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Are public subsidies effective for university spinoffs? Evidence from SBIR awards in the University of California system

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ABSTRACT

This study examines the impact of public subsidies, and specifically, Small Business Innovation Research (SBIR) awards on university spinoff companies. Using unique data for a population of University of California spinoffs, we find pronounced differences between companies commercializing digital technologies (software and hardware), and those that focus on other product spaces. For digital spinoffs, receiving an SBIR award has a negative impact on raising venture capital and no impact on IPOs, exits or first sales. Conversely, for non-digital firms (e.g., biotechnology, energy), receiving an SBIR award has a positive effect on raising venture capital and performance outcomes. We reason that digital technologies are subject to faster cycle times and higher market uncertainty, relative to technological uncertainty. Digital firms may therefore benefit less from subsidies designed to support technology development, and private investors may view the need of digital companies to obtain such subsidies as a negative certification. Our findings inform policy by suggesting that the industrial domain may be an important boundary condition for the effectiveness of SBIR-type subsidies for university spinoffs.

1. Introduction

University-generated technologies tend to be embryonic, therefore they are often too immature to secure private investment. This reality has been used as a justification for support from public sources. Globally, numerous public funding schemes have been established to help university spinoffs bridge the so-called 'valley of death'. Because many of these schemes grant non-dilutive funds to support privately held companies, it is important to understand the degree to which, and under what conditions, such public assistance is effective in leading to positive outcomes for recipients.

The case for public support of young firms commercializing university research-developed technologies rests on the assumption that, because investment from risk-averse private investors cannot be secured, promising technologies will not be commercialized. Prior research suggests that commercialization-focused subsidies can indeed play a role in helping early-stage firms achieve favourable performance outcomes (Bertoni, Martí, & Reverte, 2019 Howell, 2017 Siegel & Wessner, 2012). Subsidies can be effective in two ways: they may (a) provide recipients with resources to advance their technologies and subsequently raise private funds or achieve sales; and, (b) benefit recipients via a certification effect, as grants signal a venture's quality to potential investors (Lerner, 1996 Toole & Czarnitzki, 2009 Islam, Fremeth, & Marcus, 2018).

Yet, overall, evidence for the effectiveness of subsidies is not unanimous and often drawn from selected sectors (Pahnke, Katila, & Eisenhardt, 2015 Stevenson, Kier, & Taylor, 2021). This mixed evidence suggests that the effectiveness of subsidies may depend on specific boundary conditions that have been left unexplored in prior work. In this paper, we focus on the combination of technology and market uncertainty that commercialization projects typically face (Abernathy & Utterback, 1978). Different ventures will be characterized by a different balance between these two types of uncertainty. Because providers of public subsidies typically place more emphasis on fostering technological innovation compared to commercial innovation (Pahnke et al., 2015), we explore the extent to which such grants will be more effective

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for companies facing higher technology risk, relatively speaking. We ask whether public subsidies might be systematically more effective in supporting companies operating in industrial domains dominated by higher technological uncertainty relative to market uncertainty.

Our core argument is that public subsidies are less effective in supporting the commercialization of digital innovations, which are typically afflicted by pronounced market uncertainty and subject to faster cycle times, compared to innovations in other product spaces, such as biotechnology, materials or energy. We use the term digital to refer broadly to information and communication technology, including both software and hardware.

Empirically, we consider the specific case of the US Small Business Investment Research (SBIR) awards granted to university spinoffs commercializing licensed technology. To explore our conjecture, we use a matched pairs design to examine the effectiveness of the SBIR awards using a unique database of University of California spinoffs. Our population includes detailed administrative information on 531 University of California spinoffs, that were established between 2000 and 2013 with the specific purpose of commercializing university-licensed technology.

Our findings indicate that the receipt of an SBIR award may have a detrimental impact on some companies' fundraising and performance outcomes. For the entire population of firms, we find no evidence that obtaining an SBIR award helps firms obtain venture capital (VC) financing and only a moderate positive effect on subsequent performance outcomes, such as achieving first sales, conducting an initial public stock offering (IPO), or achieving an exit (being acquired or experiencing a merger). However, this result changes once we consider the effect of SBIR awards in different industrial domains. We find that SBIR awards have the opposite impact on digital spinoffs versus non-digital spinoffs. While the receipt of SBIR awards has a negative impact on obtaining VC financing for digital spinoffs, the effect is positive for the remainder of the population, including those in biotech and energy.

Given that few studies have considered how the effectiveness of public grants varies across technologies and sectors (Mathisen & Rasmussen, 2019), our findings have important implications for understanding university technology transfer and related policy design. The effectiveness of public support is conditional upon the kind of uncertainty that the grant is supposed to reduce. Because digital products are often subject to greater market risk than technology risk, relative to other types of products developed from university technology, public subsidies may be less effective in supporting them. Relatedly, writing a grant proposal may absorb management attention and technical talent, thereby slowing the pace of development and commercialization – a distinct disadvantage in fast-moving digital industries. Further, digital companies applying and obtaining government grants could be perceived by private investors as insufficiently focused on the market, leading them to potentially prefer those companies that are immediately seeking private funds. Hence, investors might perceive a firm's need to apply for an SBIR award as a signal indicating a "lemon" (Akerlof, 1970); a negative certification effect. As a caveat, our conclusions are derived from a dataset of limited size, and hence require validation by other studies.

2. Prior research

2.1. Subsidies and university spinoffs

Policy makers have introduced a wide variety of measures to support early-stage technology companies. The rationale given is that information asymmetries between a firm's management and outside investors prevent the latter from properly assessing the investment opportunity (Carpenter & Petersen, 2002) and that investments in early-stage technologies are perceived as too risky by private investors, even if those technologies would provide value to society (Link & Scott, 2010). The latter argument reflects the belief that early-stage firms are often the originators of major innovations, which might result in the creation of entire industries benefitting society as a whole (Lerner, 2020).

There are a variety of public support schemes targeted specifically at start-ups formed to commercialize university-generated technologies (Grimaldi, Kenney, Siegel, & Wright, 2011 Mowery & Sampat, 2005). While some measures aim to support universities and their faculty, others are targeted directly at university spinoffs (Kochenkova, Grimaldi, & Munari, 2016 Wright, Lockett, Clarysse, & Binks, 2006). University spinoffs tend to be founded to commercialize embryonic technologies that are difficult to evaluate, and are often led by academic founders who choose to remain university employees (Fini, Perkmann, & Michael Ross, 2022). This results in high levels of uncertainty that may deter private investors (Rasmussen & Sørheim, 2012). Grants can provide the time and resources for the fledgling firm to 'de-risk' its technology by performing further R&D as well as potentially investing in early customer development.

In the US, the primary support measure is the SBIR programme, which provides non-dilutive grants with the explicit purpose of supporting small businesses in commercializing new technologies. The UK government agency, Innovate UK, provides support for small technology firms via multiple instruments, including 'innovation loans' and the Biomedical Catalyst scheme. The EU established the Executive Agency for SMEs (EASME) to support innovation in start-ups and other small businesses.

Among these schemes, the long-running SBIR programme has received the most academic attention (Keller & Block, 2013).[1] Lerner (1996) found that SBIR recipients experienced substantially greater employment and sales growth than matching firms that did not receive an SBIR award. The reason, Lerner (1996) argued, was that SBIR awards have a certification effect that renders recipients more credible to private investors and thereby increases their chances of obtaining VC funding. Further studies have lent credence to this argument.Toole and Turvey (2009) concluded that SBIR Phase II awards, in particular, increased the probability of obtaining VC funding. More recently, Howell (2017) found that, for a sample of energy technology firms, the receipt of SBIR awards had positive effects on various firm-specific outcome metrics, and concluded that in addition to certification, SBIR awards enabled firms to reduce technological uncertainty, rendering them a more mature and attractive investment opportunity for private investors. Giga, Graddy-Reed, Belz, Terrile, and Zapatero (2021) established that receiving an SBIR award has a positive effect on firm patenting for small firms but not larger firms.

Internationally, and for other types of grants, further work suggests positive effects of public subsidies, albeit in many cases, only under specific boundary conditions (Berger & Hottenrott, 2021 Conti, 2018 Hottenrott & Richstein, 2020 Hottenrott, Lins, & Lutz, 2018 Meuleman & De Maeseneire, 2012 Söderblom, Samuelsson, Wiklund, & Sandberg, 2015 Zhao & Ziedonis, 2020). However, Wallsten (2000) established that SBIR awards do not affect employment outcomes and found evidence that they crowd out firm-financed R&D spending. Further, Pahnke et al. (2015) found that, more broadly, relationships with public funders including SBIR, had a negative impact on patenting and no impact on product innovation among early-stage medical device companies. Stevenson et al. (2021) reported that public grants may improve ventures' chances in obtaining venture capital, yet eventually have a negative effect on their financial performance, as grants may reduce ventures' ability to use their resources effectively.

Research on the efficacy of SBIR awards for university spinoffs in

[1] See our summary of prior research on the efficacy of SBIR and public subsidies generally in Table A1. A further body of work investigates various aspects of the SBIR program, but does not focus on exploring the effects of SBIR awards on subsequent funding or performance outcomes (Dutta, Folta, & Rodrigues, 2022; Link & Ruhm, 2009; Link & Scott, 2010; Siegel & Wessner, 2012; Toole & Czarnitzki, 2007; Toole & Czarnitzki, 2009; Woolley, 2017).

particular, is also mixed. A series of studies that explore performance drivers for university spinoffs control for the effects of SBIR awards and other subsidies. Collectively, these studies provide little support for the efficacy of public subsidies on venture funding or performance outcomes (Shane & Stuart, 2002 Woolley, 2017 Hayter, 2013). Outside the US, Ayoub et al. (2017) found that German university spinoffs that received subsidies exhibited poorer performance compared to a control sample, an outcome they attributed to adverse selection and inappropriate incentive effects on entrepreneurs.

This mixed picture may arise from unrecognized boundary conditions for the effectiveness of subsidies. Among the possible reasons may be that some university spinoffs may benefit less from the certification effect afforded by public grants because they are associated with prestigious universities or led by star scientists. Some may also be immersed in ecosystems surrounding universities that provide them with resources (e.g., alumni business angels, or networks of experienced managers familiar with building new firms) that can supplement the resources provided from a grant or operate in industries characterized by different dynamics and capital requirements.

In this paper, we explore a specific boundary condition that likely plays an important role in determining whether a grant can be effective in supporting a spinoff. As a measure of the grant's effectiveness, we consider both the raising of VC and the achievement of subsequent performance outcomes. We start with the idea that early-stage technology firms differ in terms of the balance between technology risk and market risk inherent in their project (Abernathy & Utterback, 1978 Arora, Fosfuri, & Roende, 2022). On one hand, university technologies are typically immature, and hence often require further technical development to obtain proof of concept or demonstrate scalability (Agrawal, 2006). On the other hand, like any commercialization project, they also face uncertainty with respect to target market, market need and commercial feasibility (Gruber, MacMillan, & Thompson, 2008 Gambardella, Camuffo, Cordova, & Spina, 2020). Prior research suggests that public funders are the most capable of evaluating technology and thus may prioritize technology development, hence reducing technological uncertainty when providing grants to early stage companies (Pahnke et al., 2015). This poses the question as to whether the effectiveness of grants may differ, depending on the balance between the technology and market risks faced by an early entrepreneurial project. In concrete terms, projects with high technological uncertainty, compared to market uncertainty, may benefit more from a non-dilutive grant.

We explore this boundary condition for the effect of public subsidies by considering the industrial domain, and hence the product spaces, into which university spinoffs are entering. We reason that digital innovation often differs from innovation in biopharmaceuticals as well as energy and other deep tech areas,[2] as it proceeds at a very rapid pace, depends on integration in complex ecosystems and generally faces considerable market adoption uncertainty (Kenney & Goe, 2004).

Therefore, in turn, we should observe public subsidies as less effective for digital projects, compared to other technology-intensive industrial domains. We test this conjecture by examining the impact of SBIR awards by deploying a matching approach that compares near-identical university spin-off firms that received SBIR awards to those that did not. This allows us to address the additionality of these grants, i.e., question as to whether a start-up achieves outcomes – raising of VC, and subsequent economic performance measures – that it would not have been able to achieve without the subsidy.

We now describe our data, approach and findings, before providing a more detailed conceptual elaboration and interpretation of our overall finding that the effectiveness of public subsidies is much lower and, on some counts even negative, for digital commercialization projects, compared to those associated with other sectors.

3. Research design and methodology

3.1. Data

Our dataset comprises the entire population of 531 spinoff firms founded on the basis of technology licensed from the University of California (UC) system from 2000 to 2013.[3] We extracted information on these firms from the UC Office of the President administrative records. The criterion for inclusion was that: i) a firm be incorporated independently of any pre-existing company, and ii) the firm licensed UC technology. We then matched these records with information from additional sources. We obtained information on venture capital financing from CrunchBase, patent data from PatentsView,[4] information on firm survival from the California Secretary of State's database of firm incorporations, and SBIR data from a US government website reporting all SBIR awards.[5]

SBIR awards are competitively awarded grants providing non-dilutive funds with the explicit purpose of supporting small businesses in commercializing new technologies. The SBIR programme is the single largest provider of grants for helping small firms in commercializing new technologies and disburses approximately $3.3b annually at the time of writing. The SBIR programme is funded via an obligation that all federal government entities with external research programmes exceeding $100 million devote a predefined percentage of their research funding to SBIR. Though many US states have similar programmes, for the period under consideration in our study, SBIR was by far the largest grant scheme aimed at supporting technology commercialization available to California firms.[6] The SBIR programme has a smaller sister programme, STTR (Small Business Technology Transfer), which is equivalently structured and requires recipients to collaborate with a research institution. STTR disbursed approximately $450 m annually at the time of writing.

There are two phases of SBIR funding. Phase 1 awards (SBIR 1) can grant up to $250,000 for a period of 6 to 12 months to support the technical merit, feasibility, and commercial potential of a technology. Phase 2 awards (SBIR 2) are contingent upon the outcome of Phase 1 and provide up to $1 million for a period of up to 2 years for development work, such as prototype creation or scale-up. SBIR awards are subject to a peer-review process guided by a quality assessment and a variety of other government-mandated criteria.

While an SBIR award offers funding as a non-dilutive grant, applying and obtaining support has significant opportunity costs. First, the firm company must invest key scientists' and managers' time in writing a proposal. Proposals have a success rate of between 15 and 24 % and the

[2] The notion of deep tech refers to technology areas challenged by both technological and market uncertainty (Arora et al., 2022; Portincaso et al., 2021). Hence deep tech excludes drug-focused biotechnology where market uncertainty may be low.

[3] The original list included 697 records. However, 154 were either related to firms founded before 2000, or no information was available from the California Secretary of State's firm incorporation database or from extensive Google searches. We also searched for information about these records on the Wayback Machine. It is likely that all or most of these missing firms were either incorporated outside the US or related to commercialization projects that were discontinued before they proceeded to incorporation. For 12 firms the information was only partial and was missing either the year of incorporation or the technology disclosure year, or both, and hence these were also excluded. The final dataset includes 531 firms.

[4] http://www.patentsview.org.

[5] https://www.sbir.gov.

[6] Other sources of funding for technology start-ups include CRADA, involving an agreement with a federal laboratory, iCorps, an entrepreneurial training programme, and the loans programme of the Small Business Administration (SBA). While all valuable in their own right, these schemes are different from SBIR in that they either provide in-kind support (CRADA, iCorps) or loans not specifically for high-tech development (SBA).

entire process, including writing the grant, can take up to a year between conceptualization and receipt of the funds (National Research Council, 2009). Second, grant recipients are subject to governmental audit and any restrictions imposed by government agencies that can be introduced unilaterally, even after the grant is awarded. Deciding to apply for an SBIR award is a strategic investment drawing from the most valuable resources a university technology-based firm has – the time of key technologists and managers that may lengthen time to market – for an uncertain outcome and a relatively small sum.

3.2. University of California spinoffs and SBIR awards

Before presenting the set-up and results of our multivariate analysis, we describe the features of academic entrepreneurship in the University of California system.[7] Further information can be found in Table S1 (all tables prefixed with "S" are reported in the online supplementary material, Appendix B).

Table 1 provides an overview of the funding sources for the entire population. One feature is that 34 % of the firms received at least one VC investment – a remarkable proportion – that may in part be explained by the fact that licensing from the UC system is relatively resource-intensive. The process nearly always requires significant negotiation involving legal counsel on both sides and the licensee is commonly required to absorb the cost of patenting and any defence of patents. This ensures that licensees are committed to commercialization, and likely results in lower-quality inventions being filtered out before licences are concluded. Further, 24 % of the firms (125) received at least one SBIR award; >40 % of the firms receiving an SBIR 1 award do so within the first two years of operations. Further, 40 % of firms with an SBIR award received only one award. Considering both VC and SBIR awards, 47 % of firms received at least one form of formal funding, and only 11 % received both forms of funding.

3.3. Methodology

One of the key challenges of evaluating the effect of SBIR financing on firms' outcomes is that receiving an SBIR award is endogenous to a firm's performance. Unobserved characteristics might drive both, the receiving of external funding and firms' subsequent performance. Hence, the effect of obtaining an SBIR award on firms' performance cannot be assessed by comparing firms that received a SBIR award to those which did not.

To address this issue, we employ a propensity score-matching approach to allow us to build a counterfactual by using observational data (Heckman, Ichimura, & Todd, 1997). We create two groups of firms, a treated and control group, generated based on the similarity of their propensity score. First, we calculate a propensity score using a probit model, as the predicted probability for a firm of obtaining a given treatment, conditional on pre-treatment characteristics assessed at firm foundation.[8] We use a kernel-matching algorithm, which calculates the counterfactual by using the weighted average of observations included in the control group assigning higher weights to firms with similar propensity scores. This algorithm allows us to use more information, compared to other matching methods, resulting in lower variance. For robustness, we use alternative matching approaches, employing single nearest neighbour and three nearest neighbours matching (Guerzoni & Raiteri, 2015).

Table 1
UC spinoffs by funding source.

Variable	N of firms	%
VC only	120	23
SBIR only	69	13
Both SBIR and VC	56	11
SBIR before/same year as VC	39	8
VC before SBIR	17	3
No SBIR, no VC	286	53
Total	531	100

We then compare performance differences between treated and untreated firms by calculating the average effect of treatment on the treated (ATT) firms (Wooldridge, 2010). Conceptually, the ATT measures whether treated firms' performance differs from a counterfactual scenario in which they are not treated. This allows us to compare the effect of a treatment, e.g., 'having received at least one SBIR award', on firms that are otherwise comparable (i.e., matched on pre-treatment characteristics assessed at firm foundation).

Our dataset features full cross-sectoral coverage and includes non-SBIR-recipients. Moreover, our data includes non-public information on licensing events, founding teams, inventor quality and involvement, allowing us to match companies with greater accuracy than otherwise would be the case. This information helps us to partially control for differences among companies in the latent commercializability of their technology (Marx and Hsu, 2022). Our dataset also includes non-public information on outcome dimensions, including whether and when a company made its first sales and if or when it failed.

As pre-treatment characteristics (i.e., the co-variates of the first stage probit model) we use firms' characteristics at foundation. We control for the *year of establishment* by including, for any given firm, a dummy variable equal to 1 for its founding year. We include a dummy variable for the *UC campus* where the innovation was disclosed, and a dummy variable for each of the industries represented in our population (*biomedical*, *digital*, *environment and energy*). We also include dummy variables denoting whether, at the time of founding, the UC owned equity in the company (*UC equity*) and whether the firm had already received *VC funding* at the time of founding. To account for founding team variation, we characterize *inventor involvement*, indicating the proportion of inventors of the IP underpinning the foundational UC licence to the start-up who became firm founders. We capture whether at least one of the inventors of the IP underpinning the foundational UC licence to the company is a *star scientist*, defined as a member of the National Academy of Sciences, Engineering, or Medicine or Nobel Prize winner (Azoulay, Graff Zivin, & Wang, 2010).

Furthermore, we operationalize the extent to which the UC research originating the licensed technology was supported by federal grants. We use the following dummy variables to denote at least one grant received by the following groupings of agencies: *grant: defence* (grants from Air Force, Army, Department of Defense, Department of Homeland Security, NASA, National Oceanic & Atmospheric Administration, Navy, Veterans' Administration), *grant: NIH* (National Institutes of Health), *grant: NSF* (National Science Foundation), and *grant: other* (Department of Agriculture, Department of Energy, Environmental Protection Agency, Federal Railroad Administration, Joint Services Electronics Program, National Financial Services, National Institute of Environmental Health Sciences, National Institute of Standards and Technology).

The model also controls for: the total *number of federal grants* awarded to the UC to support the licensed technology prior to a company's establishment; the number of *patents* licensed to the company by the UC at the time of founding; the *time to licence,* depicting elapsed years between technology disclosure and the foundational licensing event for each start-up, as well as the breadth of the start-up technology, operationalized by counting the *number of tech tags* assigned by UC TTOs to each licensed technology.

Table 2 reports the descriptive statistics. We note that in 23 % of the

[7] For a general discussion of the UC system and academic entrepreneurship, see Kenney and Mowery (2014).

[8] We used the Stata module psmatch2 (Leuven & Sianesi, 2003).

Table 2
Descriptive statistics – pre-treatment characteristics at establishment.

Variable	Mean	Std. dev.	Min	Max
Year of establishment 2000	0.05	0.22	0	1
Year of establishment 2001	0.05	0.21	0	1
Year of establishment 2002	0.04	0.20	0	1
Year of establishment 2003	0.04	0.19	0	1
Year of establishment 2004	0.06	0.23	0	1
Year of establishment 2005	0.08	0.26	0	1
Year of establishment 2006	0.10	0.30	0	1
Year of establishment 2007	0.07	0.26	0	1
Year of establishment 2008	0.11	0.31	0	1
Year of establishment 2009	0.08	0.27	0	1
Year of establishment 2010	0.10	0.30	0	1
Year of establishment 2011	0.12	0.32	0	1
Year of establishment 2012	0.08	0.27	0	1
Year of establishment 2013	0.03	0.18	0	1
UC Berkeley	0.16	0.37	0	1
UC Davis	0.07	0.26	0	1
UC Irvine	0.11	0.31	0	1
UC Los Angeles	0.23	0.42	0	1
UC Merced	0.01	0.08	0	1
UC Riverside	0.03	0.17	0	1
UC Santa Barbara	0.07	0.25	0	1
UC Santa Cruz	0.02	0.14	0	1
UC San Diego	0.23	0.42	0	1
UC San Francisco	0.09	0.28	0	1
Industry: biomedical	0.62	0.49	0	1
Industry: digital	0.26	0.44	0	1
Industry: environment and energy	0.12	0.33	0	1
UC equity	0.23	0.42	0	1
Inventor involvement	0.14	0.21	0	1
Star inventor	0.17	0.37	0	1
VC funding	0.06	0.23	0	1
Grant: defence	0.18	0.39	0	1
Grant: NIH	0.41	0.49	0	1
Grant: NSF	0.15	0.36	0	1
Grant: other	0.09	0.29	0	1
Number of tech tags	2.72	1.46	1	9
Time to licence	3.42	3.57	0	21
Number of federal grants	1.43	1.82	0	13
Patents	0.29	0.61	0	3
$N = 531$				

firms, the UC held an equity stake (*UC equity*). We also see that the average firm had 0.29 patents licensed to it at founding, as indicated by the *patents* measure. Patents are an important quality indictor, particularly for technology-intensive firms; the relatively low number of the initial patent endowment can be explained by the fact that many firms in the sample obtained licences to patents or other UC intellectual property, only at a later stage. For the average firm, founders account for 14 % of the inventors of the IP underpinning the UC's first licence to the company (in 183 firms, there was no inventor among the founders). In 17 % of the firms, an inventor of the UC-owned patent licensed by the firm was a star scientist, as indicated by *star inventor*.

We evaluate the quality of the matching approach as follows. First, Rosenbaum and Rubin (1985) suggested computing the standardized bias for each covariate, calculated as a percentage of the square root of the sample variance in the treated and untreated group. A bias reduction under 5 % is considered a success: in our case this value drops from 12.8 to 3.1 after performing the matching. Second, we compare the pseudo-R square of the unmatched and matched samples (Sianesi, 2004). As the pseudo-R square measures the extent to which the sample variation is explained by the covariates; the matched sample should exhibit lower values compared to the unmatched sample: in our case the pseudo-R square drops from 0.143 to 0.01. Lastly, consistent with Guerzoni and Raiteri (2015), the likelihood ratio test for the joint insignificance of all covariates should be rejected before matching and not rejected after matching: in our case, p > chi2 switches from 0 to 1. Table 3 and Fig. 1a report the results. Finally, we tested the quality of the matching procedure by plotting the propensity score density distribution of the treatment and control groups before and after the matching. As we

Table 3
Matching quality.

Sample	Pseudo R2	LR chi2	p > chi2	MeanBias	MedBias
Unmatched	0.143	82.95	0	12.8	11.3
Matched	0.01	3.44	1	3.1	2.2

expect a partial overlap before implementing the matching procedure, the two distributions should exhibit a high degree of overlap after matching (as suggested by Fig. 1b). Table S2 reports the coefficients of the first stage probit model used to calculate the propensity score.

3.4. Outcome variables

We have a panel of annual observations for each firm from inception up to either 2013 or the year in which the firm leaves the sample because of an IPO, exit, or failure. Firm outcomes are operationalized using two sets of indicators assessed over the observation period (see Table 4). First, we consider VC financing using five measures including: a binary indicator of VC financing (outcome 1), a measure of the number of VC deals (both cumulative and per year) (outcomes 2 and 3), and a measure of the USD funding amount raised (both cumulative and per year) (outcomes 4 and 5). Second, we depict performance using the following outcomes: whether a firm has made a first sale (outcome 6), conducted an IPO (outcome 7), achieved an exit (i.e., by being acquired or merged with another firm) (outcome 8), or has failed (outcome 9). Pairwise correlations are reported in Table S3.

In our main analysis, we investigate the effect of obtaining an SBIR 1 award on firm outcomes. We consider those firms that receive at least one SBIR 1 award over the observation period as treated. For robustness, we operationalize the treatment in additional ways, namely, whether the firm has received an SBIR 1 award only, at least one SBIR 1 award or an SBIR 2 award, and at least one SBIR 1 and an STTR award.

The descriptive evidence reported in Table 5 suggests that treated firms (that obtained at least one SBIR 1 award) systematically differ from untreated firms across virtually all outcome variables, with the only exception being the probability of exit (outcome 8). Treated firms, vis-à-vis the untreated counterparts, are more likely to: obtain VC financing, do more VC deals (cumulative and per year), and attract a higher amount of VC financing (cumulative and per year as expressed in logarithmic terms, see outcomes 1–5). Also, they are more likely to achieve a first sale, an IPO, and are less likely to fail (see outcomes 6, 7, and 9).

4. Results

4.1. Main analysis: digital vs. non-digital firms

We show estimations of the effect on firms of receiving an SBIR 1 award on VC-related outcomes in Table 6. For dichotomous outcome variables, the average effect of treatment on the treated (ATT) should be interpreted as the difference in percentage points, between untreated (baseline) and treated observations, of the value of the given outcome. For example, the chances of obtaining VC financing are eight percentage points higher for firms that have received at least one SBIR 1 award (note, however, that this value is not significant, t-stat = 1.41). For all VC-related outcomes, the ATT is positive but insignificant.

This is our first key result: there is no evidence that, for the spinoffs in our sample, obtaining an SBIR award is conducive to raising VC. Conversely, considering performance outcomes (Table 6), we find a positive and weakly significant effect of receiving at least one SBIR 1 award on the probability of making a first sale (0.09, $p < 0.1$) and conducting an IPO (0.03, $p < 0.1$). Also, we find a negative and strongly significant effect of receiving at least one SBIR 1 award on the probability of failure (−0.14, $p < 0.01$).

These findings suggest the following noteworthy conclusion: the

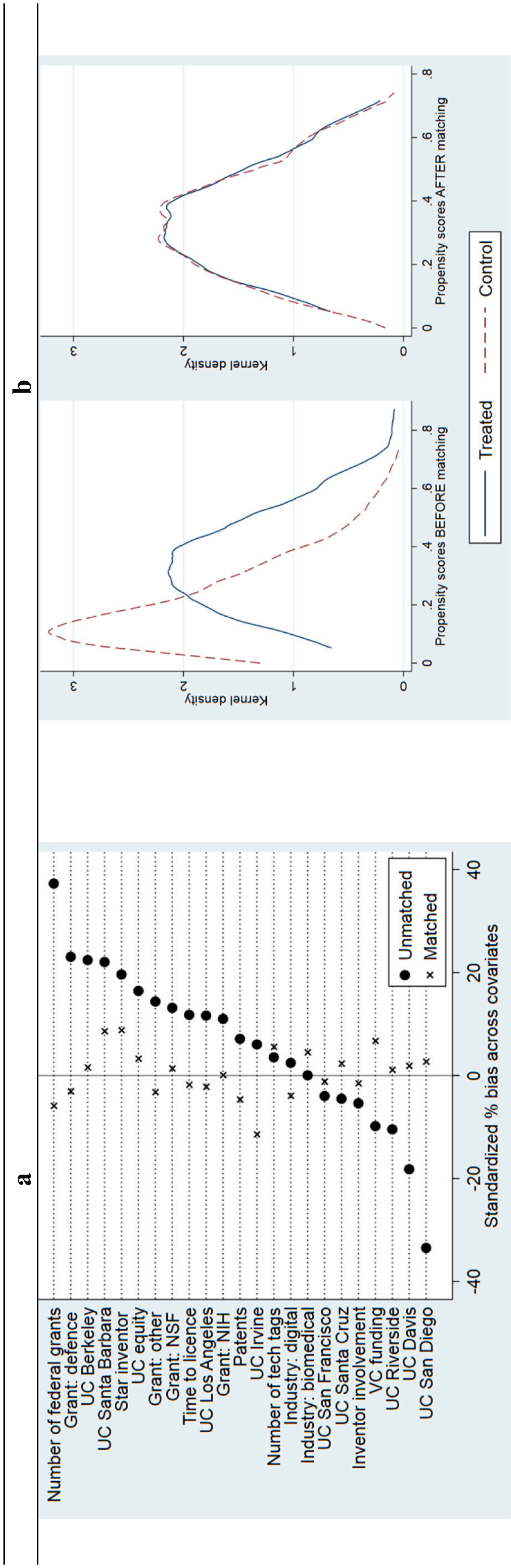

Fig. 1. Matching quality.
Kernel matching – Firms' year of incorporation dummy variables are excluded from graph panel a.

Table 4
Treatment and outcomes descriptive statistics – full sample.

	Mean	Std. Dev	Min	Max
Treatment				
At least one SBIR1	0.24	0.42	0	1
Outcomes				
1. VC (Y/N) [at least one VC financing deal]	0.33	0.47	0	1
2. Number of VC deals	0.80	1.57	0	9
3. VC deals per year [average number of VC deals per year]	0.12	0.23	0	1.5
4. VC (total $) [Ln($Amount of VC financing+1)]	4.96	7.40	0	19.1
5. VC ($ per year) [Ln(Average $ amount of VC financing per year+1)]	4.37	6.54	0	17.2
6. First sale (Y/N)	0.18	0.38	0	1
7. IPO (Y/N)	0.01	0.10	0	1
8. Exit (Y/N)	0.08	0.28	0	1
9. Failure (Y/N)	0.18	0.38	0	1

$N = 531$.

Table 5
Outcomes descriptive statistics – SBIR vs non-SBIR recipients.

	Sample	Mean	Std. Dev.	t	Pr(|T| > |t|)	Std. Err.
1, VC (Y/N)	U	0.30	0.46	3.19	0.002	0.02
	T	0.45	0.50			0.04
2, Number of VC deals	U	0.65	1.36	3.92	0.000	0.07
	T	1.27	2.05			0.18
3. VC deals per year	U	0.11	0.22	1.88	0.061	0.01
	T	0.15	0.24			0.02
4. VC (total $)	U	4.34	7.08	3.50	0.001	0.35
	T	6.96	8.10			0.72
5. VC ($ per year)	U	3.85	6.28	3.33	0.001	0.31
	T	6.06	7.07			0.63
6. First sale (Y/N)	U	0.15	0.36	2.46	0.014	0.02
	T	0.25	0.43			0.04
7. IPO (Y/N)	U	0.00	0.05	3.01	0.003	0.00
	T	0.03	0.18			0.02
8. Exit (Y/N)	U	0.08	0.27	**0.52**	0.606	0.01
	T	0.10	0.30			0.03
9. Failure (Y/N)	U	0.20	0.40	−2.46	0.014	0.02
	T	0.10	0.31			0.03

U = Untreated (non SBIR recipients) $N = 406$; T = Treated (SBIR recipients) $N = 125$; t-stat in bold are non-significant.

primary benefit of receiving an SBIR award is that it reduces the likelihood of failure during our observation period – an expected result, as the firm received a cash infusion.

Table 6 also presents the results of a split-sample analysis, where we compare digital firms to non-digital firms. For the digital firms, we observe a negative effect of receiving at least one SBIR 1 award on obtaining VC across all five measures. Specifically, digital firms with SBIR awards achieve fewer VC deals and raise less VC funding, both cumulatively and on a yearly basis, compared to their untreated counterparts. Conversely, for non-digital firms, we find a weakly significant positive effect of receiving at least one SBIR 1 award on achieving VC deals (0.47 $p < 0.1$).

For digital firms, receiving at least one SBIR 1 award does not increase the probability of making a first sale, exiting, or failing. By contrast, we see significant effects for non-digital firms that are more likely to achieve a first sale (0.14; $p < 0.05$), make an IPO (0.04; $p < 0.1$) and less likely to fail (−0.14; $p < 0.01$).

Taken together, these findings constitute the second set of key insights from our analysis: for university spinoffs in digital industries, the effect of receiving SBIR awards on acquiring VC financing is negative and significant, while the effect on subsequent performance outcomes is negligible. By contrast, non-digital firms benefit from SBIR awards, both

Table 6
Main analysis – effect of receiving at least one SBIR 1 on venture capital financing and on performance outcomes.

	VC (Y/N)	Number of VC deals	VC deals per year	VC (total $)	VC ($ per year)	First sale (Y/N)	IPO (Y/N)	Exit (Y/N)	Failure (Y/N)
Full sample									
ATT	0.08	0.28	0.02	1.39	1.18	0.09*	0.03*	−0.01	−0.14***
SE	0.06	0.20	0.03	0.88	0.77	0.05	0.02	0.03	0.04
Treated	123	123	123	123	123	123	123	123	123
Untreated	406	406	406	406	406	406	406	406	406
N	529	529	529	529	529	529	529	529	529
T-stat	1.41	1.36	0.91	1.57	1.52	1.86	1.80	−0.35	−3.52
Digital sample									
ATT	−0.22**	−0.55**	−0.10***	−2.90**	−2.61**	−0.07	0.00	0.03	−0.07
SE	0.09	0.21	0.03	1.34	1.17	0.11	0.00	0.10	0.07
Treated	25	25	25	25	25	25	25	25	25
Untreated	99	99	99	99	99	99	99	99	99
N	124	124	124	124	124	124	124	124	124
T-stat	−2.46	−2.57	−2.95	−2.16	−2.22	−0.68	0	0.28	−0.99
Non-digital sample									
ATT	0.06	0.47*	0.05	1.09	0.95	0.14**	0.04*	−0.02	−0.14**
SE	0.07	0.28	0.04	1.20	1.05	0.06	0.02	0.04	0.06
Treated	89	89	89	89	89	89	89	89	89
Untreated	300	300	300	300	300	300	300	300	300
N	389	389	389	389	389	389	389	389	389
T-stat	0.78	1.68	1.28	0.91	0.91	2.54	1.77	−0.70	−2.41

Treatment = at least one SBIR1; ATT = Average effect of Treatment on the Treated; SE = Standard Error; Models include all pre-treatment characteristics and are specified with a kernel matching; First stage probit is included in Table A3.
Full sample $N = 529$ (2 observations are off common support and are excluded from the analysis).
Digital sample $N = 124$ (16 observations are excluded because are off common support and/or might be dropped by the first stage probit (e.g., no variance in the dependent variable)).
Non-digital sample $N = 389$ (2 observations are excluded because are off common support and/or might be dropped by the first stage probit (e.g., no variance in the dependent variable)).
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

in terms of raising VC (on several measures), and some performance outcomes.

4.2. Additional measures for technological and market uncertainty

Our main proposition in this study is that the effect of public subsidies for university-based start-ups is subject to a product-specific boundary condition, pitching digital versus non-digital products. For digital products, technological uncertainty is often relatively less pronounced than market uncertainty, in combination with faster cycle times in digital product development. To probe these underlying mechanisms, in Table 7 we performed the following additional analyses using several measures of uncertainty.

First, we focus on *time to licence*, which measures the time between the disclosure of the technology to UC and the foundational licensing event for each start-up. We reason that the longer the time from disclosure to licensing, the more technological development was needed and thus the higher the initial technological uncertainty. We find that for start-ups with lower *time to licence* (values below or equal to 1), the effect of obtaining SBIR awards on the amount of VC financing received is negative but not significant, while for those with greater *time to licence* values the effect of obtaining SIBRs on obtaining VC financing, first sales and survival (avoiding failure) is positive and significant. The latter set of findings supports the conjecture that for companies subject to greater technological uncertainty, SBIR awards may be more effective in achieving performance outcomes.

Second, we use the number of *federal grants* awarded to the university in relation to the invention licensed to a start-up. We reason that, the more grants that were obtained to develop the technology, the more embryonic it was, and thus the higher the initial technological uncertainty. We find that for start-ups with no federal grants, the effect of obtaining SIBRs on achieving an IPO and survival (avoiding failure) is negative and significant, while for those with at least one federal grant, the effect of obtaining SIBRs on attracting VC financing, achieving an IPO and survival (avoiding failure) is positive. Both sets of findings support the conjecture that for companies with lower technological uncertainty, receiving SBIR awards is less likely to improve outcomes.

Third, we created a measure (*time to start-up*) indicating the time between technology disclosure and the establishment of the start-up. This measures the amount of time that passed between the first disclosure of a technology to the university and the founding of the start-up, based on that technology. We reason that the longer the time from disclosure to start-up, the more technological development was required and the higher the initial technological uncertainty. We find that for start-ups with lower *time to start-up* values (values equal to 0 or below) the effect of obtaining SBIR awards on both the number of VC deals and VC raised is negative and significant, while for those with greater *time to start-up* values, the effect of obtaining SBIR awards on the number of VC deals and VC raised, as well as achieving an IPO and survival (avoiding failure) is positive and significant. Both sets of findings support the conjecture that for companies subject to lower technological uncertainty, receiving SBIR awards is less likely to improve outcomes.

Fourth, we created a measure (*product on market*) indicating whether a start-up had at least one product on the market in the period under observation. We reason that market uncertainty is lower when a start-up has brought a product to market. We find that, start-ups with at least one product on market, the effect of obtaining SBIRs on the number of VC deals per year is negative and significant while for those with no product on the market, the effect of obtaining SBIR awards on several VC-related outcomes, as well as survival, is positive and significant.

Each of these measures is a necessarily partial approximation for technological or market uncertainty. Nonetheless, in combination, these

Table 7
Alternative operationalization of the market vs. technology uncertainty.

	VC (Y/N)	Number of VC deals	VC deals per year	VC (total $)	VC ($ per year)	First sale (Y/N)	IPO (Y/N)	Exit (Y/N)	Failure (Y/N)
Low time to licence									
ATT	−0.08	−0.41	−0.05	−1.54	−1.42	0.02	0.05	0.01	−0.04
SE	0.10	0.31	0.04	1.57	1.37	0.09	0.04	0.07	0.08
Treated	35	35	35	35	35	35	35	35	35
Untreated	151	151	151	151	151	151	151	151	151
N	186	186	186	186	186	186	186	186	186
T-stat	−0.75	−1.33	−1.32	−0.98	−1.04	0.25	1.16	0.12	−0.51
High time to licence									
ATT	0.10	0.41	0.04	2.16*	1.87*	0.13**	0.01	−0.06	−0.16***
SE	0.07	0.27	0.04	1.11	0.98	0.06	0.01	0.04	0.05
Treated	83	83	83	83	83	83	83	83	83
Untreated	232	232	232	232	232	232	232	232	232
N	315	315	315	315	315	315	315	315	315
T-stat	1.47	1.55	1.12	1.94	1.91	2.32	1.00	−1.42	−3.31
No federal grant									
ATT	−0.09	−0.03	−0.03	−1.58	−1.44	0.08	−0.02**	−0.07	−0.10*
SE	0.10	0.38	0.05	1.54	1.35	0.10	0.01	0.07	0.05
Treated	28	28	28	28	28	28	28	28	28
Untreated	144	144	144	144	144	144	144	144	144
N	172	172	172	172	172	172	172	172	172
T-stat	−0.95	−0.08	−0.71	−1.03	−1.06	0.81	−2.19	−0.94	−1.89
At least one federal grant									
ATT	0.10	0.39	0.04	2.08*	1.81*	0.08	0.05**	−0.03	−0.14**
SE	0.07	0.25	0.03	1.10	0.97	0.05	0.02	0.04	0.05
Treated	88	88	88	88	88	88	88	88	88
Untreated	251	251	251	251	251	251	251	251	251
N	339	339	339	339	339	339	339	339	339
T-stat	1.49	1.52	1.30	1.89	1.87	1.45	2.04	−0.69	−2.54
Low time to start-up									
ATT	−0.20*	−0.57*	−0.07*	−2.76*	−2.50*	0.01	0.04	−0.06	−0.04
SE	0.10	0.33	0.04	1.57	1.38	0.10	0.04	0.08	0.08
Treated	38	38	38	38	38	38	38	38	38
Untreated	131	131	131	131	131	131	131	131	131
N	169	169	169	169	169	169	169	169	169
T-stat	−1.94	−1.73	−1.72	−1.75	−1.81	0.12	1.07	−0.76	−0.43
High time to start-up									
ATT	0.13*	0.59**	0.06*	2.50**	2.17**	0.16**	0.02	−0.04	−0.13**
SE	0.07	0.27	0.04	1.14	1.00	0.06	0.02	0.04	0.05
Treated	83	83	83	83	83	83	83	83	83
Untreated	245	245	245	245	245	245	245	245	245
N	328	328	328	328	328	328	328	328	328
T-stat	1.85	2.18	1.65	2.19	2.16	2.67	1.42	−0.98	−2.51
At least one product									
ATT	−0.20	−0.70	−0.16*	−2.71	−2.60	−0.07	0.06	−0.27**	0.00
SE	0.16	0.68	0.09	2.55	2.24	0.16	0.04	0.11	0.06
Treated	32	32	32	32	32	32	32	32	32
Untreated	73	73	73	73	73	73	73	73	73
N	105	105	105	105	105	105	105	105	105
T-stat	−1.24	−1.03	−1.75	−1.06	−1.16	−0.42	1.44	−2.45	0.01
No product									
ATT	0.12*	0.43*	0.04	2.04*	1.78*	0.07	0.01	0.04	−0.16***
SE	0.07	0.23	0.03	1.08	0.95	0.05	0.01	0.04	0.05
Treated	81	81	81	81	81	81	81	81	81
Untreated	324	324	324	324	324	324	324	324	324
N	405	405	405	405	405	405	405	405	405
T-stat	1.78	1.90	1.51	1.90	1.88	1.52	0.77	1.01	−2.97

Treatment = at least one SBIR1; ATT = Average effect of Treatment on the Treated; SE = Standard Error; Models include all pre-treatment characteristics and are specified with a kernel matching; First stage probit is included in Table A3; Observations that are off common support are excluded from the analysis.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

additional analyses provide empirical support for our overall conclusion - new firms with lower technological but greater market uncertainty are likely to benefit less from early public subsidies during commercialization.

4.3. Robustness checks

To validate the stability of our results, we perform several robustness tests.

First, we implement two alternative matching procedures, using a single nearest neighbour and a three nearest neighbours matching approach, both with a caliper radius of 0.05. As suggested by Rosenbaum and Rubin (1985), we use a caliper equal to 0.25 times the standard deviation of the propensity score estimated in the probit models. Tables S4 and S5 report the results for the single and the three nearest neighbours matching approaches, respectively. The results of the two matching strategies are qualitatively in line with our main analyses and in no case contradict the main analyses. Using the alternative matching procedure, for the full sample, the treatment 'receiving at least one SBIR 1' increases the chances of obtaining a first sale, achieving an IPO, as well as decreases the odds of failure, confirming our main analysis. Also, the different treatment effects for digital and non-digital firms are confirmed in the robustness check analysis. For digital firms, receiving at least one SBIR 1 award reduces the odds of obtaining VC financing. Conversely, for non-digital firms, receiving at least one SBIR 1 award increases the chance of obtaining a first sale and reduces the likelihood of failure.

Second, given the limited size of our sample, consistent with Autio and Rannikko (2016), we perform a sensitivity analysis to further corroborate the validity and stability of the results. To validate the kernel-based matching estimator in small sample sizes,[9] different bandwidth values and trimming levels should be accounted for (Guo & Fraser, 2010). In our analysis, we first impose no trimming, testing three bandwidth values: 0.01, 0.05, and 0.8. We then apply the three trimming levels (2 %, 5 %, and 10 %) while fixing the bandwidth at the default level (0.06). Results reported in Table S6 are confirmed.

Third, we exclude the 17 firms that obtained their first SBIR award after the first round of VC financing from the sample.[10] The non-significance of the effect of receiving at least one SBIR 1 award on receiving VC, as per Table 6, is confirmed. Moreover, the patterns exhibited in the split sample analysis are confirmed: receiving at least one SBIR 1 award has a negative effect on obtaining VC for digital firms, whereas it has a positive effect on first sale and survival for non-digital firms. Results are shown in Table S7.

Fourth, we alternatively operationalize the treatment as having received only one SBIR 1 award (rather than any number), using the kernel matching algorithm. Table S8 summarizes the results. For digital firms, consistent with the main analysis, obtaining just one SBIR 1 significantly reduced the odds and amount of VC financing. As per firms' performance, receiving just one SBIR 1 award, decreases the odds of failure and, for non-digital firms, reduces the probability of achieving an exit.

Fifth, we acknowledge that firms, in addition to receiving at least one SBIR 1 award, might also have been subject to different combinations of SBIR awards that could influence both their ability to secure VC financing and their market performance. To account for this, we operationalize the treatment as having received at least one SBIR 1 award and at least one SBIR 2 award, using the kernel matching algorithm. Table S8 summarizes the results, which suggest that having received both types of SBIR awards reduces the ability to secure VC for digital companies. Also, consistent with the main analysis, it increases the odds of having a first sale and survival for both the full and non-digital sample.

Sixth, we consider the receipt of STTR awards, in addition to SBIR awards. A total of 126 firms were awarded at least one SBIR or STTR[11] award (only one firm obtained an STTR and no SBIR award). The main results are confirmed (see Table S8).

Seventh, it may be the case that firms that only ever obtained VC financing (and no SBIR award) are outside the risk set for obtaining SBIR awards. We therefore removed the 120 firms that had only raised VC (not in conjunction with SBIR) anytime over the observation period from our sample and tested the effect of having received at least one SBIR 1 award on this reduced sample. The main results, only available for IPO, exit, first sale and failure are confirmed and included in Table S9.

Finally, we perform tests to explore specific contingencies or boundary conditions. Specifically, if, for digital firms, obtaining an SBIR award has adverse consequences on raising VC, this effect should be even more pronounced for firms for whom VC is more accessible. To this purpose we estimate the ATT for digital and non-digital firms in considering whether the technology originates from the most highly ranked campuses (i.e., UCB, UCLA, UCSD, and UCSF) or from campuses located in the Silicon Valley area (i.e., UCB and UCSF). Firms from top campuses command a certification advantage with VC, and firms located near Silicon Valley are likely to have closer relationships with VC firms.

As reported in Table S10, the effect of receiving at least one SBIR 1 award on VC acquisition is strongly negative for digital firms coming from highly ranked campuses. Conversely, as per Table S11, the effect of receiving at least one SBIR 1 award on VC acquisition is positive for non-digital firms, not located in the Silicon Valley area. While these results should be interpreted cautiously, due to the small sample size for each of the categories, the overall direction of effects supports our main conjecture. The results also provide some degree of reassurance against an alternative explanation of our findings, namely that the relative prestige of the UC might lead venture capital firms to overinvest in UC spinoffs, obviating the need for public grants. While our effect is particularly pronounced for digital companies from the UC's top campuses, we do not see the same pattern for non-digital firms on the same campuses. In other words, even within the cohort of elite start-ups, venture capitalists appear to discriminate against digital SBIR-grantees more (compared to non-digital grantees in the same cohort).

4.4. Further analyses using different specifications

To complement the matched-pairs approach, we exploit the longitudinal nature of our data and create a panel dataset containing 3073 firm-year observations for 531 firms between 2000 and 2013.[12] The panel is unbalanced and dynamic, characterized by a relatively short period of observation. We model the effect of receiving SBIR 1 awards prior to year t on the amount of VC financing acquired in year t and, alternatively, on whether a firm has received VC financing in t. As the

[9] The issue of sample size in propensity score matching has been discussed in various bodies of research, including clinical settings (Cheung, Chung, & Fung, 2015; Medaglio, Stephens-Shields, & Leonard, 2022). Scholars have also tested the performance of the propensity score models using small sample sizes. Using simulation, Pirracchio, Resche-Rigon, and Chevret (2012) suggested that, even in cases of very small samples (40 observations), propensity score matching yields unbiased results. Yet, attention needs to be paid to the variables included in the estimations: only the true confounders (i.e., variables related to the treatment and to the outcome) and variables related to the outcome only, should be included in the specifications.

[10] Of the 56 firms that received both SBIR and VC financing, 17 were awarded their first SBIR after the first VC round (see Table 1).

[11] A total of 35 firms have at least one STTR: 24 firms have one, 7 firms have two, 4 firms have three, four, five and six STTRs, respectively.

[12] Consistent with robustness check seven, we performed this specification both on the full sample as well as the full sample excluding the 120 firms that had only raised VC (not in conjunction with SBIR) anytime over the observation period.

criteria used for awarding an SBIR award might be similar to those used by a venture capitalist in judging a potential investment, our main predictor—the cumulative number of SBIR 1 awards—is potentially endogenous. To account for this, we model the amount of VC financing acquired in year t, using a single equation instrumental variable linear estimator, fitting a two-stage least squares (2SLS) linear model with an endogenous regressor (i.e., the cumulative number of SBIR 1 awards) and instrumental variables. Similarly, to model whether a firm has received VC financing in t, we use a probit model with a continuous endogenous covariate (i.e., the cumulative number of SBIR 1 awards) and instrumental variables.

We identify two time-varying, reasonably exogenous (instrumental) variables, which may predict SBIR award acquisition, without being necessarily correlated with a firm's ability to secure VC financing. The first instrumental variable – *budget allocated to SMEs by SBIR* – measures the actual yearly budget, adjusted for inflation, allocated by the SBIR programme up to t-1.[13] We use its logarithmic transformation. The second instrumental variable – *SBIR acceptance rate* - is calculated as the number of SBIR 1 and 2 awards in any given year divided by the total number of proposals submitted in the same year.[14] We use values at t-1. Table S12a-b reports the pairwise correlations and descriptive statistics, whereas Tables S13 and S14 include the models specified, using the full sample and the full sample excluding the 120 firms financed by VC only, respectively. We assess the validity of the instruments by including F-statistic values for the first-stage models. We also report the minimum distance version of the Anderson-Rubin (AR) test statistic, the conditional likelihood ratio (CLR) test, the Lagrange multiplier (LM) test, the J overidentification test, and the Wald test of exogeneity. All F-statistic values are higher than the suggested threshold of 10 (Staiger & Stock, 1994) and virtually all tests are significant at the 5 % level (except models M9 in Tables S13 and S14), confirming the validity of the selected instruments. The results of the main analysis are confirmed, suggesting a positive effect of the cumulative number of SBIR 1 awards on VC acquisition for non-digital firms and no effect in the digital sample.

As a robustness check for both continuous and dichotomous outcomes, we employ a GMM dynamic panel estimator (Arellano & Bond, 1991 Roodman, 2009), which allows us to include lagged dependent variables as regressors and specify instrumental variables. The dependent variables measuring VC financing might be correlated with their past values. We employ a system GMM rather than a difference GMM, as the former accounts for firm fixed effects and simultaneously allows for the inclusion of time-invariant firm-level regressors. We assess the validity of the GMM estimator and the two selected standard instruments via serial correlation tests (AR(1) and AR(2)).

Results are confirmed and are presented in Tables S15 and S16. Consistent with the main specifications shown in Table 6, the effect of an SBIR award on VC financing is positive but marginally significant. The split sample analysis reveals that, for digital firms, receiving SBIR awards have no effect on subsequent VC financing. In contrast, for non-digital firms, the effect is positive and strongly significant.

Finally, as the budget allocated by SBIR as well as SBIR acceptance rates might be heterogeneous across sponsoring federal agencies, we re-specified both the two-stage least squares linear model as well as the probit model, operationalizing the two instrumental variables to account for differences across funding bodies in terms of the allocation of funds and acceptance rates. Consistent with the main analysis, the results suggest that the effect on both the amount of VC raised as well as VC deals made of the cumulative number of SBIR 1 awarded to spin-off companies is (marginally) significant (Table S17).

To further corroborate the results obtained for the probability of obtaining a first sale, IPO, exit, and failure, in Table S18 we specify four outcome variables that account for the number of days from inception to first sale, IPO, exit, and failure. The descriptive analysis, as shown in Table S19, suggests that the number of days to first sale, IPO, exit, and failure is systematically higher for treated firms than for non-treated firms: treated firms take longer to achieve those outcomes. Moving to the multivariate analysis, to test the effect of SBIR acquisition on any given outcome variable, consistent with the main analysis, we first estimate the propensity score on the matched sample with kernel matching. The weights created in the propensity score are then imputed as weights to recalibrate the second stage Cox survival models. We employ the following specifications. First, as outcomes of the propensity score models, we use both dichotomous indicators, measuring the occurrence of a given event, and time to the specific event. Second, we run Cox models that include: i) all predictors included in the propensity score models; ii) the main predictor only (i.e., acquisition of at least one SBIR award); and, iii) only predictors with a *p*-value smaller than 0.25 in the univariate Cox proportional hazard regression.[15] Results are robust and confirm the main analysis conducted using dichotomous outcome variables. Table S20 reports the fully specified models only; the other results are available upon request.

4.5. Summary of results

We examined the effect that public subsidies – SBIR awards – have on university spinoffs' ability to raise VC and achieve performance milestones. Examining our population of spinoffs from the University of California system, we obtained noteworthy findings. First, for the entire population, we have inconclusive evidence as to whether receiving an SBIR award makes it more likely for a spinoff to raise VC. Relatedly, obtaining an SBIR has no or only weakly significant effects on performance outcomes, such as achieving first sales, conducting an IPO, or obtaining an exit. The only exception to this pattern is that receiving an SBIR award significantly reduces the odds of failure during our time window.

Second, our key finding is that the effects of SBIR awards are contingent on whether the company is commercializing a digital product. For digital firms, we find that obtaining an SBIR award negatively affects the raising of VC and has little discernible effect on performance outcomes. By contrast, for non-digital firms (e.g., those in biotechnology, as well as energy and other deep tech areas), we find that receiving an SBIR has a positive, significant effect upon raising VC as well as performance outcomes.

We further confirm these patterns by using different measures of technological uncertainty, namely: *time to licence* (depicting the time between the technology disclosure and the foundational licensing event for each start-up), number of *federal grants* (capturing the number of grants from federal funding bodies awarded to the laboratory in relation to the technology licensed to a start-up), *time to start-up* (depicting the time between technology disclosure and the establishment of a start-up), and *product on market* (indicating whether a start-up had at least one product on the market in the period under observation). Overall, our results suggest that firms characterized by lower technological, but higher market uncertainty, are likely to benefit less from SBIR-like subsidies during early-stage commercialization. A summary of the results is reported in Table 8.

The article by Howell (2017) is a key reference point for research on this topic, and hence we comment on how our findings compare to that study. Howell's study reported largely positive effects of SBIR awards on VC and performance outcomes, based on a sample of firms with SBIR awards from the Department of Energy (DoE) and focusing on two subject areas (fossil fuels, and energy efficiency and renewable energy). Our results for the full sample are in partial support of Howell's findings:

[13] Source: https://www.sbir.gov/about/about-sbir.

[14] Source: https://www.sbir.gov/about/about-sbir.

[15] The rationale is that predictors with a *p*-value >0.25 in a univariate analysis are unlikely to contribute anything in a fully specified model (Allison, 1984).

Table 8
Summary of results.

	N	Treated	% of treated	VC	First sale	IPO	Exit	Failure
Full sample	529	123	23.3		+	+		–
Digital firms	124	25	20.2	–				
Non-digital firms	389	89	22.9	+	++	+		–
Low time to licence	186	35	18.8					
High time to licence	315	83	26.3	+	++			–
No federal grant	172	28	16.3			–		–
At least one federal grant	339	88	26.0	+		++		–
Low time to start-up	169	38	22.5	–				
High time to start-up	328	83	25.3	++	++			–
At least one product	105	32	30.5	–			–	
No product	405	81	20.0	+				–

Treatment = at least one SBIR1; Overview of ATT results from Tables 6 and 7 (all kernel matching); ATT = Average effect of Treatment on the Treated;
- or + Indicates that the result is negative/positive and significant at $p < 0.1$.
– or ++ Indicates that the result is negative/positive and significant at $p < 0.05$.
— or +++ Indicates that the result is negative/positive and significant at $p < 0.01$.

SBIR awards have a positive, significant effect on IPOs and survival, and a positive, but not significant, effect on VC financing.

Our sample features wide sector variation, while Howell's dataset is highly focused. When we differentiate by sector, we find that SBIR awards have different effects for digital and non-digital companies, respectively. Overall, our findings are broadly in line with Howell's findings but allow us to examine sectoral effects.

5. Discussion

Prior research has documented that public grant schemes such as the SBIR program can result in two types of benefits for early-stage technology start-ups: (a) certification, whereby the reception of a grant represents a quality signal for VC investors; and, (b) de-risking early-stage technologies, as the grant helps the firm bridge the valley of death by funding its technological progress.

Our findings pertaining to the divide between digital and non-digital university spinoffs provide an opportunity for refining the way in which we understand the efficacy of public grants by differentiating effects depending on a spinoff's industry. Our results suggest that, for digital companies, receiving an SBIR award does not appear to certify their quality to prospective investors. This insight is reinforced by the finding that the negative effect of having obtained an SBIR award on attracting VC is even more pronounced for spinoffs originating from top-ranking campuses – if an SBIR award provided certification signals, then this should be less pronounced for start-ups that already have a certification advantage based on their affiliation with a high-prestige campus.

Also, digital spinoffs do not appear to require SBIR funding to advance their technologies. While digital firms receive no performance boost from SBIR awards, non-digital firms benefit measurably from receiving an SBIR award, suggesting that the latter firms benefit more from the influx of capital and opportunity to advance their technologies that these grants provide.

An explanation underpinning both observations may be that digital products commonly have two specific characteristics that differentiate them from other products, and notably biomedical innovations. The first characteristic relates to the high-velocity character of the digital industry. Digital products typically have short development- and product-cycle times (Eisenhardt, 1989), and are also often rapidly adopted by customers. Hence, speed-to-market is essential, particularly for products with platform characteristics, given the winner-takes-all nature of the related product spaces (Schilling, 2002). Relatedly, digital products do not need to be tested and then submitted to government regulators for approval. The fast-paced nature of digital products implies that they can be tested relatively quickly for market acceptance and improved through customer feedback, reducing the costs and time needed for market-side experimentation (Contigiani & Levinthal, 2019). In addition, the last 20 years have seen the development of an industrial context that provides digital companies with a vast external infrastructure they can use for conducting market-side experiments with minimal fixed cost expenditure required (Ewens, Nanda, & Rhodes-Kropf, 2018).

Second, digital projects often differ from other technology commercialization projects, in that they suffer from pronounced market uncertainty compared to technological uncertainty. This characteristic is particularly evident when compared to innovations in biotechnology where technological uncertainty tends be high, but market uncertainty can be lower because, if the resulting drug successfully improves clinical outcomes it is likely to be adopted. Digital innovations are also different from deep tech projects, which are typically afflicted by high levels of both technological and market uncertainty (Arora et al., 2022).

The relatively stronger tilt towards market uncertainty faced by digital products may be due to the fact that they are conceived as demand-driven, rather than technology-push propositions (Agarwal & Shah, 2014). In this instance, the challenge is to validate initially highly uncertain market-side hypotheses (Murray & Tripsas, 2004) while technology uncertainty is less pronounced. In other cases, digital products result from technology-push opportunities (e.g., a new search algorithm) for which market applications have to be found (Andries, Clarysse, & Costa, 2021). Even in this case, market uncertainty will often prevail as digital products are often more (quickly) imitable, subject to ecosystem interdependencies and amenable to a variety of possible business models. Digital products are also, in almost all cases, conceived to operate within complex ecosystems populated by suppliers, competitors and complementors, meaning that the crafting of suitable business models will be crucial in determining success (McDonald & Eisenhardt, 2020).

For investors, firms that face market uncertainty are easier to evaluate and fund than those that have technological uncertainty - and thus require long-term investments to confirm whether the technology actually works (Gompers, 1995). Venture capitalists have particular capabilities in helping portfolio companies reduce market risk (Arthurs & Busenitz, 2006). As a result, many VCs would rather invest in firms whose business models can be tested relatively quickly and cheaply, rather than technologies that are more complex, require significant further research and development, and are expensive to test and introduce to the market (Ewens et al., 2018).[16] While venture capitalists may at times oppose ventures' pivoting attempts in some circumstances. as they remain committed to companies' initial proposition (Snihur & Clarysse, 2022 McDonald & Gao, 2019), on an aggregate level they may have a preference to invest (Ewens et al., 2018), even with smaller initial amounts, in digital companies that can test market acceptance in this

[16] See also Maryann Feldman's congressional testimony, supporting this point. Accessible at: https://science.house.gov/imo/media/doc/Feldman%20Testimony.pdf.

way.

The above considerations help shed some light on the empirical patterns that we uncovered. For two reasons, for digital spinoffs, applying for public support may not contribute to securing venture capital or achieving positive performance outcomes, for two reasons. First, regarding the raising of VC, the SBIR certification effect may not apply to digital companies in the same way as in other industries. Certification means that private investors use the SBIR vetting process as an indicator of the quality of the technology a company is seeking to commercialize, and thus ceteris paribus, are more likely to invest in spinoffs that have received such an award. Our conjecture reinforces the argument by Pahnke et al. (2015), according to which government funders have a tendency to put emphasis on technical innovation, and comparatively less emphasis on commercial feasibility. Firms applying and obtaining public grants may be signalling a more academic, research-based approach than a commercial approach (Powell & Sandholtz, 2012). Hence the signalling effect of having obtained an SBIR award may be less pronounced or even counterproductive for products such as software and computers, for which technological uniqueness and extensive R&D are relatively less important than product development speed and a resolution of market uncertainty.

Second, with respect to performance outcomes, such as IPOs or first sales, the relative penalty for digital companies from obtaining SBIR awards could be due to the fact that product cycles in the digital space tend to be much shorter than in other industries, particularly the biomedical field (Bilir, 2014). Applying for and awaiting a decision for an SBIR award takes time that might be better invested in advancing the product to the market. Similarly, producing the deliverables promised for an SBIR award may also divert a spinoff's focus away from customer discovery and acquisition. By contrast, firms in sectors other than digital may well benefit from proceeding in a technology-focused manner, as it allows them to fund research that is necessary to reduce technology risk, such as getting a compound into Phase 1 trials (Molner, Prabhu, & Yadav, 2019). In summary, our insights from investigating multiple performance outcomes suggest that both audience effects as well as resource allocation effects are likely to play together in generating the overall picture.

The key finding of our study is that the benefits university spinoffs may reap from non-dilutionary public support schemes are conditional upon the nature of products they are seeking to commercialize. Firms developing science-based innovations characterized by technological uncertainty and long-cycle times appear to benefit from public grants that provide the time and resources for advancing their immature technology and represent a quality signal for commercial investors. The situation for firms commercializing digital products is different. Obtaining public support could signal to venture capitalists that a firm may privilege technical development over ensuring product-market fit, and may be slower in working towards commercialization. Hence, they might conclude that the firm is a lemon (Akerlof, 1970). Consequently, such firms might benefit from not using valuable manager and researcher time for writing a grant proposal and concentrate on product development and securing VC investment.

Our insight is novel, as relatively few prior studies have examined the role that types of products or technologies play in shaping the effectiveness of grants (Mathisen & Rasmussen, 2019 Kenney & Patton, 2011). By probing the role played by product type, and pinpointing cycle times and market uncertainty as key underlying factors, our study contributes more broadly to the literature on how characteristics of university technologies, such as breadth or tacitness (Clarysse, Wright, & Van de Velde, 2011), IP protection (Clarysse, Wright, Lockett, Mustar, & Knockaert, 2007), and radicalness (Nerkar & Shane, 2003), determine the growth and success of university spinoffs.

6. Conclusion

6.1. Limitations and further research

In this study, we have shown that the effect of SBIR-like grants on university spinoffs is not universally positive, but rather conditioned by the types of products the spinoff intends to commercialize.

Our study has some limitations. First, our population is spinoffs from the University of California system, thus that our sample size is relatively small and may not be representative of all university spinoffs. The drawback of a small sample size is partly alleviated by the fact that we can draw upon information that would commonly be unavailable, which allows for higher quality matching. Nevertheless, our conclusions are based on a relatively small number of treated cases and should therefore be interpreted cautiously. Further research, using larger samples across a larger number of universities, is required to further support our inferences.

Our population is also drawn from a single, research-intensive university system, meaning our findings may not be generalizable, and could be overturned in other contexts or with larger samples. Four universities in the UC system are in the global top 20 research universities and two more are in the top 50. Furthermore, some campuses are in proximity to the San Francisco Bay Area or San Diego, which have vibrant entrepreneurial ecosystems. As a result of both historic relationships and geographic location, UC spinoffs may have easier access to VC, thereby decreasing their need to apply for public funds. For example, a remarkably large percentage (23 %) of the population received only VC funding. This suggests that this population may not be representative of all spinoffs licensing university technology, and thus our study may underestimate the importance of public support in other regions where VC is less readily available. However, this limitation is mitigated by the fact that the quality of inventions emanating from UC campuses, as is likely to be the case with other prominent research universities, is probably high on average and that this (rather than UC specificities) may explain the substantial flow of VC that we observe.

Second, our study uses the categorization of a company as 'digital' to imply that a company faces higher market uncertainty, relative to technological uncertainty. It is likely that some digital companies in our sample do not adhere to the assumed uncertainty profile; likewise, some non-digital companies may have an uncertainty profile akin to the one we assume only digital companies have. Future research should deploy measures of both types of uncertainty that are independent of sectoral classification and operationalize uncertainty more directly.

Third, we do not have information on whether the firms applied for SBIR awards, as a result, our analysis could be subject to selection bias. It is likely that some companies with weaker technologies also applied for an SBIR award but were unsuccessful, meaning that our companies with SBIR awards are likely to be of higher quality than those that received neither VC nor SBIR awards.

Fourth, we only consider the effectiveness of SBIR and STTR awards. Though the SBIR/STTR scheme is by far the largest accessible to our population of firms, it is possible that we may be missing specialist grants given to firms in specific sectors or product areas (e.g., agriculture) and also grants that are provided to small or new firms more generically, rather than specifically to support innovation efforts. However, there is little reason to assume that these possibilities would unequally affect digital or non-digital companies.

6.2. Policy implications

Our study has noteworthy implications for policy, particularly if validated by future studies using larger datasets or data from other contexts. Non-recoverable, publicly funded grants awarded to university spinoffs should result in revenue growth and employment creation. Even against these relatively narrow criteria – as a policy intervention may conceivably aspire to go beyond merely helping privately held companies be more successful – our findings suggest that SBIR-like public subsidies may be less effective in certain industrial domains. Despite some recent evidence showing that SBIR evaluation processes are able to identify promising companies (Dutta et al., 2022), our research suggests that government agencies that allocate grants could be more selective in terms of the companies they fund. They may be well advised to focus on funding projects characterized by high technical risk and longer product cycles, compared to those with relatively higher commercial risks in short life-cycle industries. In those latter cases, VC is likely to have both a structural advantage and the ability to evaluate new firms, hence SBIR-like funding might be better allocated to projects with more fundamental technological problems to resolve and longer product cycles. Overall, our study does suggest that SBIR awards are beneficial in terms of helping companies progress – a primary objective of the SBIR program. However, we do suggest that it might be more effective to direct government commercialization grants towards fields where they are more likely to have the greatest positive impact.

CRediT authorship contribution statement

Riccardo Fini, Markus Perkmann and Martin Kenney contributed equally to this manuscript. Kanetaka Maki contributed to the original draft preparation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A

Table A1
Prior work on public grant/SBIR effectiveness for small firms (including new ventures and university spin-offs).

Reference	Sample	Findings
Ayoub et al. (2017)	1568 German academic spin-offs	Firms that obtain a start-up grant grow less, make higher losses and record lower return on capital.
Berger and Hottenrott (2021)	9743 German new ventures (multi-sectoral)	Positive relationship between public subsidies and subsequent VC financing. The relationship is driven by government VC and business angels, but not independent (conventional) VC.
Conti (2018)	2304 Israeli start-ups (multisectoral)	R&D subsidies enhances firm survival rates, the likelihood of attracting external investment, and innovation, but only for recipients applying once the criteria for receiving funding had been relaxed.
Giga et al. (2021)	1794 firms that applied for NASA SBIR	Receiving an SBIR has a positive effect on firm patenting for small firms but not larger firms.
Hottenrott and Richstein (2020)	5267 firm-year observations (German new ventures, multi-sectoral)	Both grants and subsidized loans facilitate tangible investment, employment and revenue growth.
Hottenrott et al. (2018)	2745 German new ventures (multi-sectoral)	Receipt of public subsidy positively impacts new ventures' ability to raise bank loans (signalling effect)
Howell (2017)	4545 US firms that applied for SBIR in two subsectors at Dept of Energy	Receipt of SBIRs has positive effects on various firm-specific outcome metrics
Lerner (1996)	294 multi-sector SBIR recipients, matched with 300 non-recipients	SBIR recipients experience substantially greater employment and sales growth than matching firms
Meuleman and De Maeseneire (2012)	1185 Belgian firms that applied for R&D subsidy (multi-sectoral)	R&D subsidies improve SME's access to financing
Pahnke et al. (2015)	198 US firms with products in minimally invasive surgery devices	Federal grants have a negative impact on patenting and no impact on product innovation among early-stage medical device companies
Söderblom et al. (2015)	284 firms that applied to Vinnova (Sweden) agency for funding	Grants have positive effects on fundraising and attraction of human capital, leading to improved performance
Stevenson et al. (2021)	129 multi-sector firms in a US incubator	Securing a grant has a positive effect on raising VC but not on revenue.
Toole and Turvey (2009)	10,914 US multisector firms (SBIR recipients only)	SBIR Phase II awards increase the probability of obtaining VC funding.
Wallsten (2000)	481 US firms; 367 with SBIRs from Dept of Defence, NASA	SBIRs awards to not affect employment outcomes
Zhao and Ziedonis (2020)	241 start-ups (multi-sectoral) competing for loans from a Michigan programme	Firms that obtained a publicly backed loan show higher survival and raise more follow-on VC. Effect is stronger for very young, inexperienced, non-central firms (reason: financing frictions).

Appendix B. Supplementary material

Supplementary material, including all tables prefixed with "S", can be found online at https://doi.org/10.1016/j.respol.2022.104662.

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