Impact of government grants on venture capital funding of deep technology university spinoffs

Abstract

Because both scientific research and startups contribute strongly to major economic outcomes, university spinoffs (USOs) have been the subject of great interest and new policies. Unfortunately, prior research on early steps as firms coalesce and make their first decisions has been sparse, in part because of the difficulty of identifying USOs at the time that the firm launches. We use a dataset of participating academic entrepreneurs identified through the National Science Foundation Innovation Corps ("I-Corps") program to study newly formed USOs. We find a firm formation rate of roughly 60%; of those, roughly 2/3 apply for an SBIR award. We find that few of these firms migrate from the region of their home universities, negating the idea of a "brain drain" following experiential entrepreneurship training, and those that do move do not experience greater success in raising venture capital (VC). While a single SBIR award does not predict VC success, two or more SBIR awards generate an average marginal effect of approximately 30% on the likelihood of raising venture capital.

Keywords: University spinoffs, venture capital, I-Corps, SBIR

JEL Classification: O32, O38

I. Introduction

Over the last four decades, increased recognition of the role of university science in economic growth prompted broad interest; it has been suggested that 30% of the NASDAQ exchange's value stems from university-based, federally-funded research [1]. Independently, growing evidence suggests that new companies are the source of new jobs [2], driving policies that support science-based ventures. Interest in academia as a source of potential growth dates back to the Bayh-Dole Act of 1980, which allowed universities to retain intellectual property rights in federally funded research, prompting a wave of studies in university spinoffs (USOs) commercializing academic research [3], [4], [5], [6], [7], [8], [9], [10], [11]. However, less is known about these important firms as they initiate their first key decisions, in part because of the paucity of data of USOs in the formative stages.

It is critical to understand how these companies launch because of changes in the private capital markets. Although in the past venture capital firms concentrated in early-stage, high-technology companies to exploit information asymmetries [12], increases in capital efficiency have drawn venture capital away from manufacturing technologies toward software, potentially affecting companies stemming from universities (Figure 1) [13], making research subsidies even more critical to the success of these firms. This trend has exacerbated the so-called "Valley of Death", or funding gap to bring a technology to market. Venture capital has been linked to faster commercialization [14], making this an important intermediate outcome. Furthermore, while they typically remain near their parent universities [15], [16], [17], the concentration of venture capital in the Bay Area [18] leads to a desire to ensure that USOs do not leave local regions to raise funding.

[Figure 1 about here.]

The United States American Innovation and Competitiveness Act of 2017, calling for accelerated education of potential academic entrepreneurs and university spinoffs (USOs), has intensified the need to explore how these firms form, select their location, and raise initial capital. In particular, it is important to understand how additional public funds, such as the Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs[1], can support the growth of these companies. The SBIR program has been studied extensively [19], [20], [21], [22], [23], [24], [25]; and SBIR firms with academic scientists may perform particularly well in attracting venture financing [26].

Overall, despite extensive scholarship in USOs and the SBIR program, little is known about the early performance of university teams as they coalesce into companies, select their firm location, and raise capital from public and private sources. To contribute to addressing this gap, we study the financing processes of nascent USOs to determine the impact of public grants on private financing. To identify nascent university spinoff teams, we use a public database of participants in the National Science Foundation (NSF) Innovation

[1]While these two programs are funded separately, they typically are managed jointly. For the purposes of this paper, both these programs will be grouped under the term "SBIR".

Corps ("I-Corps") Program [27], [28], a technology transfer initiative offering business training of university scientific researchers. Although developed by the NSF, the program and variants have been adopted by many federal agencies, including the Department of Defense, the National Institutes of Health, the Department of Energy, the National Aeronautics and Space Administration, and many others. The first report of its outcomes was published in 2019 [29] and indicated that roughly half the participating teams had formed companies, and on average those firms raised half a million dollars. Because the program funds self-identified entrepreneurial researchers, often prior to company formation, following these teams gives a new opportunity to obtain rich information regarding early strategic decisions of USOs and the subsequent impact on company success.

This paper studies the propensity of USOs to attract venture capital, isolating the separate effects of the strategic decisions to apply for and win SBIR awards, as well as select the region in which the firm is located. We control for important determinants such as the venture's age [30], team financing contributions [31], industry [32], and prior patenting [33], [34]. We use two different methods to address possible selection effects and find that while one award does not show a strong effect on the probability of raising venture capital, multiple awards do. In addition, we find a small incidence of migrating from one region of the United States to another; and those that do move are not more likely to raise funding. With this approach, our work represents one of the first empirical studies of nascent academic firms during their formation and contributes to the literature on public and private support of USOs, entrepreneurial financial decisions and strategy, and policy regarding high-tech entrepreneurship.

II. Background

A. University spinoffs

Fundamental science contributes to economic development [35], [36], [37] and enables new sources of industrial and national competitiveness. Good science can lead to strong performance indicators in public companies [38], [39], [40], [41]. On a broader scale, startups contribute disproportionately to economic growth [2], [42], [43], and concern has grown at the national level because the pace of entrepreneurship of high-growth firms has declined over the last two decades [44].

Interest in academia as a source of potential growth dates back to the Bayh-Dole Act of 1980, which allowed universities to retain intellectual property rights in federally funded research. The propensity and success of university entrepreneurs creating high-growth firms is complicated by strong heterogeneity because individual, team, departmental, university, firm-level, and other factors affect outcomes [3], [4], [5], [6], [7], [8], [9], [10], [11]. High-profile, exceptionally productive faculty members founding companies show improved outcomes [45], as do faculty with consulting experience [46]. Effective sequencing of entrepreneurial skill development and financing in successful USOs, particularly through experience and mentoring, is unclear [9], [47].

University entrepreneurship has important effects for regional growth because interactions between entrepreneurs and local resources contribute to the development of industrial clusters [48], and knowledge spillovers may drive entrepreneurship [49]. Firm location is an important early strategic decision and may include personal networks [50]. Universities may impact local invention outputs and general growth by serving as a source of both knowledge and human capital [51], [52], particularly to small firms [53]. USOs based on deep technology tend to stay near the parent university [15], [16], [17], but do not tend to cluster [54]

B. Subsidies

Small technology firms face difficulty in attracting resources with private capital potentially limited by the high level of risk [55]. This challenge may vary with the business cycle and exit conditions [56], [57], [58]. While both angel and venture groups contribute to innovation, VC-funded ventures experience faster commercialization paths [14]. Although in the past venture capital firms concentrated in early-stage, high-technology companies to exploit information asymmetries [12], increases in capital efficiency have drawn venture capital away from manufacturing technologies toward software, potentially affecting companies stemming from universities [13].

Market failures have been well described in the literature and are often addressed with subsidy programs around the world [59], [60]. In the United States, the SBIR program represents the major federal initiative to help launch and promote new businesses. Although federal funding could in principle “crowd-out” or displace private investment [61], the subsidy instead enables the firm to continue research that would be rationally discontinued ([62], [63]), and private investments may follow [64], [65], [66]. SBIR awards have been associated with increases in entrepreneurial activity, venture capital, company growth, high-tech entrepreneurship, patent generation, and patents acquired from external sources [20], [21], [22], [23], [24], [25], [31]. Select studies to date validate the link between USOs and SBIR awards, as start-ups with closer ties to universities show higher performance and SBIR success [67], and SBIR firms with academic scientists may perform particularly well in attracting venture financing [26].

These three levers – location choice, public financing, and private financing, are individually important and may interact. In general, although proximity to knowledge and funding assets could affect location decisions, the entrepreneur’s personal characteristics and the lead scientist’s role may dominate the choice of location [68], [69]. Public financing may offer a “certification” or “halo” effect in obtaining private financing and mitigating risk [22], [23], [55], [63], [70], [71], [72]. It is therefore desirable to study a population of USOs as their teams coalesce into new firms and execute their initial strategies to better explore these linkages.

III. Data and approach

A. The I-Corps sample population

To identify nascent university spinoff teams, we use a public database of participants in the National Science Foundation (NSF) Innovation Corps (“I-Corps”) Program [27], [28], a technology transfer initiative directly funding business training specifically for university scientific researchers. The I-Corps award is a six-month grant with a maximum value of $50,000[2] supporting expenditures in two required activities: 1) participation in a seven-week course in business model development [73]; and 2) extensive primary market research in the form of 100 interviews of industrial experts conducted concurrently with the class. The award period is six months but may be extended as per NSF policies. In contrast to SBIR awards to small companies, I-Corps grants are issued via traditional sponsored project arrangements to university faculty or research staff identified as principal investigators (PIs). A PI must form a team comprising him/herself, an "entrepreneurial lead" (usually a graduate student or postdoctoral fellow), and a mentor with industry experience. The team must be fully formed upon applying for funding, but a firm need not exist. To be eligible, a team must have a so-called "deep technology" – i.e., the commercialization opportunity must be defined by developing a product with technical risk, as well as a history or lineage with NSF. Teams developing simple software applications based on existing tools may not participate, nor may teams with retail concepts for existing products; further exclusions include companies with significant revenues, private financing, and/or public grants (including SBIR awards). While the technology need not have a patent issued or in process, this is highly encouraged.

Applications for the program are solicited on a rolling basis and approximately 10-15 cohorts of about 20 teams are taught each year since 2013. The success rate for applications is approximately 50%. Importantly, the grant funds registration in the required class and travel to trade shows, meetings, and other venues to facilitate interviews; it does not fund technology development. At the end of the seven-week course, the team delivers a report on the readiness of the commercial opportunity and is not required to license the technology nor to start a company. As application to the program is voluntary, the I-Corps pool represents a set of self-identified early-stage entrepreneurial academic teams that may not even form a company. This data set is important because prior studies have indicated that university technology transfer reports may underestimate entrepreneurial activity [74], [75]. The immersive seven-week class and the relatively modest award size (relative to corporate financing levels for early-stage ventures) combine to select a population that is typically relatively new to entrepreneurship, with minimally developed business models for the candidate technology.

B. Startup Progress in Formation and Financing for I-Corps (SPIFFI) survey

As recipients of federal funds from the National Science Foundation, PIs are named publicly in searchable databases. We analyze a subset of the teams via the Startup Progress in Formation and Financing for I-Corps (SPIFFI) project, a survey instrument designed to examine drivers and performance in early strategic decisions of USOs. We distributed an electronic survey to recipients of 950 I-Corps awards, comprising 904 unique PIs, identified through public records from the program's pilot in 2012 through February 1, 2017 in two waves: one in the winter of 2017-8 and the second in early 2020. Awardees could re-direct the survey to

[2]The award is limited to 10% indirect costs, and thus the funding of direct costs available to the team is approximately $45,000.

key team members or principals in the company if appropriate. The survey link was configured such that it could be forwarded if appropriate. Respondents were asked to identify funding levels in various ranges, and these were converted to binary outcome variables.

The survey collected information on financing activities to date and firm location. After elimination of incomplete submissions, the response pool comprised 292 I-Corps awardees (an effective response rate of 32%, consistent with similar surveys [76]) As shown in Table 1, not all I-Corps participants formed companies; of the responses, 163 (56%) provided complete responses regarding a firm's creation either before or after the award, based on the technology related to their I-Corps grants. A critical question for our analysis is whether the USO had applied for and received an SBIR Phase I award. The SBIR program funds companies in two tranches or Phases; a Phase I award is a requirement for Phase II eligibility. To ensure that teams did not double-count the two Phases of the staged program, the survey specifically denoted Phase I awards. Of the 163 companies with full information, 115 submitted SBIR Phase I applications and thus formed our final sample population, with 50 of them obtaining SBIR awards. All firms were presumed to be seeking venture capital, and an introduction to this financing source is presented in the final sessions of the I-Corps class.

[Table 1 about here.]

C. Variables

1) Control and instrumental variables: Elapsed time. The elapsed time indicated the duration between the I-Corps award date and the electronically coded survey response date. The elapsed time is calculated as a simple difference between these dates. It is reasonable to imagine that the time would impact the success in winning an SBIR award - namely, that researchers may have to wait to align with a deadline (but cannot precede it). For instance, if an agency has a six-month cycle with deadlines on June 30 and December 31, a team completing I-Corps on January 1 would have to wait until the June deadline [3] . Venture age is important because older ventures are more likely to have made progress [30].

Team's funding contribution. The survey asked whether the team had contributed funding. This is coded as a binary variable. These ventures likely do not have founders with significant assets to contribute to the firm, as the founders are principally the graduate students and postdoctoral fellows participating in the program. Founders of larger firms typically use debt [77] and founding team contributions may serve as signals to investors [31]. Therefore, even if the funding is *de minimis*, it may still fund initial operations and serve as an indicator of team commitment.

[Table 2 about here.]

High patents. We seek a variable that would indicate the technical novelty independently of the business model, and thus we use patents. Patents may serve as signals for raising capital [33], [34], and is likely

[3] Each agency manages its SBIR deadlines independently.

highest for the earliest funding rounds [78], [79]. We developed software to extract patent information from the United States Patent and Trademark Office database in which the PI was an inventor for a year-year period preceding the award date. The assignee is not used as an identifier for several reasons: 1) in some cases, a university or prior employer could be the assignee; 2) as the goal of I-Corps is to commercialize federally-funded technologies, it is reasonable to assume that the faculty PI is an inventor.

Partial name matches were identified and retained in the database because of name variations - for example, the inventor may not have used his/her middle name consistently in all filings, or hyphenated versions of a last name may have appeared. As an additional check, we extracted the patent's location and compared it with the parent university location; however, in some cases this differed because the inventor's location was different from that of the university assignee (for instance, the inventor could be listed in Maryland, though the parent university was located in Washington, DC). In other cases, the location was different because the inventor had moved (e.g., filing a patent as a post-doctoral fellow in one university and then moving to another as a faculty member). We therefore used both the name and location as general guides and manually compared them with information provided in the inventor's curriculum vitae, where available.

The USPTO database assigns a unique inventor identification (ID) number to each inventor. However, due to variations in the filing process, the inventor ID is a many-to-one match; that is, an inventor may have multiple ID numbers, but a single number is assigned to only one inventor. Thus, in addition to names and locations, we also tracked ID numbers. In some cases, a prolific (patent count exceeding 50) PI could have several identification numbers. Patent titles were reviewed for consistency with the I-Corps award abstract and the inventor's CV to ensure that the patent described a technology related to the PI's field of study.

Another concern in the USPTO database was the presence of inventor ID numbers incorrectly linked to highly disparate technologies, assignees, and These cases were also indicated by the number of locations linked to the inventor. We surmised that patents had incorrectly been aggregated under the same ID number. To identify these potential errors, we extracted the number of locations associated with the inventor (mean value of 1.8) and excluded observations where the number of locations exceeded 10. In aggregating the number of patents, we calculated the sum of the patents issued in the five-year window preceding the award so that the technology under study in the I-Corps program was likely to be the result of a relatively recent invention. Of 904 unique PIs, we identified 660 inventor ID numbers, with 17 having more than 10 locations associated with the inventor (Table 3). Consolidating multiple ID numbers for a given inventor led to a pool of 564 inventors (defined as a positive number number of patents in the five-year period preceding the award) in the parent population, with a mean number of patents of 4 for those who patented. Our sample represented less seasoned inventors; only 13% had patents, compared with the parent population of 62%, and that group had 3 patents on average per inventor.

[Table 3 about here.]

Industry. Because early-stage investors show preferences for specific industries [32], we used the publicly available abstracts to sort the survey responses into one of three mutually exclusive categories: data sciences, life sciences, and engineering (Table 2). However, science can be difficult for investors to assess accurately [80] and may vary between industries [81].

2) Predictor variables: Our goal was to broadly align firm location and its university home consistently with studies of venture capital. We therefore sought to sort the universities and firms with a regional weighting scheme based on the well-regarded Thomson Reuters database, which can be easily accessed through its Money Tree survey (https://www.pwc.com/us/en/industries/technology/moneytree.html).

Migration. The migration binary variable was set to one if the university's study region differed from that of the firm. First, we extracted the parent university name, city, and state from the I-Corps database. The I-Corps program draws teams from around the country, but the program initially launched at the University of Michigan and the Georgia Institute of Technology; as a result, those states are highly represented in the I-Corps population (Table 4). Furthermore, because the funding goes directly to universities, states with higher research activity are disproportionately (relative to per capita) represented in this study. Based on this information, the teams were assigned to the regions of interest (Panel A of Table 5). Nonetheless, as our goal is to ensure that we were sampling from various states, we compare the distribution of our respondents with that of the I-Corps award recipients. The results (Table 4) suggest that the respondents represent a reasonable sample of states with I-Corps participants.

[Table 4 about here.]

[Table 5 about here.]

Next, we extracted the response for the firm location because in most cases, it has not yet executed a financing round that would be recorded in standard data resources, such as VentureXpert. Therefore, we relied on the respondent, asking him/her to report the location on a scheme that aligned with the Thomson Reuters database. Regions were aggregated because of the sample size. The resulting six regions are listed in Panel B of Table 5. Finally, regions of the parent universities and firms were tabulated (Table 6) and differences were coded as "migrated."

[Table 6 about here.]

SBIR awards. We asked the respondent about the number of SBIR Phase I awards. Fifty of the companies had received them and the mean number of awards was 1.26. We consolidated these into a categorical variable of three levels: None, One, and Two-Plus.

3) Outcome variables: The survey included questions regarding the team's funding in a pre-specified set of ranges from venture capital. Affirmative answers to any ranges were coded as a binary variable indicating that the firm had obtained capital from that source.

D. Descriptive statistics

We seek to understand the impact of SBIR Phase I awards on the likelihood of attracting venture capital and therefore we sort the data into SBIR-selected and not. Descriptive statistics (Table 7) include the number of SBIR applications to verify that the likelihood of receiving an award did not simply reflect a higher application rate. Means are reported for continuous variables and proportions for binary variables. Correlations between these variables are shown in Table 8.

[Table 7 about here.]

[Table 8 about here.]

IV. Analyses and results

Initially we conduct logistic regressions of the probability of raising venture capital funding(Table 9). Model 1 indicates a baseline using the elapsed time and the team funding binary variable as controls. Model 2 evaluates whether migration impacts this outcome and indicates that this is not a significant effect. In Model 3, we add the categorical variable representing the effect of winning two or more SBIR awards without the migration predictor. The fourth model is complete and shows an average marginal effect (AME) of 26.2% (p-value of 0.09).

[Table 9 about here.]

This analysis is potentially subject to a selection bias - namely, that the better firms attract funds from both public and private sources [82]. This problem is endemic to policy studies and many statistical techniques address it. All of them require the estimation of the probability of participating in the treatment group (in our case, SBIR award selection) through the use of independent predictors that are at most weakly linked to the outcome. These predictors, or instrumental variables (IVs), can be used in a variety of ways, such as excluding untreated samples from the control group (matching processes), estimating weights for untreated data to include them in the control group on a partial basis (balancing processes), or aggregating them to form a new predictor for further analysis (two-step models).

In many matching methodologies, untreated samples are either accepted into a control group (weight of 1) or discarded entirely (weight of 0), based on a propensity score or similar measure of similarity between untreated and treated samples. However, information of the sample distribution's moments is discarded in this case, and statistical power is reduced because of the all-or-nothing method to manage untreated observations. Two-step methods assume a censoring mechanism preventing some outcomes from being observed and the treatment is initially modeled (typically using a probit function), and then one of the fit parameters is used as an additional explanatory variable in an OLS estimation. However, this method is poorly suited for binary outcomes, nor does it allow for categorical explanatory variables.

With the current availability of computing power, it is now possible to conduct more sophisticated analyses of covariate moments to assess weights at the observation level. Entropy balancing [83] is such a method; it assigns a real number as a weight to each observation, which allows the researcher to keep data without imposing rigid constraints or calipers. We use an entropy balancing algorithm embedded directly in our statistical software to create weights for the untreated observations to create a control group. Entropy balancing assigns weights of 1 to treatment observations, with real numbers assigned to untreated ones for use in standard regressions. We identify three covariates of interest: elapsed time, the team's funding contribution, and a binary variable indicating if the PI had patents. The threshold of 1 patent was set to maintain a sufficiently large sample in the covariates. Use of a binary variable allows us to create a simple indicator that is not biased toward particularly high performers with larger patent portfolios; in effect, we need a variable that simply characterizes the investigators as "inventors" rather than their productivity. An added benefit of this binary approach is that it does not favor more senior or experienced researchers. The results are robust to the choice of threshold. We use a five-year window to ensure that the commercialization process focuses on relevant patents. We also use the time elapsed from the I-Corps award date to the survey response as a proxy for the venture's age, based on the fact that the company may have been involved in both private financing (through informal meetings and other communication) and in public financing (SBIR applications) prior to incorporation. Finally, a binary variable that indicates whether the team itself has contributed funding is also used as a selection predictor.

We use an entropy balancing algorithm to compare the moments of the IVs of appropriate untreated firms (those that applied for SBIR awards but were not selected) with the treatment group. We assigned a score to each observation by estimating the likelihood of selection (treatment) for the SBIR award based on these three covariates. Weights were then assigned to each untreated observation by comparing the covariate values with those of the treated population. The resulting scores for the treated and untreated populations were compared before and after applying the weights (Figure 2). The distributions are much more similar after the weighting. To further verify that the weighting created comparable distributions in these covariates, we conducted t-tests on the selected and unselected observations, before and after weighting (Table 10). The associated p-values indicate that it succeeded in aligning these distributions.

[Figure 2 about here.]

[Table 10 about here.]

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With this new weighting scheme, we re-visit the regressions on the likelihood of raising venture capital (Table 11). We presume that the elapsed time, team funding, and patents serve as exclusion restrictions [84], [85] and thus they are not listed as controls in the regression, although we will revisit the question of the patents. The first model indicates that migration does not drive the likelihood of obtaining venture capital. Models 2 and 3 test for the importance of winning two or more SBIR awards, with model 3 including migration for completeness, with (AME = 0.35, $p < 0.03$). In the fourth model, we include industry with a reference of data sciences, and do not see a change in the size of the effect. Finally, in model 5 we include patents again because this may certainly impact the likelihood of raising capital and see consistent results.

[Table 11 about here.]

Our robustness checks include conducting a Heckman two-stage analysis in which the selection (probit) is driven by the same instrumental variables defined earlier. The second stage of a Heckman analysis is an ordinary least squares (OLS) tobit model and thus the regressor cannot be our three-stage (none, one, or two or more) SBIR award scheme. However, we can create an analogue with a binary variable set to one if the firm has two or more SBIR awards. This check gave consistent results (Tables 12 and 13. Model 1 is distinct from 2 and 3 in that the latter two include industry as a potential selection variable for the SBIR program (Table 12), and model 3 differs from 2 by including the possibility of migration as a predictor. The fourth model includes the patents again as a possible predictor; even though this increases the likelihood that the errors in selection and outcome are correlated, it is important to validate how the patents can contribute to obtaining venture capital beyond simple SBIR selection. All four models are consistent with the weighted logistic regressions.

[Table 12 about here.]

[Table 13 about here.]

V. Discussion

The analysis of these data allows us to report several stylized facts of interest to the science policy community. In agreement with legislatively mandated reporting [29], we estimate a firm formation rate of roughly 50-60% from a population of self-identified scientific entrepreneurs participating in an experiential course in business model development [73]. A possible outcome of the course is the decision not to proceed with commercialization, based on new insights gained through the program as participants discover that the technology is either unready for the marketplace or the opportunity was previously poorly understood. In addition, because the I-Corps program is designed for a team with a graduate student, the corporate formation rate may be a byproduct of the population of participating entrepreneurial graduate students or postdoctoral fellows: Roughly one-third of the United States science and engineering doctorates in 2015 were awarded to students on international visas [86]. In the United States, it is difficult for immigrants to qualify for visas if they are employed by startups, and SBIR eligibility requirements include citizenship or permanent residency. If the I-Corps program samples the population of doctoral students proportionately, it is not surprising that the corporate formation rate is roughly 60%. This is important given that immigrants are more likely to start science-based businesses [87] but face significant challenges in working for startups [88]. These facts may also be related to the observation that roughly 2/3 of self-identified USOs apply for an SBIR award.

Our finding that multiple SBIR awards impact the likelihood of raising venture capital offers another view into whether the main benefit of the subsidy is the implicit certification or the monetary value of the award. If certification operates as the primary mechanism, then a single award should be enough to impact the outcome. However, if multiple awards are required, then either the certification is conferred by the repeat success [89], or the financial benefit drives the impact. A Phase I award is roughly $200,000 in size, with the amount varying by federal agency, and thus a single award simply may not be enough to make the firm attractive for venture investment. This finding could be studied further as these teams evolve toward Phase II SBIR awards. We can now posit that it is worth the venture's time to apply for multiple SBIR awards. Careful consideration of this early strategic decision is consistent with the sobering reality that the long time it takes to apply for and receive a SBIR award presents its own risks; one estimate suggests that even a three-month delay in receipt of the SBIR award can be equivalent to a $20,000 loss for the project [62] a potentially catastrophic loss to the new firm.

While we confirm that there is some USO geographic migration, we conclude that it does not lead to improved financing outcomes. Leaders of regional development efforts need not fear a so-called "brain drain" resulting from USOs seeking to migrate to regions with higher concentrations of venture capital. We also see that the industry type does not impact the likelihood of raising funding from venture capital. These findings should impact the policy discussion regarding the significance of SBIR awards for manufacturing-oriented technologies as a way to mitigate risk for the venture capital community. This is particularly important because the market failures for engineering-oriented technologies can be severe, such as in the crowdfunding context [90]. Indeed, these findings are even more important given the change in economic circumstances following the global pandemic of 2020 in which capital could be severely constrained for these risky ventures.

The patent portfolios described in Table 3 independently provide interesting information regarding the program. The award's PI could choose not to participate; for instance, s/he could be awarded the grant but delegates the role of the technical lead to a postdoctoral fellow. This could potentially bias the sample toward less seasoned inventors. However, this makes the study even more relevant, if the sample population draws from new ventures where the so-called "star faculty member" [45] is less engaged.

It is important to note that this is not an evaluation of the I-Corps program as we do not have a counterfactual. While some outcomes have been reported previously [29], a rigorous assessment of the program has not been presented to date. Future research will benefit from a panel study of this population to examine economic outcomes, such as new jobs created and returns to investors. Instead, this work serves as an examination of the early decision making of self-selected nascent ventures.

VI. Conclusion

The I-Corps program is designed to provide introductory business model education to novice academic entrepreneurs, and thus serves as a source of information regarding new USOs. We show that roughly half the teams form companies, and that approximately three-fourths apply for SBIR Phase I grants. We see strong evidence that the likelihood of raising venture capital is impacted by the firm having two or more SBIR awards. While this is naturally subject to endogeneity concerns, this study presents evidence using two different methodologies addressing selection bias.

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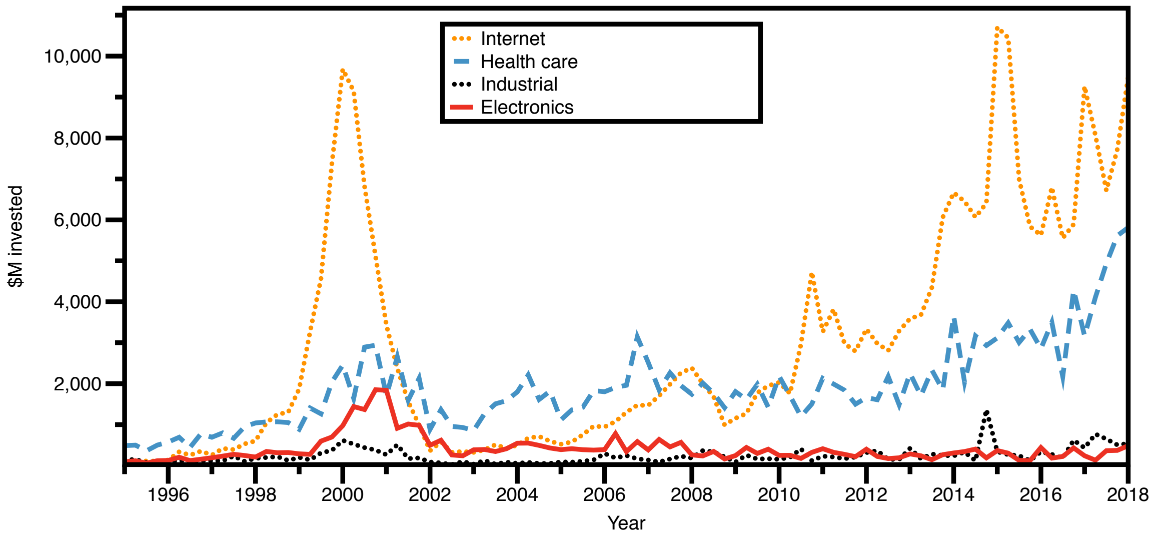

Figure 1: Annual venture investment (data from PricewaterhouseCoopers MoneyTree Survey)

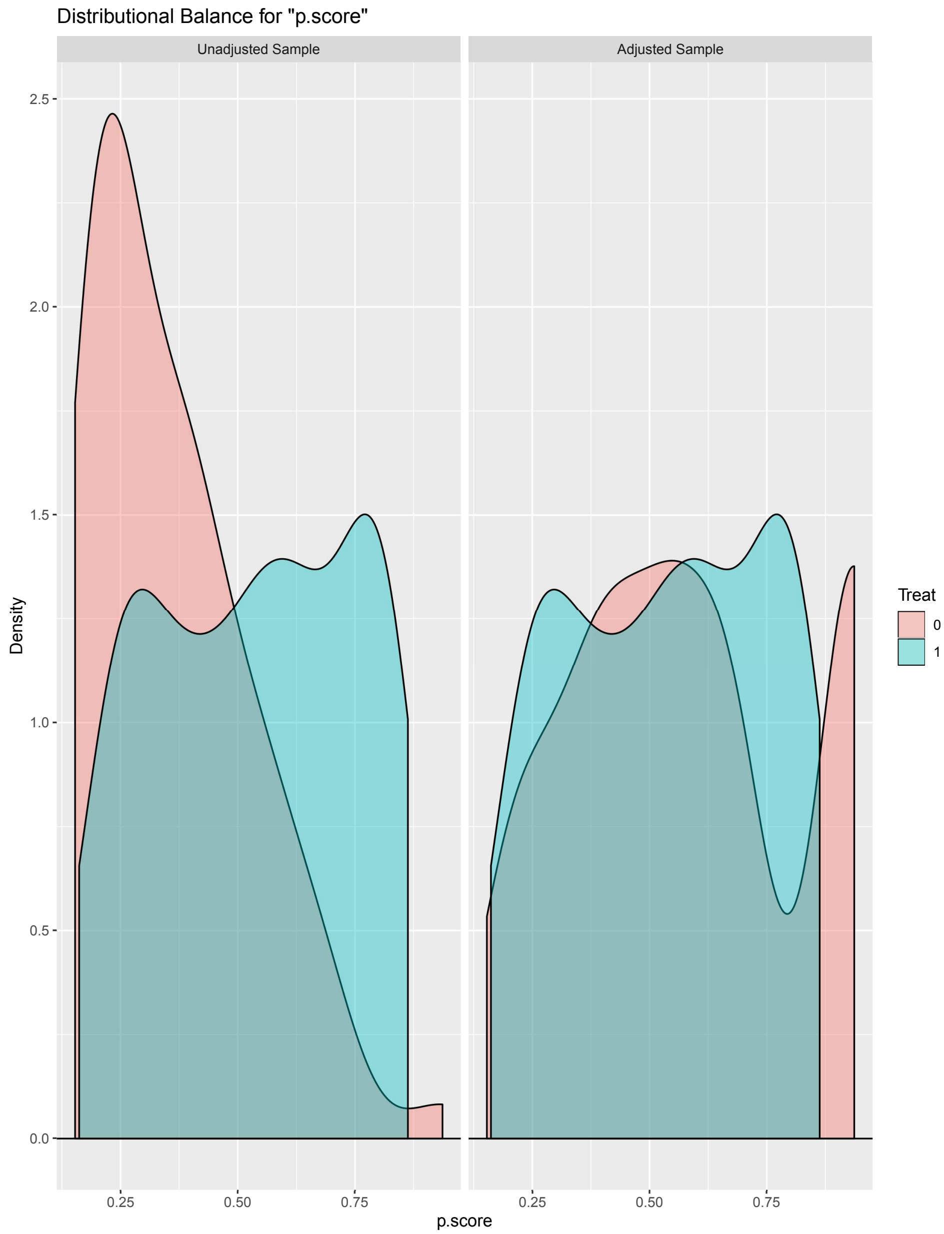

Figure 2: Propensity score distribution before (left) and after (right) weighting

List of Tables

Table 1: Data summary

Item	Number
I-Corps awards	950
Unique PIs	904
Responses to survey	292
Formed a company and provided information	163
Applied for SBIR Phase I awards (study sample)	115

Table 2: Industries of sample

Industry	Number	Fraction
Data sciences	30	0.26
Life sciences	33	0.29
Engineering	52	0.45

Table 3: Patent data summary

Item	Number
Number of inventor IDs in parent population	660
Number of inventor IDs with fewer than 10 locations	643
Number of inventors in parent population	564
Fraction of inventors in parent population	0.624
Mean patents/inventor in parent population (5-year window)	1.427
Mean patents/inventor in parent population (5-year window), given patents	4.019
Number of inventors in sample population	38
Fraction of inventors in sample population	0.33
Mean patents/inventor in sample population (5-year window)	1.017
Mean patents/inventor in sample (5-year window), given patenting	3.079

Table 4: Distribution of states in the parent and sample populations

State	Parent	Sample
AL	5	1
AR	4	0
AZ	16	0
CA	83	12
CO	16	3
CT	10	1
DC	11	2
DE	5	1
FL	45	5
GA	49	6
HI	4	0
IA	7	2
ID	2	0
IL	40	6
IN	23	2
KS	6	1
KY	8	0
LA	10	4
MA	51	6
MD	28	4
MI	70	8
MN	4	0
MO	11	1
MS	3	1
NC	19	0
ND	4	1
NE	2	0
NH	1	1
NJ	26	1
NM	8	0
NV	2	0
NY	74	9
OH	38	8
OK	4	0
OR	7	1
PA	44	3
PR	4	2
RI	4	0
SC	14	2
SD	3	2
TN	9	0
TX	83	8
UT	6	1
VA	22	6
WA	6	1
WI	13	3
Total	904	115

Table 5: Assignments to regions of the United States

Panel A: Assignment of university state to study region

AR, AK, KS, LA, MS, NE, ND, OK, SD, TN	Central
AL, DC, FL, GA, MD, NC, PR, CS, VA, WV	DC Southeast
KY, IA, IL, IN, MI, MN, MO, OH, PA (except Pittsburgh), WI	Midwest
CT, DE, MA, ME, NH, NY, Pittsburgh, NJ, RI, VT	Northeast
AZ, CO, ID, MT, NM, NV, TX, UT, WY	West
CA, HI, OR, WA	West Coast

Panel B: Assignment of firm location to study region

North Central or South Central	Central
Southeast and DC/Metroplex	DC Southeast
Midwest	Midwest
New England, NY Metro, Upstate NY, and Philadelphia Metro	Northeast
Southwest, Texas and Colorado	West
LA/Orange County, Sacramento/Northern California	WestCoast
Silicon Valley, San Diego, California, Northwest, Alaska/Hawaii/Puerto Rico	

Table 6: Regional distribution of I-Corps teams

Region	I-Corps teams	Fraction	Firms	Fraction
Central	45	0.05	9	0.08
DCSoutheast	197	0.22	28	0.24
Midwest	234	0.26	32	0.28
Northeast	195	0.22	20	0.17
West	133	0.15	12	0.10
WestCoast	100	0.11	14	0.12

Table 7: Descriptive statistics, where selected indicates SBIR Phase I award

	Full sample	Selected	Not selected
SBIR applications	1.93	2.06	1.83
Std. error, applications	0.13	0.24	0.23
SBIR awards	0.55	1.26	0.00
Std. error, awards	0.07	0.09	0.00
Migration (binary)	0.13	0.10	0.15
Team investment (binary)	0.34	0.40	0.29
Venture capital raised (binary)	0.13	0.20	0.08
High patents (binary)	0.21	0.32	0.12

Table 8: Correlations

	Elapsed time	High patent	Team funding	Migrated	VC funded	SBIR applications
Elapsed time						
High patent	0.16					
Team funding	0.19*	-0.01				
Migrated	-0.07	-0.14	-0.06			
VC funded	0.24*	0.12	0.16	0.00		
SBIR applications	0.11	0.09	0.13	-0.05	0.07	
SBIR selected	0.36***	0.25**	0.11	-0.11	0.23*	0.39***

Table 9: Probability of raising venture capital

	Logistic regressions			
	(1)	(2)	(3)	(4)
Elapsed time	0.18	0.17	0.18	0.14
	(0.28)	(0.28)	(0.28)	(0.29)
Team funding	0.61	0.65	0.56	0.61
	(0.59)	(0.60)	(0.61)	(0.61)
Migration		0.45		0.92
		(0.95)		(1.00)
1 SBIR win			0.36	0.45
			(0.72)	(0.73)
2+ SBIR wins			1.75*	1.96**
			(0.95)	(0.99)
Constant	−19.14	−19.05	−19.29	−19.12
	(2,797.40)	(2,796.73)	(2,791.03)	(2,779.68)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	115	115	115	115
Log Likelihood	−38.80	−38.69	−37.03	−36.64
Akaike Inf. Crit.	95.59	97.38	96.06	97.28
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 10: T-tests for covariates of used in weighting; unweighted and weighted covariates compared

	High pat.	High pat. (wt)	Team fund	Team fund (wt)	Elapsed time	Elapsed time (wt)
selected - mean	0.32	0.32	0.40	0.40	3.80	3.80
not selected - mean	0.12	0.36	0.29	0.29	2.32	4.01
statistic	2.52	-0.15	1.19	1.14	4.22	-0.11
p-value	0.01	0.88	0.24	0.26	0.00	0.92

Table 11: Entropy-balanced probability of raising venture capital

	Logistic regression				
	(1)	(2)	(3)	(4)	(5)
Migration	0.82		1.13	0.99	0.88
	(0.74)		(0.77)	(0.77)	(0.81)
1 SBIR win		0.51	0.49	0.76	0.73
		(0.62)	(0.63)	(0.64)	(0.65)
2+ SBIR wins		2.05**	2.22***	2.29***	2.28***
		(0.79)	(0.81)	(0.83)	(0.85)
Engineering				−0.53	−0.46
				(0.85)	(0.87)
Life Sciences				0.60	0.71
				(0.79)	(0.84)
Patents					−0.33
					(0.66)
Constant	−1.89***	−2.27***	−2.44***	−2.63***	−2.57***
	(0.29)	(0.45)	(0.48)	(0.76)	(0.78)
Observations	115	115	115	115	115

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 12: Probability of SBIR selection

	First-stage Heckman model: probit			
	(1)	(2)	(3)	(4)
Elapsed time	0.16	0.15	0.15	0.15
	(0.14)	(0.14)	(0.14)	(0.14)
Team funding	0.14	0.18	0.18	0.18
	(0.28)	(0.28)	(0.28)	(0.28)
Patents	0.78**	0.83**	0.83**	0.83**
	(0.35)	(0.36)	(0.36)	(0.36)
Engineering		−0.28	−0.28	−0.28
		(0.33)	(0.33)	(0.33)
Life sciences		−0.17	−0.17	−0.17
		(0.36)	(0.36)	(0.36)
Constant	−1.59	−1.30	−1.30	−1.30
	(1.29)	(1.32)	(1.32)	(1.32)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	115	115	115	115
ρ	−0.17	−0.23	−0.24	−0.05
Inverse Mills Ratio	−0.07 (0.13)	−0.09 (0.13)	−0.09 (0.13)	−0.02 (0.15)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Probability of raising venture capital

	Second-stage Heckman model: OLS			
	(1)	(2)	(3)	(4)
2+ SBIR wins	0.28*	0.27*	0.28*	0.28*
	(0.15)	(0.15)	(0.15)	(0.15)
Migration			0.07	0.08
			(0.18)	(0.18)
Patents				0.13
				(0.13)
Constant	0.20*	0.21*	0.21*	0.11
	(0.12)	(0.12)	(0.12)	(0.15)
Observations	115	115	115	115
ρ	−0.17	−0.23	−0.24	−0.05
Inverse Mills Ratio	−0.07 (0.13)	−0.09 (0.13)	−0.09 (0.13)	−0.02 (0.15)

Note: *p<0.1; **p<0.05; ***p<0.01