697	− 1354
Firms Missing a Technical Score	− 501	− 5
Firms with > 249 Employees	− 24	− 24
Final Sample Size	1794	1794
Firms with 1–9 Employees	774	774
Firms with 10–49 Employees	766	766
Firms with 50–249 Employees	254	254

Technical Scores became available in the dataset in 2002; thus the timeframe is reduced to 2002–2012 for our analysis

NASA SBIR data used for this analysis were compiled from the Electronic Handbook (EHB) with permission from the NASA SBIR program. This data set is for restricted use, but is searchable over many years of the program. To protect the procurement sensitive nature of these data, we compiled data from 1999 to 2012 over all NASA Mission Directorates and present only aggregated results to prevent identification of individual companies. A portion of the EHB data was previously used in a pilot study.

For the present study, we examine the Phase II selection process and subsequent patenting activity of applicants. We define the unit of observation as that of a firm in a given year with firms with proposals in multiple years treated as independent observations. The dataset includes all NASA SBIR Phase II applicants from 1999 to 2012. We complement this with patents granted to the applicants from both the US Patent and Trademark Office (USPTO) and Google Patents databases until the end of 2015. Phase II applicants are matched via firm name to patent assignee name.

To link the appropriate patents to firms, we first match via firm name. To minimize errors, further validation is conducted using the firm's address and the Principal Investigator (PI) name listed in the SBIR proposal. Specifically, after matching via firm name, we count matches as valid only if the PI name has at least an 80 percent fuzzy match to one of the names on the patent's inventor list, or if the city and the state of the firm matches the patent's assignee address. Once we create this subset of validated patents, we identify other inventors and possible address changes connected to the firm. We then use this information to further validate other patents that share the same firm name but were not initially counted as valid. Finally, random manual inspection confirmed the quality of the matching.

The full NASA proposal database includes 4,016 Phase II proposal observations. We reduce the sample across three dimensions for improved analysis. First, we remove observations of firms with multiple proposals within the same year to resolve potential ambiguities resulting from a firm that may both win and lose in a given year; this restriction is more likely to impact the larger firms than the small ones of interest. Additionally, because patents are assigned to a firm and not on a project basis, focusing on firms with one proposed project in a year allows us to link the patents to the firm while properly maintaining a constant relationship of attempts to awards. This reduction should also remove so-called "SBIR mills", firms that generate revenue mainly from SBIR contracts and may not be focused on transitions to broader commercial markets. Second, we remove observations that are missing a Technical Score. This variable is discussed in detail in the following

Table 2 Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Phase II Award Status		Firm Size Employee Bin		
		Selected	Non-Selected	1 to 9	10 to 49	50 to 249
Any Forward Patents	0.26	0.30	0.22	0.12	0.33	0.42
Count of FP within 3 Years, 0–245	1.03	1.26	0.83	0.24	0.98	3.63
	(6.97)	(9.44)	(3.59)	(1.08)	(2.81)	(17.65)
Number of Employees, 1–247	26.59	27.16	26.08	4.82	21.64	107.84
	(39.28)	(38.95)	(39.59)	(2.25)	(10.43)	(49.40)
Technical Score, 20–100	92.51	95.82	89.56	92.33	92.71	92.47
	(7.05)	(3.46)	(8.07)	(7.30)	(7.05)	(6.26)
Any Prior Patents	0.46	0.48	0.45	0.25	0.59	0.72
Any Prior Phase II Awards	0.49	0.52	0.47	0.32	0.61	0.66
Observations	1794	846	948	774	766	254

Means (standard deviations) reported for continuous variables; proportions presented for binary variables

section, but is critical to the selection process. Technical Scores become available in our dataset in 2002, thus this decision also reduces our timeframe to 2002 to 2012. Finally, we also remove observations from firms with 250 to 499 employees. This is the largest, and arguably more mature, bin of firms eligible for SBIR funding, but represents a very small sample—just 24 proposals. These selections reduce our full sample to 1,794 firm-year observations. Table 1 details the sample selection process.

Table 2 presents the descriptive statistics of the reduced sample and stratified across two dimensions: Phase II selection status and firm size by employee bins. Overall, 26 percent of the sample has subsequent patent activity after their Phase II proposal with an average of 1.03 patents within three years of proposal. This is driven both by selected firms and firms with higher employee headcounts. Nearly half of firms in the sample have prior patents (46 percent); again, driven by the larger firms. Of the firms with fewer than 10 employees, only 25 percent have prior patenting activity and only 12 percent go on to have patents issued after the Phase II proposal.

4 Research design

Intervention programs often suffer from potential endogeneity problems—i.e., the better companies are more successful and more likely to be award recipients, thereby confounding the study of the impact of the program (Bertoni et al., 2011). To address this, we use the Technical Score assigned to proposals at the time of selection. Multiple reviewers, both internal and external to NASA, independently provide appraisals of the scientific merit and feasibility, the capability of the team to execute, and the proposed plan's effectiveness. These scores are averaged in an aggregated Technical Score ranging from 1 to 100, a key factor in the selection process. As expected, higher scores enjoy a higher likelihood of selection (Table 3). The minimum Technical Score for consideration in the selection process is 85.

Table 3 Correlation Matrix

	Any Forward Patents	FP Count in 3 Yrs-Post	Tech. Score	Any Prior Patents	Any Prior Phase II Awards	Win Current Phase II Award
FP Count in 3 Yrs-Post	0.240***					
Tech. Score	0.0265	0.0274				
Any Prior Patents	0.399***	0.139***	0.00551			
Any Prior Phase II Awards	0.145***	0.00766	0.0688**	0.228***		
Win Current Phase II Award	0.0948***	0.0309	0.437***	0.0354	0.0483*	
Log of Employee Count	0.302***	0.157***	0.0156	0.406***	0.336***	0.0375

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; the treatment variable is whether the firm was selected for a Phase II award with this proposal. Outcome variables include the binary variable of any forward patents and the continuous variable of count of forward patents within three years of the proposal year. Selection variables include the Technical Score at time of selection (continuous), log of employee count at time of application (continuous), whether the firm had any prior patents before the year of selection (binary), and whether the firm had previously won any Phase II awards (binary)

To obviate this endogeneity issue, we match selected and non-selected firms using propensity score matching (PSM) (Caliendo & Kopeinig, 2008; Rosenbaum & Rubin, 1983) to control for these selection effects. Like other empirical studies (Bertoni et al., 2011), we borrow experimental concepts, such as "treated" and "untreated" observations, to indicate if an observation was impacted by the main independent variable. In our case, a firm selected for an award in a given year is considered "treated", and non-selected counterparts are regarded as "untreated". However, to create both the treatment sample and the control group, it is important to verify that the untreated and treated observations are sufficiently similar to justify a comparison.

Matching methodologies identify selected and non-selected observations appropriate for comparison; propensity score matching is such a method measuring the likelihood of selection with relevant predictors. In particular, we use the Technical Score because it impacts selection significantly by design, but is not directly related to patent outcomes. This excludes outliers, such as exceptionally strong selected proposals, or particularly weak ones not selected, from inclusion in the sample.

We estimate a propensity score through a logit model. Other predictors are used to refine the understanding of selection. These include employee headcount at the time of Phase II application using the natural logarithm functional form. A prior study on a reduced data sample shows that it has only a minimal effect in Phase II selection (Belz et al., 2019). Fixed effects are included for the proposal year. Finally, we include fixed effects for the technology type by controlling for the NASA Center because each technology topic is managed at a specific Center. Table 3 presents a correlation matrix of the outcome variables and selection variables. Appendix Table 7 presents the logistic regression estimations of the propensity scores for the full sample as well as stratified by employee headcount bins.

The estimated propensity scores are then used to identify the observations appropriate for the treatment and control groups by matching selected firms with non-selected ones. We used two different matching methodologies. The first, radius matching, matches a selected observation to *all* non-selected ones within 0.01 (the radius) of their propensity score. Non-selected observations identified by matching are included in the control group. This technique allows for replacement—i.e., a single non-selected observation may be matched with multiple selected counterparts, rather than creating a one-to-one sample selection process. Figure 1 presents the distribution of propensity scores that spans the selected and non-selected groups for the full sample and by employee headcount bins. Unmatched selected observations (such as those with particularly high Technical Scores without equivalent non-selected firms) that cannot be matched are excluded from the analysis, as are those non-selected observations that do not fall within the radius. Selected and non-selected observations that can be matched are assigned to treatment and control groups, respectively. To validate the matching, a series of t-tests is conducted comparing the covariate distributions of the newly formed treatment and control groups. These results are presented in Appendix Table 8 for the full sample and by employee headcount bins and indicate that the matched samples are not statistically different across the four variables of selection. To illustrate the effect of matching, we consider Technical Score: in the pre-matched sample, selected firms have an average score of 95.8 compared to 89.6 for non-selected firms. Post-matching, the selected firms remain with an average score of 95.8, but now the non-selected firms have an average score of 95.9.

The second matching methodology is nearest-neighbor matching, a close relative of radius matching. For this method, up to three untreated observations can be matched to one treated counterpart if they are within 0.01 propensity score. Table 9 presents the results and covariate comparison using the nearest-neighbor approach. The results between the two methods are consistent and robust. However, radius matching yields a larger sample size and thus is used as the primary analysis.

Using the radius-matched treatment (selected) and control (non-selected) groups, we then assess the average treatment effect on the treated (ATET) on the probability of patenting by using t-tests for the full matched sample and employee headcount bins. We conduct a series of regression analyses to further examine the relationship between Phase II selection and future patenting. Our objectives are to examine if selection: (1) impacts the likelihood of patenting; and (2) affects the number of subsequent patents.

To estimate these effects, we use a two-part model to first assess the award's impact on the probability of patenting; and then, conditional on patenting, its extent. We estimate two models for comparison. First, we estimate an independent two-part model using the matched groups. In this method, we first estimate a logistic regression on the probability of patenting after the Phase II proposal. Specifically, this estimates the impact on generating any patents after the proposal year (2002–2012) through 2015, when patent data were obtained. Second, we reduce the matched sample to those with any forward patents over the full time frame and estimate an OLS regression on the number of forward patents within three years of the proposal using the natural log functional form. We truncate the count outcome variable after three years because our set of proposals range from 2002 to 2012 and our patent data is through 2015. Thus, with a three-year window, each proposal is given a comparable range of time to patent and compare counts. Alternate calculations of forward patents were considered including the sum of forward patents across the full available timeframe as well as the annual average count of forward patents; both alternatives produce consistent results. We weight the observations in the regression analyses to account for repeated non-selected (control) observations used by the radius and nearest neighbor matching methodologies.

It is important to note that an independent two-part model assumes that the errors from each part are independent. Should this not be the case, an alternative method is necessary. To address this issue, we also estimate a Heckman selection model on the matched subsamples as a robustness check. The Heckman analysis uses a probit model for the selection stage (any forward patents) and then OLS for the second stage (natural log of count of patents within three years). The end estimation provides the marginal effects of the potential outcome—that is, the effect on the rate of forward patenting if we had observed it for the full sample. The test of independent equations confirms the use of the selection model in three of the four regression samples. This is discussed in turn in the results section below (Sect. 5). The Heckman model estimated includes the same set of covariates as in Part 1 of the independent two-part model. The second stage, however, excludes the Technical Score and prior patent activity as it is assumed these variables matter in determining whether a firm patents, but not the extent to which they patent.

5 Results

Table 4 presents the Average Treatment Effect on the Treated using the radius matching technique. The simple difference of means between the matched treatment and control groups finds an average treatment effect of 6.1 percentage points for the full sample on the probability of patenting. This difference is driven by the sample of microfirms, those with fewer than 10 employees. For this sub-sample, selected firms show a 7.9 percentage point

Table 4 PSM ATET Estimation of the Probability of Patenting

	(1) Full Sample	(2) 1 to 9 Employees	(3) 10 to 49 Employees	(4) 50 to 249 Employ-ees
Treated Mean	0.30	0.16	0.35	0.44
Control Mean	0.24	0.082	0.35	0.47
Difference (ATET)	**0.061****	**0.079****	0.0036	−0.031
	(0.030)	(0.037)	(0.050)	(0.110)
Observations	1683	618	642	174
Matched Treated	842	323	331	102
Matched Control	841	295	311	72

T-tests of matched sample treated vs. control using radius caliper (0.01) propensity score matching with replacement; standard errors in parentheses; ***$p<0.01$, ** $p<0.05$, * $p<0.1$

increase in the probability of patenting compared to non-selected firms, yet their probability of patenting is the lowest across firm sizes at 12 percent (Table 2).

To better assess this impact, a two-part model is estimated using the matched sub-samples. Table 5 presents these results. Panel A presents the marginal effects from the logistic regressions on the probability of patenting. Panel B presents the OLS regression estimations on the log of forward patents within three years, conditional on ever patenting after the proposal. The results from part 1 (Panel A) are consistent and robust with the ATET presented in Table 4. Selection for a Phase II award is associated with a 6.7 percentage point increase in the probability of patenting. Firms with fewer than ten employees exhibit an increase of 7.3 percentage points, with no statistically significant difference between selected and non-selected firms for larger firms. Also of note but not surprising, prior patenting activity is positively associated with future patenting across all firm sizes. Similarly, receiving a prior Phase II award is positively associated with patenting for the full sample and sub-sample of the largest firms (column 4).

To investigate these findings further, we estimate these models on two sub-samples: one omitting firms with prior Phase II awards and the other omitting firms with prior patents. the sub-sample of firms without previous Phase II awards (Table 10). Among the firms that did not patent previously, the positive award impact is present among microfirms as well as the larger firms with fewer than 50 employees (Table 11). Due to sample size limitations, we are not able to estimate on the subset of largest firms, those with 50 to 249 employees.

Panel B shows a different story on the conditional count of forward patents. Conditional on forward patenting, Phase II selection is not a significant predictor of the *number* of patents within three years. Consistent with Part 1, prior patenting activity is a positive indicator of a higher count of future patents. The results on the sub-samples by firm size should be interpreted with caution given the small sample sizes of firms with at least one forward patent.

As discussed in the methodology, the independent model assumes the errors of each part to be independent. However, this is often not the case. As an alternative, a Heckman selection model is estimated. The results are presented in Table 6. The assumption of independent equations is rejected for the full sample estimation as well as the sub-samples of firms with fewer than 10 employees and those with 10 to 49 employees. However, for these

Table 5 Independent Two-Part Model Estimation Results on PSM Sub-Sample

	(1) Full Sample	(2) 1 to 9 Employees	(3) 10 to 49 Employees	(4) 50 to 249 Employees
Panel A: Logistic Marginal Effects on Any Forward Patents				
Win Phase II Award	**0.067*****	**0.073****	0.012	0.023
	(0.025)	(0.029)	(0.040)	(0.069)
Technical Score	−0.003	−0.010***	−0.001	0.006
	(0.004)	(0.004)	(0.006)	(0.011)
LN Employees	0.044***	0.019	0.053	0.046
	(0.012)	(0.025)	(0.043)	(0.090)
Prior Patents	0.272***	0.158***	0.314***	0.462***
	(0.022)	(0.029)	(0.035)	(0.076)
Prior Phase II Awards	0.046*	−0.034	0.054	0.195***
	(0.025)	(0.031)	(0.044)	(0.059)
Observations	1,683	572	642	156
Log Likelihood	−730.3	−177.2	−333.0	−72.09
Chi-2	223.8	89.38	87.02	46.18
P-value	0	9.04e-10	4.47e-09	0.00188
Year Controls	Yes	Yes	Yes	Yes
Center Controls	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes
Panel B: If Any: OLS Estimations on LN of Forward Patent Count within 3 Years of Proposal				
Win Phase II Award	−0.113	0.500	−0.128	0.212
	(0.138)	(0.311)	(0.112)	(0.373)
Technical Score	0.004	−0.037	0.010	0.009
	(0.020)	(0.059)	(0.018)	(0.082)
LN Employees	0.239***	0.227	0.216	0.947*
	(0.080)	(0.275)	(0.140)	(0.528)
Prior Patents	0.624***	0.433*	0.688***	0.429
	(0.163)	(0.215)	(0.140)	(1.389)
Prior Phase II Awards	−0.206	−0.306	−0.135	−0.653
	(0.188)	(0.305)	(0.152)	(0.667)
Constant	−0.361	3.292	−1.929	−2.919
	(1.885)	(5.440)	(1.756)	(7.994)
Observations	354	61	171	65
Adjusted R-squared	0.148	0.00678	0.198	0.0181
Year Controls	Yes	Yes	Yes	Yes
Center Controls	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes

Marginal effects presented from logistic regressions on any forward patents using radius caliper propensity score matched sample; weights, based on the matching methodology, are used to account for repeated control observations; standard errors in parentheses; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

Conditional OLS coefficients presented on LN count of forward patents within 3 years of proposal using radius caliper propensity score matched sample if any forward patents; weights, based on the matching methodology, are used to account for repeated control observations; standard errors in parentheses; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

Table 6 Heckman Selection Model Estimation Results on PSM Sub-Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample		1 to 9 Employees		10 to 49 Employees		50 to 249 Employees	
Win Phase II Award	−0.193	0.203*	0.269	0.426**	−0.102	−0.090	0.164	0.106
	(0.136)	(0.106)	(0.210)	(0.178)	(0.118)	(0.144)	(0.323)	(0.283)
Technical Score		−0.012		−0.051**		−0.014		0.024
		(0.015)		(0.024)		(0.020)		(0.055)
LN Employees	0.185**	0.174***	0.246	−0.007	0.119	0.310**	0.941**	0.093
	(0.081)	(0.052)	(0.238)	(0.146)	(0.137)	(0.149)	(0.442)	(0.351)
Prior Patents		1.221***		1.074***		1.334***		2.024***
		(0.104)		(0.172)		(0.144)		(0.392)
Prior Phase II Awards	−0.237	0.095	−0.247	−0.323*	−0.139	0.053	−0.810	0.987***
	(0.195)	(0.106)	(0.251)	(0.176)	(0.148)	(0.152)	(0.603)	(0.301)
Constant	1.304***	−0.829	1.110	2.802	0.368	−0.959	−1.476	−3.888
	(0.474)	(1.434)	(0.773)	(2.335)	(0.620)	(1.924)	(2.167)	(5.375)
Observations	1,683		618		642		174	
Selected Observations	354		61		171		65	
Log Likelihood	− 1122		− 191.1		− 484.6		− 197.0	
Rho Indep. Eq. Chi− 2	21.89		8.806		23.39		1.022	
P− Value	(0.000)		(0.003)		(0.000)		(0.312)	
Year Controls	Yes		Yes		Yes		Yes	
Center Controls	Yes		Yes		Yes		Yes	
Weights	Yes		Yes		Yes		Yes	

Heckman selection model estimation results presented using radius caliper propensity score matched sample; part 1 estimates probability of any forward patents and part 2 estimates the count of forward patents within three years of the SBIR proposal, conditional on any patenting. For each estimation result, part 2 (part 1) is presented in the left (right) column. Weights, based on the matching methodology, are used to account for repeated control observations; standard errors in parentheses; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

two samples, the limited sample size impacts the overall validity of the model. As a result, we concentrate our discussion on the full sample estimation presented in columns 1 and 2. Column 2 presents the coefficients of the Probit selection model. Column 1 presents the marginal effects of the potential outcome. The results are consistent with the independent two-part model. While Phase II selection positively impacts the probability of future patenting, it does not impact the number of patents within three years of the award.

6 Discussion

While companies prefer to fund R&D internally (Brown et al., 2009; Hall, 1992; Himmelberg & Petersen, 1994; Ughetto, 2008), small firms may not have enough internal funds to finance risky but potentially rewarding R&D projects (Ughetto, 2008), and are likely to be financially constrained in several ways. Debt financing may be difficult to obtain for R&D

projects generating intangible assets; in particular, new, small firms may not have the track records attractive to banks and other traditional lenders, and even older small firms may not have easily valued assets (i.e., assets outside the patent portfolio) to collateralize a loan. In addition, independent equity investors may demand too high a price for their capital, due to the intrinsic uncertainty of the projects and the fact that, as outsiders, they cannot fully evaluate the technical merit and potential benefit. Therefore, a firm may not credibly prove to an investor that "the view is worth the climb." These constraints define the "Valley Of Death" (VOD) (Auerswald & Branscomb, 2003).

The SBIR award acts as an important funding source of attempting to cross the VOD. We observe the award's impact only on the microfirms because they are likely the most constrained group within the universe of small firms. For example, in our sample, microfirms are less likely to have prior Phase II awards or prior patenting that the investors may use as evidence of market potential (Tables 2 and 3). Given the fixed award amount and the general absence of the effect among larger firms, we posit that the effect is driven by the relaxation of the cash constraints that microfirms face. Phase II funding may provide enough resources ($500,000–750,000) and time to bring the technology to a patentable level and to free additional cash for the costs related to the patenting process. This also explains why award effect is stronger among microfirms with no prior Phase II awards (Table 10) as they are likely to be younger and less liquid. Similarly, the benefit of the reduced cash constraint also applies to larger firms that have not patented previously (Table 11). In contrast, Phase I is not likely to provide such an opportunity. It offers a considerably smaller award ($70,000–125,000) and only a six-month window, most of which is spent working to secure Phase II funding.

Preceding sales or employment growth, patents are evidence of firms achieving early milestones to cross the VOD. This is particularly significant in the case of technologies sponsored by NASA. As deep technologies (i.e. sensors, equipment for aerospace vehicles) they are more likely to turn to patents as their source of competitive advantage. Additionally, once the microfirms protect the technology, they may turn to other priorities such as turning the invention into a commercialized product. That is likely why we do not observe an impact on the number of patents produced, but rather on the likelihood of patenting.

Given that our results pertain to the aerospace industry, it may not only be the lack of private financing that drives the differential award impact of firm sizes. It may be the ability of the company to become a government vendor. The aerospace industry caters to mission-driven agencies such as NASA and the Department of Defense. At least in the case of the military, the agency may serve as both the sole investor and the sole initial buyer of the technology (Laguerre, 2009; Mowery, 2012). In addition, the small companies face a bigger challenge in becoming prime contractors (Leitzel, 1992). It is not hard to believe that the same market structure and challenges operate in NASA's case. Therefore, observing differential impact may mean that larger companies have already established procurement relationship with the government, of which SBIR awards are a small part. However, for the fledgling companies, an SBIR award may be the only such source. Thus, an SBIR award may serve an essential function of being the first step in establishing a procurement relationship.

While we observe that the award impacts microfirms companies the most, this may not imply necessarily that NASA ought to change their funding strategy. As a mission-driven agency, NASA solicits technologies that it wishes to infuse in its missions, and hence faces a trade-off. It may increase the impact of the award by funding microfirms more, but it may reduce the number of the technologies that fulfill programmatic needs. Further research is necessary to correctly evaluate such trade-off.

7 Limitations and future research

Our reduced sample does not represent the entirety of the program. Furthermore, our dataset does not include the firm age, but our measurements seem to indirectly align with those of Howell (2017), who found a larger impact of Department of Energy SBIR Phase I awards on younger firms. This has significant implications because young firms, rather than small firms, spur innovation and growth (Haltiwanger et al. 2013).

In addition, this study sheds light on the invention outcomes of firms of various sizes but only hint at their innovation—that is, generating value from invention. Further research can elaborate on whether a larger firm, potentially closer to the marketplace and possessing prior experience at product launch, will have stronger innovation capabilities. The measures of commercialization and market activity may show a different effect on the extensive margin. While it may not be expected that microfirms produce many patents, it may be expected that existing intellectual property produces larger value in the market (measured by revenue generation and employment growth), and that this intellectual capital contributes to the combination of resources leading to greater outcomes from SBIR funding (Audretsch & Link, 2018).

Finally, it would be interesting to examine the role of the SBIR award as a steppingstone to a vendor role of a mission-driven agency. In particular, does the award prove more valuable for the firms without prior procurement, and if so, how long and how many SBIR investments are required for a small technology company to become a government contractor? Future research can focus on the impact of NASA awards on the measures reflecting further progress across the VOD: survival and commercial success.

8 Conclusion

To date the literature has documented the generally positive effects of the SBIR program, including an increase in innovation. In this paper, we use a proprietary database of the NASA SBIR program that allows exploration of the underlying mechanisms, as measured by patents issued to award recipients. Using a propensity score matching methodology, we show that Phase II award recipients are more likely to patent. The effect seems to stem from the impact the award has on the smallest firms (9 employees or fewer). In addition, we observe no measurable impact on the total number of patents produced. This work contributes to the literature on R&D subsidies with insight specifically for the smallest firms and their invention output. In addition, this is one of the first comprehensive examinations of the NASA program, studying small businesses in an industry of great importance to the United States economy.

Appendix

See Tables 7, 8, 9, 10, 11 and Fig. 1.

Table 7 Propensity score logistic regression estimations

	(1) Full Sample	(2) 1 to 9 Employees	(3) 10 to 49 Employees	(4) 50 to 249 Employees
LN Employees	0.039	0.192	0.129	0.235
	(0.055)	(0.172)	(0.202)	(0.391)
Technical Score	0.267***	0.299***	0.243***	0.331***
	(0.015)	(0.026)	(0.023)	(0.049)
Prior Patents	0.173	0.141	0.268	−0.010
	(0.128)	(0.219)	(0.186)	(0.385)
Prior Phase II Awards	0.125	0.161	−0.034	0.561
	(0.124)	(0.201)	(0.192)	(0.360)
Constant	−24.323***	−27.383***	−22.788***	−31.014***
	(1.483)	(2.516)	(2.244)	(5.174)
Observations	1794	774	766	254
Year Controls Included	Yes	Yes	Yes	Yes
Center Controls Included	Yes	Yes	Yes	Yes

Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 8 Comparison of covariate distributions post-matching

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample		1 to 9 Employees		10 to 49 Employees		50 to 249 Employees	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
LN Employees	2.59	2.6	1.46	1.44	2.96	2.95	4.57	4.58
	−0.18 (0.861)		0.51 (0.611)		0.37 (0.710)		−0.22 (0.829)	
Technical Score	95.8	95.9	95.8	95.8	95.6	95.4	95.3	95.8
	−0.68 (.495)		−0.10 (0.924)		0.43 (0.667)		−1.33 (0.184)	
Prior Patenting	0.48	0.46	0.25	0.21	0.61	0.60	0.74	0.75
	1.00 (0.319)		1.15 (0.252)		0.31 (0.759)		−0.24 (0.813)	
Prior Phase II Awards	0.52	0.53	0.35	0.34	0.62	0.66	0.67	0.65
	−0.50 (0.615)		0.21 (0.837)		−1.06 (0.287)		0.32 (0.746)	
Observations	842	841	323	295	331	311	102	72

The treatment variable is whether the firm was selected for a Phase II award with this proposal. T-tests of treated and control means from matched sample using radius caliper propensity score matching with replacement; T-stats (p-values) presented below sample means; ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 9 Alternate estimation of propensity scores via nearest neighbor matching

Panel A: Average Treatment Effect on the Treated (ATET) on Probability of Patenting	(1) Full Sample	(2) 1 to 9 Employees	(3) 10 to 49 Employees	(4) 50 to 249 Employees
Treated Mean	0.30	0.16	0.35	0.44
Control Mean	0.23	0.085	0.35	0.48
Difference (ATET)	**0.069****	**0.076*****	0.0045	− 0.39
	(0.031)	(0.037)	(0.052)	(0.11)
Observations	1357	544	573	167
Matched Treated	842	323	331	102
Matched Control	515	221	242	65

Panel B: Comparison of Covariate Distributions Post-Matching	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample		1 to 9 Employees		10 to 49 Employees		50 to 249 Employees	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
LN Employees	2.59	2.55	1.46	1.44	2.96	2.95	4.57	4.58
	0.68 (0.495)		0.40 (0.692)		0.50 (0.619)		− 0.29 (0.776)	
Technical Score	95.8	95.9	95.9	95.8	95.6	95.4	95.3	95.8
	−0.55 (0.579)		−0.03 (0.976)		0.59 (0.556)		−1.22 (0.223)	
Prior Patenting	0.48	0.46	0.25	0.19	0.61	0.62	0.74	0.75
	1.10 (0.272)		1.63 (0.104)		−0.33 (0.740)		−0.32 (0.749)	
Prior Phase II Awards	0.52	0.53	0.35	0.34	0.62	0.64	0.67	0.65
	−0.36 (0.718)		0.34 (0.736)		−0.58 (0.564)		0.29 (0.769)	
Observations	842	515	323	221	331	242	102	65

Note: T-tests of treated and control means from matched sample using nearest neighbor (3) propensity score matching with replacement; T-stats (p-values) presented below sample means; ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 10 Estimation results on sub-sample omitting prior phase II awardees

	(1) Full Sample	(2) 1 to 9 Employees	(3) 10 to 49 Employees
Panel A: ATET Estimation of the Probability of Patenting			
Treated Mean	0.24	0.18	0.33
Control Mean	0.17	0.066	0.35
Difference (ATET)	**0.077****	**0.12*****	− 0.018
	(0.038)	(0.045)	(0.098)
Observations	801	392	197
On-Support Treated	372	211	100
Matched Control	429	181	97
Panel B: Logit ME's on Any Forward Patents			
Win Phase II Award	**0.077****	**0.088****	0.010
	(0.034)	(0.036)	(0.074)
Engineering Score	−0.005	−0.005	0.002
	(0.006)	(0.005)	(0.006)
LN Employees	0.029*	0.054*	0.078
	(0.017)	(0.031)	(0.081)
Prior Patents	0.225***	0.138***	0.275***
	(0.033)	(0.032)	(0.073)
Observations	748	354	173
Log Likelihood	−283.1	−114.8	−89.09
Chi-2	90.22	72.57	34.87
P-value	3.14e-10	1.35e-07	0.0292
Year Controls	Yes	Yes	Yes
Center Controls	Yes	Yes	Yes
Weights	Yes	Yes	Yes

Panel A shows T-tests of matched sample treated vs. control using radius caliper (0.01) propensity score matching; Panel B shows marginal effects of logistic regressions on any forward patents using radius caliper propensity score matching. weights, based on the matching methodology, are used to account for repeated control observations. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 11 Estimation results on sub-sample omitting firms with prior patents

	(1) Full Sample	(2) 1 to 9 Employees	(3) 10 to 49 Employees
Panel A: ATET Estimation of the Probability of Patenting			
Treated Mean	0.13	0.10	0.22
Control Mean	0.089	0.048	0.093
Difference (ATET)	0.038	0.048	**0.13****
	(0.027)	(0.033)	(0.060)
Observations	818	457	217
On-Support Treated	424	250	109
Matched Control	394	207	108
	Full Sample	1 to 9 Employees	10 to 49 Employees
Panel B: Logit ME's on Any Forward Patents			
Win Phase II Award	0.042	**0.064***	**0.133****
	(0.027)	(0.034)	(0.054)
Engineering Score	−0.007**	−0.002	−0.011
	(0.003)	(0.005)	(0.008)
LN Employees	0.022*	0.020	−0.032
	(0.013)	(0.033)	(0.078)
Prior Phase II Awards	0.005	−0.044	0.111*
	(0.029)	(0.040)	(0.062)
Observations	760	324	195
Log Likelihood	−251.6	−98.13	−75.66
Chi-2	52.26	34.15	37.03
P-value	0.000287	0.0121	0.0167
Year Controls	Yes	Yes	Yes
Center Controls	Yes	Yes	Yes
Weights	Yes	Yes	Yes

Panel A shows T-tests of matched sample treated vs. control using radius caliper (0.01) propensity score matching; Panel B shows marginal effects of logistic regressions on any forward patents using radius caliper propensity score matching. weights, based on the matching methodology, are used to account for repeated control observations. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

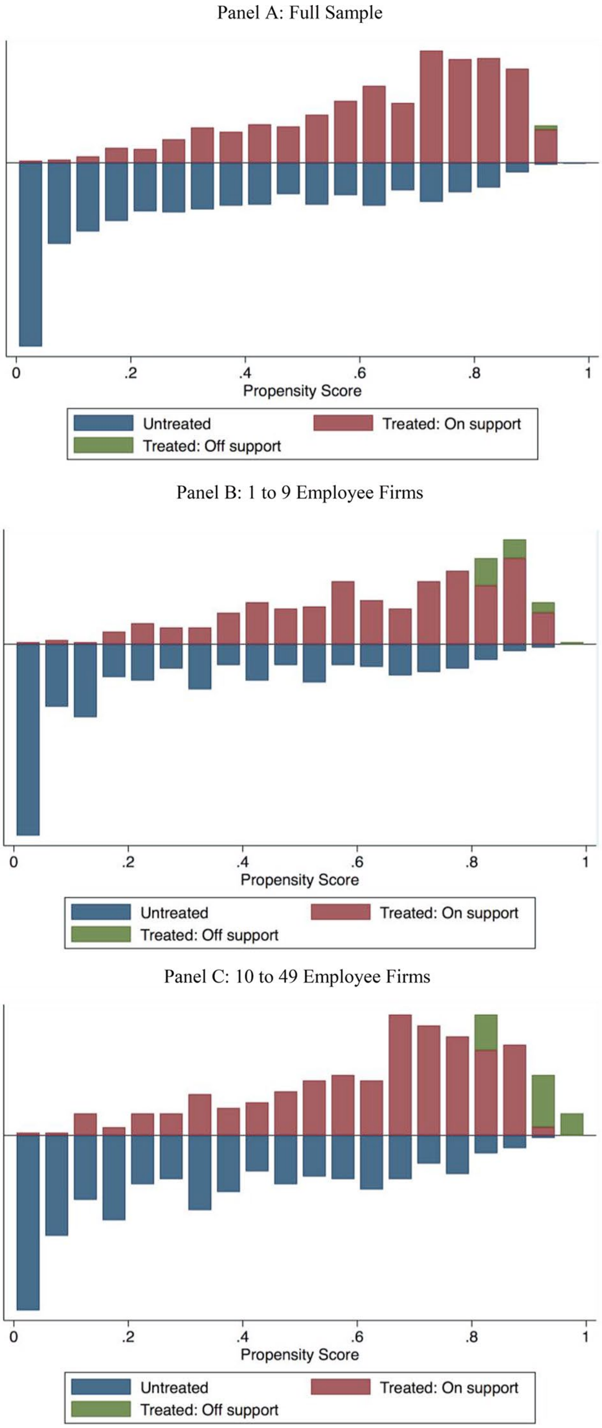
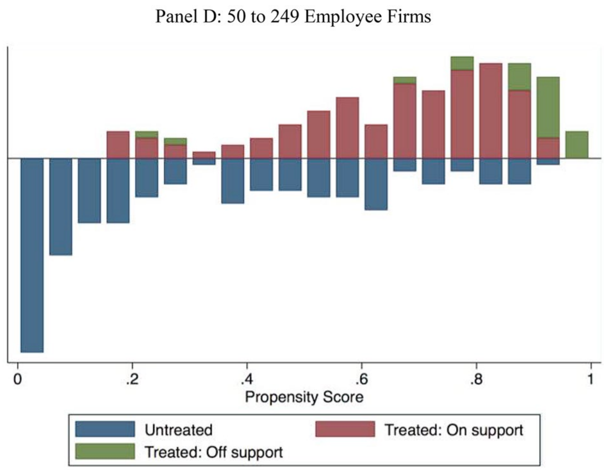


Fig. 1 Common Support Graphs. *Note:* The red bars above the line are observations treated (selected) and matched (on-support); green above the line observations are treated and unmatched (off-support); blue below the line observations are matched untreated (non-selected) observations. Firms are off support (unmatched) if their pre-selection characteristics conducive to selection are too high (low) to be matched to a non-selected (selected) counterpart (Color figure online)

Fig. 1 (continued)



Acknowledgements We are grateful to the National Science Foundation, Jet Propulsion Laboratory, California Institute of Technology, and the National Aeronautics and Space Administration for the funding and support. We appreciate the help of Saarthak Khanna, Anusha Ramakrishnan, and Dalia Yadegar. We also thank seminar and conference participants at the NASA Jet Propulsion Laboratory, 2018 Industry Studies Association Conference, 2018 North American Summer Meeting of the Econometric Society, United States Patent and Trademark Office (Washington, D.C. Headquarters and Silicon Valley Office), Department of Engineering Management and Systems Engineering (George Washington University), 2018 West Coast Research Symposium, and 2019 Atlanta Conference on Science and Innovation Policy for their comments. Finally, we thank the entßire USC Viterbi Management of INnovation, Entrepreneurial Research, and Venture Analysis (MINERVA) laboratory team for their comments.

Funding NSF awards 1444080 and 1740721, and Jet Propulsion Laboratory sub-award 1550874. The research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (80NM0018D0004).

Declaration

Conflict of interest Andrea Belz served previously as co-Principal Investigator and Research PI on the awards acknowledged herein. She currently serves as Division Director of Industrial Innovation and Partnerships at the National Science Foundation in which the NSF SBIR/STTR programs reside. Her research group obtained these data prior to her selection as Division Director. To manage the potential conflicts of interest she has resigned from all roles associated with the NSF awards that funded this research and is recused from all matters related to the awards named herein.

References

Akcigit, U., & Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy, 126*, 1374–1443

Alberti, F. G., & Pizzurno, E. (2015). Knowledge exchanges in innovation networks: evidences from an Italian aerospace cluster. *Competitiveness Review, 25*, 258–287. https://doi.org/10.1108/CR-01-2015-0004

Almus, M., & Czarnitzki, D. (2003). The effects of public R&D subsidies on firms' innovation activities: the case of eastern Germany. *Journal of Business and Economic Statistics, 21*, 226–236. https://doi.org/10.1198/073500103288618918

Archibald, R. B., & Finifter, D. H. (2003). Evaluating the NASA small business innovation research program preliminary evidence of a trade-off between commercialization and basic research. *Research Policy, 32*, 605–619

Archibugi, D., & Pianta, M. (1996). Measuring technological through patents and innovation surveys. *Technovation, 16*, 451–468

Ardito, L., Petruzzelli, A. M., & Panniello, U. (2016). Unveiling the breakthrough potential of established technologies: an empirical investigation in the aerospace industry. *Technology Analysis and Strategic Manage, 28*, 916–934. https://doi.org/10.1080/09537325.2016.1180356

Arora, A., Belenzon, S., & Patacconi, A. (2018). The decline of science in corporate R&D. *Strategic Management Journal, 39*, 3–32. https://doi.org/10.1002/smj.2693

Arora, A., Ceccagnoli, M., & Cohen, W. M. (2008). R D and the patent premium. *International Journal of Industrial Organization, 26*, 1153–1179. https://doi.org/10.1016/j.ijindorg.2007.11.004

Audretsch, D. B., & Link, A. N. (2018). Innovation capital. *The Journal of Technology Transfer, 43*, 1760–1767. https://doi.org/10.1007/s10961-018-9700-6

Auerswald, P. E., & Branscomb, L. M. (2003). Valleys of death and darwinian seas: financing the invention to innovation transition in the United States. *Journal of Technology Transfer, 28*, 227–239. https://doi.org/10.1023/A:1024980525678

Ayoub, M. R., Gottschalk, S., & Müller, B. (2017). Impact of public seed-funding on academic spin-offs. *The Journal of Technology Transfer, 42*, 1100–1124. https://doi.org/10.1007/s10961-016-9476-5

Beard, T. R., Ford, G. S., Koutsky, T. M., & Spiwak, L. J. (2009). A valley of death in the innovation sequence: An economic investigation. *Research Evaluation, 18*, 343–356. https://doi.org/10.3152/095820209X481057

Belz, A.P., 2016. Trends in Industry-University relationships. Washington, DC.

Belz, A. P., & Giga, A. (2018). Of mice or men: management of federally funded innovation portfolios with real options analysis. *Engineering Manage Review, 46*, 75–86

Belz, A.P., Terrile, R.J., Zapatero, F., Kawas, M., Giga, A., (2019). Mapping the "Valley of Death": Managing Selection and Technology Advancement in NASA's Small Business Innovation Research Program. IEEE Trans. Eng. Manag. In press.

Bertoni, F., Colombo, M. G., & Grilli, L. (2011). Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. *Research Policy, 40*, 1028–1043. https://doi.org/10.1016/j.respol.2011.03.008

Blonigen, B. A., & Taylor, C. T. (2000). R&D intensity and acquisitions in high-technology industries: evidence from the us electronic and electrical equipment industries. *The Journal of Industrial Economics, 48*, 47–70

Bronzini, R., & Iachini, E. (2014). Are incentives for R&D effective? Evidence from a regression discontinuity approach. *American Economic Journal: Economic Policy, 6*, 100–134. https://doi.org/10.1257/pol.6.4.100

Bronzini, R., & Piselli, P. (2016). The impact of R&D subsidies on firm innovation. *Research Policy, 45*, 442–457

Brouwer, E., & Kleinknecht, A. (1999). Innovative output, and a firm' s propensity to patent. An exploration of CIS micro data. *Research Policy, 28*, 615–624

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: cash flow, external equity, and the 1990s R & D boom. *Journal of Finance, 64*, 151–185

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economy Survey, 22*, 31–72

Caloffi, A., Mariani, M., Rossi, F., & Russo, M. (2018). A comparative evaluation of regional subsidies for collaborative and individual R & D in small and medium-sized enterprises. *Research Policy*. https://doi.org/10.1016/j.respol.2018.04.022

Choi, J., & Lee, J. (2017). Repairing the R&D market failure: Public R&D subsidy and the composition of private R&D. *Research Policy, 46*, 1465–1478. https://doi.org/10.1016/j.respol.2017.06.009

Conti, A., Thursby, J., & Thursby, M. (2013). Patents as signals for startup financing. *The Journal of Industrial Economics, 61*, 592–622

Cooke, P., & Ehret, O. (2009). Proximity and procurement: a study of agglomeration in the welsh aerospace industry. *European Planning Studies, 17*, 549–567. https://doi.org/10.1080/09654310802682115

Corallo, A., Errico, F., & Lazoi, M. (2014). The aerospace "networked " business model: evidences and suggestions. *Universal Journal of Manage, 2*, 151–159

Corallo, A., Laubacher, R., Margherita, A., & Turrisi, G. (2009). Enhancing product development through knowledge-based engineering (KBE) a case study in the aerospace industry. *Journal of Manufacturing Technology Management, 20*, 1070–1083. https://doi.org/10.1108/17410380910997218

Corallo, A., Lazoi, M., & Secundo, G. (2012). Inter-organizational knowledge integration in collaborative NPD projects: evidence from the aerospace industry. *Knowledge Management Research and Practice, 10*, 354–367. https://doi.org/10.1057/kmrp.2012.25

Cumming, D. J., & Li, D. (2013). Public policy, entrepreneurship, and venture capital in the United States. *Journal of Corporate Finance, 23*, 345–367. https://doi.org/10.1016/j.jcorpfin.2013.09.005

Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2016). Where has all the skewness gone? The decline in high-growth (young) firms in the U.S. *European Economic Review, 86*, 4–23. https://doi.org/10.1016/j.euroecorev.2015.12.013

Dimos, C., & Pugh, G. (2016). The effectiveness of R & D subsidies: A meta-regression analysis of the evaluation literature. *Research Policy, 45*, 797–815. https://doi.org/10.1016/j.respol.2016.01.002

Dumont, M. (2017). Assessing the policy mix of public support to business R&D. *Research Policy, 46*, 1851–1862. https://doi.org/10.1016/j.respol.2017.09.001

Edler, J., & Fagerberg, J. (2018). Innovation policy: What, why, and how. *Oxford Review Economic Policy, 33*, 2–23. https://doi.org/10.1093/oxrep/grx001

Edwards, K.L., Gordon, T.J., (1984). Characterization of Innovation Introduced on the US Market in 1982.

Feldman, M. P., & Kelley, M. R. (2006). The ex ante assessment of knowledge spillovers: government R&D policy, economic incentives and private firm behavior. *Research Policy, 35*, 1509–1521. https://doi.org/10.1016/j.respol.2006.09.019

Fontana, R., Nuvolari, A., Shimizu, H., & Vezzulli, A. (2013). Reassessing patent propensity: Evidence from a dataset of R&D awards, 1977–2004. *Research Policy, 42*, 1780–1792. https://doi.org/10.1016/j.respol.2012.05.014

Frank, C., Sink, C., Mynatt, L., Rogers, R., & Rappazzo, A. (1996). Surviving the valley of death: A comparative analysis. *The Journal of Technology Transfer, 21*, 61–69. https://doi.org/10.1007/BF02220308

Galope, R. V. (2016). A different certification effect of the small business innovation research (SBIR) program: evidence from the kauffman firm survey. *Economic Development Quarterly, 30*, 371–383. https://doi.org/10.1177/0891242416658346

Gompers, P., & Lerner, J. (2001). The venture capital revolution. *Journal of Economic Perspective, 15*, 145–168. https://doi.org/10.1257/jep.15.2.145

González, X., & Pazó, C. (2008). Do public subsidies stimulate private R&D spending? *Research Policy, 37*, 371–389. https://doi.org/10.1016/j.respol.2007.10.009

Grant J, (2016, September 27). Small Business Innovation Research/Small Business Technology Transfer. https://osbp.nasa.gov/docs/event-presentations/2016-Sept-27_1415-Grant-SBIRSTTR-General-Presentation_JGrant_FAMU-Draft-Second_tagged.pdf

Graham, S. J. H., Merges, R. P., Samuelson, P., & Sichelman, T. (2009). High technology entrepreneurs and the patent system: results of the 2008 Berkeley patent survey. *Berkeley Technology Law Journal, 24*, 255–327. https://doi.org/10.2139/ssrn.1429049

Hall, B.H., (1992). Investment and Research and Development at the Firm Level: Does the Source of Financing Matter? (No. 4096), National Bureau of Economic Research.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *The Rand Journal of Economics, 36*, 16–38

Hall, B.H., Lerner, J., (2010). The financing of R&D and innovation, in: Handbook of the Economics of Innovation, Vol. 1. North-Holland, pp. 609–639.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics, 95*, 347–361. https://doi.org/10.1162/REST_a_00288

Helmers, C., & Rogers, M. (2011). Does patenting help high-tech start-ups? *Research Policy, 40*, 1016–1027. https://doi.org/10.1016/j.respol.2011.05.003

Himmelberg, C. P., & Petersen, B. C. (1994). R & D and internal finance: A panel study of small firms in high-tech industries. *Review of Economics and Statistics, 76*, 38–51

Hoenen, S., Kolympiris, C., Schoenmakers, W., & Kalaitzandonakes, N. (2014). The diminishing signaling value of patents between early rounds of venture capital financing. *Research Policy, 43*, 956–989. https://doi.org/10.1016/j.respol.2014.01.006

Hottenrott, H., Hall, B. H., & Czarnitzki, D. (2016). Patents as quality signals? The implications for financing constraints on R & D. *Economics of Innovation and New Technology, 25*, 197–217. https://doi.org/10.1080/10438599.2015.1076200

Howell, S. T. (2017). Financing Innovation: Evidence from R & D Grants. *The American Economic Review, 107*, 1136–1164. https://doi.org/10.2139/ssrn.2687457

Huergo, E., & Moreno, L. (2017). Subsidies or loans ? Evaluating the impact of R & D support programmes. *Research Policy, 46*, 1198–1214. https://doi.org/10.1016/j.respol.2017.05.006

Islam, M., Fremeth, A., & Marcus, A. (2018). Signaling by early stage startups: US government research grants and venture capital funding. *Journal of Business Venturing, 33*, 35–51. https://doi.org/10.1016/j.jbusvent.2017.10.001

Islam, N. (2017). Crossing the valley of death-an integrated framework and a value chain for emerging technologies. *IEEE Transactions on Engineering Management, 64*, 389–399. https://doi.org/10.1109/TEM.2017.2685138

Jaffe, A.B., Le, T., (2015). The Impact of R&D Subsidy on Innovation: A Study of New Zealand [WWW Document]. NBER Work. Pap. Ser. URL http://www.nber.org/papers/w21479

Lach, S., (2002). Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel. Journal of Industrial Economic, pp. 369–390.

Laguerre, C. (2009). Is the defence market contestable? the case of military aerospace. *Defence and Peace Economic, 20*, 303–326. https://doi.org/10.1080/10242690802365044

Leitzel, J. (1992). Competition in procurement. *Policy Sciences, 25*, 43–56. https://doi.org/10.1007/BF00144632

Lerner, J. (1999). The government as venture capitalist: the long-run impact of the SBIR program. *Journal of Business, 72*, 285–318. https://doi.org/10.1086/209616

Marino, M., Lhuillery, S., Parrotta, P., & Sala, D. (2016). Additionality or crowding-out? An overall evaluation of public R & D subsidy on private R & D expenditure. *Research Policy, 1*, 1715–1730. https://doi.org/10.1016/j.respol.2016.04.009

Mazzucato, M., & Semieniuk, G. (2017). Public financing of innovation: new questions. *Oxford Review of Economic Policy, 33*, 24–48. https://doi.org/10.1093/oxrep/grw036

McAdam, R., O'Hare, T., & Moffett, S. (2008). Collaborative knowledge sharing in composite new product development: an aerospace study. *Technovation, 28*, 245–256. https://doi.org/10.1016/j.technovation.2007.07.003

Mcguire, S., & Islam, N. (2015). Indigenous technological capabilities, emerging market firms and the aerospace industry. *Technology Analysis and Strategic Manage, 27*, 739–758. https://doi.org/10.1080/09537325.2014.959482

Meuleman, M., & De Maeseneire, W. (2012). Do R&D subsidies affect SMEs' access to external financing? *Research Policy, 41*, 580–591. https://doi.org/10.1016/j.respol.2012.01.001

Mowery, D. C. (2012). Defense-related R&D as a model for "Grand Challenges" technology policies. *Research Policy, 41*, 1703–1715. https://doi.org/10.1016/j.respol.2012.03.027

Nanda, R., & Rhodes-Kropf, M. (2013). Investment cycles and startup innovation. *Journal of Financial Economics, 110*, 403–418. https://doi.org/10.1016/j.jfineco.2013.07.001

Niosi, J., & Zhegu, M. (2010). Anchor tenants and regional innovation systems: the aircraft industry. *International Journal of Technology Management, 50*, 263–284

Niosi, J., & Zhegu, M. (2005). Aerospace clusters: local or global knowledge. *Industry and Innovation, 12*, 5–29. https://doi.org/10.1080/1366271042000339049

Pérez-Cano, C., & Villén-Altamirano, J. (2013). Factors that influence the propensity to patent. *Engineering Management Journal, 25*, 27–38

Qian, H., & Haynes, K. E. (2014). Beyond innovation: The small business innovation research program as entrepreneurship policy. *The Journal of Technology Transfer, 39*, 524–543. https://doi.org/10.1007/s10961-013-9323-x

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*, 41–55

Sammarra, A., & Biggiero, L. (2008). Heterogeneity and specificity of inter-firm knowledge flows in innovation networks. *Journal of Management Studies, 45*, 800–829

Siegel, D. S., & Wessner, C. (2012). Universities and the success of entrepreneurial ventures: evidence from the small business innovation research program. *The Journal of Technology Transfer, 37*, 404–415. https://doi.org/10.1007/s10961-010-9186-3

Smith, D., Feldman, M. P., & Anderson, G. (2018). The longer term effects of federal subsidies on firm survival: evidence from the advanced technology program. *The Journal of Technology Transfer, 43*, 593–614. https://doi.org/10.1007/s10961-017-9633-5

Strumsky, D., & Lobo, J. (2015). Identifying the sources of technological novelty in the process of invention. *Research Policy, 44*, 1445–1461. https://doi.org/10.1016/j.respol.2015.05.008

Svensson, R. (2013). Publicly-funded R& Dprograms and survival of patents. *Applied Economics, 45*, 1343–1358

Szajnfarber, Z. (2014). Space science innovation: How mission sequencing interacts with technology policy. *Space Policy, 30*, 83–90. https://doi.org/10.1016/j.spacepol.2014.03.005

Szajnfarber, Z., & Weigel, A. L. (2013). A process model of technology innovation in governmental agencies: Insights from NASA' s science directorate. *Acta Astronautica, 84*, 56–68

Terrile, R.J., Jackson, B.L., 2013. Balancing Innovation with Commercialization in NASA's Science Mission Directorate SBIR Program, in: Proceedings of the IEEE Aerospace Conference, Big Sky, Montana. pp. 1–9.

Terrile, R. J., Jackson, B. L., & Belz, A. P. (2014). *Consideration of Risk and Reward in Balancing Technology Portfolios*. (pp. 1–8). Proceedings of IEEE Aerospace Conference on Big Sky.

Toole, A. A., & Turvey, C. (2009). How does initial public financing influence private incentives for follow-on investment in early-stage technologies? *The Journal of Technology Transfer, 34*, 43–58. https://doi.org/10.1007/s10961-007-9074-7

Trajtenberg, M. (1990). A penny for your quotes: patent citations and the value of innovations. *RAND Journal of Economic, 21*, 172–187

Turkina, E., Van Assche, A., & Kali, R. (2016). Structure and evolution of global cluster networks : evidence from the aerospace industry. *Journal of Economic Geographic, 16*, 1211–1234. https://doi.org/10.1093/jeg/lbw020

Ughetto, E. (2008). Does internal finance matter for R&D ? New evidence from a panel of Italian firms Cambridge. *Journal of Economic, 32*, 907–925. https://doi.org/10.1093/cje/ben015

Wallsten, S. J. (2000). The effects of government-industry R & D programs on private R&D: The case of the small business innovation research program. *The Rand Journal of Economics, 31*, 82–100

Wessner, C.W. (Ed.), 2008. An Assessment of the SBIR Program. National Academies Press.

Wicht, A., & Szajnfarber, Z. (2014). Portfolios of promise: A review of R & D investment techniques and how they apply to technology development in space agencies. *Space Policy, 30*, 62–74. https://doi.org/10.1016/j.spacepol.2014.03.003

Zahringer, K., Kolympiris, C., & Kalaitzandonakes, N. (2018). Time to patent at the USPTO: the case of emerging entrepreneurial firms. *The Journal of Technology Transfer, 43*, 923–952. https://doi.org/10.1007/s10961-016-9524-1

Zúñiga-Vicente, J. Á., Alonso-Borrego, C., Forcadell, F. J., & Galán, J. I. (2014). Assessing the effect of public subsidies on firm R&D investment: A survey. *Journal of Economic Survey, 28*, 36–67. https://doi.org/10.1111/j.1467-6419.2012.00738.x