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**State Governments as Financiers of Technology Startups:  
Evidence from Michigan's R&D Loan Program\***

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State governments in the United States often fund and support technology startups within their borders. Yet little is known about the magnitude with which these place-based policy interventions shift the performance trajectories of entrepreneurial firms. We provide new evidence based on 241 startups that compete for advanced research and technology commercialization loans between 2002 and 2008 through a Michigan-based program. Among applicants with project scores near the threshold required for funding, we find that award recipients are 20 to 30 percent more likely to remain in business four years after the competition relative to similar companies that seek but fail to receive funding. We also find that award receipt stimulates follow-on venture capital (VC) investments in surviving companies. The VC stimulus effect is, however, disproportionately driven by subsets of firms that are very young, relatively inexperienced at external fundraising, or located outside the dominant hub of entrepreneurial activity within the state. This distinctive pattern of heterogeneous effects remains visible for follow-on R&D financing from federal government sources, and for supplemental outcome measures that use news articles to track shifts in financing and business development activities. These findings are consistent with the view that public R&D programs are particularly beneficial when frictions in private resource markets are more severe.

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## 1. Introduction

Aiming to ignite economic growth and diversify the tax base within their borders, state governments in the United States are playing a more prominent role as financiers of young science and technology companies (Lerner, 2009; Wessner, 2013; Lanahan and Feldman, 2015). Between 2002 and 2009, for example, the state of Ohio financed over 570 young Ohio-based companies through its \$1.6 billion Third Frontier Program (SRI 2009). Similarly, the Utah Science Technology and Research (USTAR) program has subsidized hundreds of technology projects for startups within the state (Duran, 2010). Many of these “place-based” policy interventions<sup>1</sup> are motivated by concerns that local markets for entrepreneurial resources are underdeveloped, potentially leading good ideas to go unfunded and promising ventures to languish. As Chatterji, Glaeser, and Kerr (2014) report, new science and technology companies spawn from universities, research labs, and established firms throughout the United States, yet the venture capital (VC) typically required to grow such companies is tightly agglomerated in the bicoastal regions.

Despite widespread experimentation by state governments in financing technology startups, little is known about the effects of these local policy interventions on entrepreneurial firms and their endeavors (Armanios, Lanahan, and Yu, 2019). This study provides new evidence based on an R&D loan program in the state of Michigan. Through a series of competitions administered during the decade of the 2000s, the state provided credit access and support services to entrepreneurial firms with advanced research and technology commercialization projects. As reported below, the program was competitive, with only 21 percent of applicant-startups winning funding. The average loan size was quite large, at \$1.2 million, and the typical awardee was a four-year-old life science company.

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<sup>1</sup> Place-based policies refer to government initiatives that impose geographic restrictions on participation by, for example, limiting eligibility to firms based in a given state or region. See Kline and Moretti (2014) and Neumark and Simpson (2015) for more extensive discussion.

Through access to proprietary government archives, we identify all entrepreneurial firms that apply for funding through the program ( $n=241$ ) between 2002 and 2008, including those that seek but fail to receive an award.<sup>2</sup> Importantly, the archives also report the score each proposal receives from an external review panel. Similar to recent studies of competitions for entrepreneurial financing (e.g., Kerr et al., 2014; Söderblom et al., 2015; Howell, 2017), we use these scores to proxy for hard-to-measure quality differences and to isolate more comparable companies that (a) make it to the final round of a competition and (b) receive scores slightly above or below the cutoff required for funding. We follow applicant companies for four years following the competition, test the effects of award receipt on both the extensive (survives/fails) and intensive (outcomes conditional on survival) margins, and explore differences among firms in the magnitude of the effects.

We find a large and enduring effect of award receipt on firm survival. Relative to near-threshold startups that seek but do not receive funding, awardees are 20 to 30 percent more likely to remain in business four years after the competition. The survival effect remains large in magnitude and statistically significant for a six-year window that extends well beyond the three-year payback period typically required for the loans. The finding is robust to the inclusion of numerous applicant- and industry-level controls, is not driven by differential IPO or acquisition exits, and is unlikely to be explained by simple selection bias through our research design. In combination, we interpret this evidence as indicative of binding capital constraints: absent an award, otherwise comparable startups with near-threshold scores are less likely to obtain the resources required to commercialize technological discoveries and remain in business.

Our evidence further suggests that, conditional on surviving, award receipt disproportionately stimulates follow-on VC financing for near-threshold firms that are very young, relatively

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<sup>2</sup> The data were provided for research purposes provided that private information about applicants and projects is not disclosed. We lack reliable information on specific contract terms and repayment histories.

inexperienced in external fundraising, or located outside the dominant hub of entrepreneurial activity within the state—characteristics that plausibly correlate with heightened frictions sourcing resources from private markets. This distinctive pattern of heterogeneous effects is also visible, with minor exception, for follow-on national grants from the Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs.<sup>3</sup> Supplemental analyses of media mentions of applicant-firms’ financing and business development activities yield a similar pattern.

In combination, these findings reveal that even among close-call applicants for state-level R&D funding, award receipt benefits some firms more than others. The magnitude of the effects on firm-level outcomes varies substantially within the program, and is amplified for entrepreneurial firms likely to face more severe informational frictions absent the policy intervention. We test but fail to discern a statistically significant effect of award receipt on patent output measures either overall or for subsets of firms, a somewhat surprising result that we discuss later in the paper.

This study contributes to an ongoing debate on whether financial constraints are a first-order impediment for technology startups in advanced economies. Surveys suggest that securing adequate access to capital ranks among the most substantial barriers for starting and growing a business, particularly in countries with inefficient capital markets (Hyytinen and Toivanen, 2005; Kerr and Nanda, 2011, 2015). Whether financing frictions constrain entrepreneurial activity in advanced economies like the United States is more contentious. Prior evidence is largely based on aggregate state-level shifts in capital inflows (e.g., Samila and Sorenson, 2011), banking regulations (e.g., Chava et al., 2013) and bankruptcy laws (e.g., Cerqueiro et al., 2016). The consensus is that the severity of constraints in entrepreneurial capital markets varies widely across U.S. states and regions, fueling

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<sup>3</sup> The SBIR and STTR programs of the U.S. Small Business Administration (SBA) are the largest source of federal R&D subsidies for small and young companies in the United States (Lerner, 1999, 2009). STTR grants require collaboration with a government research laboratory or university, while SBIR grants do not. For brevity, we refer to these programs collectively as “SBIR” throughout.

concern about widening opportunity gaps within the country and calls for larger-scale policy intervention (e.g., Gruber and Johnson, 2019). We offer a complementary firm-level view and contribute the first systematic evidence from a state-level R&D loan program. In doing so, we add to a small but growing strand of research on state and local innovation policies in the United States and their effects on entrepreneurial activity (Feldman et al., 2005; Safford 2009; Moretti and Wilson, 2017; Lanahan and Feldman, 2018; Lanahan and Armanios, 2018).

The study also contributes to a longstanding and related literature on the private returns to public R&D programs, much of which focuses on the near-term effects on R&D spending (Hall and Lerner, 2010; Becker, 2015). Not surprisingly, most programs allocate R&D subsidies to firms on a competitive and non-random basis. From a policy perspective, this raises the concern that government agencies simply “pick winners” likely to succeed absent the intervention (Wallsten, 2000; Lerner, 2009). Within the empirical literature, our study most closely relates to a small strand of recent research that uses applicant-level data and breakpoints in the awards allocation process to help isolate the potential treatment effects of public R&D programs. Consistent with applicant-pool evidence from grant programs in Italy (Bronzini and Iachini, 2014; Bronzini and Piselli, 2016), Sweden (Söderblom et al., 2015), and the federal SBIR program in the United States (Howell, 2017), our findings add credence to the view that public R&D programs are particularly beneficial for smaller and younger firms. We further show that this pattern holds for a program that provides credit access rather than grants, and reveal a geographic source of variation previously undocumented in the literature.

## **2. The Michigan R&D Loan Program**

Like other states in the Great Lakes region of the United States, Michigan faces longstanding declines in traditional manufacturing industries yet houses top-tier medical and research institutions

(Austin and Affolter-Caine, 2006; Samuel, 2010).<sup>4</sup> In 1999, the state created the Michigan Life Science Corridor (MLSC) program to better leverage institutional strengths and diversify the tax base. Funded with \$1 billion from a legal settlement with the tobacco industry, the MLSC was the largest state-level policy intervention at the time aiming to strengthen innovative and entrepreneurial activity within its borders (Zhao, 2013). In 2004 and after gubernatorial turnover, the MLSC expanded to include other industrial sectors and was renamed the Michigan Technology Tri-Corridor (MTTC) initiative. Soon thereafter, the MTTC initiative became part of the 21<sup>st</sup> Century Jobs Fund (21CJF) program that remains active in the state.

As part of these umbrella initiatives, the state ran a series of competitions from 1999 through 2008 that provided credit access and support services to young companies with innovation-related projects.<sup>5</sup> For brevity, we refer to these competitions as the “Michigan R&D loan program.” The Michigan Economic Development Corporation (MEDC), a quasi-governmental agency, managed the program and oversaw the competitions. From 1999 to 2003, eligibility was restricted to life science-related projects. After 2003 and in line with the broader mandate of the follow-on programs, eligibility expanded to three other sectors: advanced manufacturing and materials; alternative energy; and homeland security and defense. To be eligible, a company had to conduct (or agree to conduct) a substantial portion of business in the state, provide matching funds, and meet other

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<sup>4</sup> The Great Lakes region is one of eight U.S. regions defined by the Bureau of Economic Analysis (BEA), and includes Indiana, Illinois, Ohio, Michigan, and Wisconsin. As reported in Zhao (2013), between 1990 and 2009, the region received 29.1% of all National Institutes of Health (NIH) research funding but only 15.8% of national VC investments in life science startups. By comparison, the bicoastal states of California and Massachusetts received 25.8% of NIH funding but over 55.9% of VC investments in the life sciences. This longstanding disparity between research inputs and the local supply of growth capital for startups was a primary impetus for the policy intervention. Michigan has three tier-one research universities (Michigan State University, the University of Michigan, and Wayne State University) and is the former headquarters location of the Upjohn Corporation and Pfizer’s global R&D center.

<sup>5</sup> This section draws on conversations with program managers, annual Battelle/BIO State Bioscience Initiatives reports, government reports (e.g., MEDC, 2010), and notes from meetings of the Strategic Economic Investment and Commercialization (SEIC) Board archived at <http://mi21cjf.proboards.com/board/1>.

requirements in the Request for Proposals (RFP).<sup>6</sup> Applicants were required to submit a maximum 25-page proposal and to pay a \$500 application fee.

The competitions elicited proposals for “applied research” and “technology commercialization” projects. Applied research projects required collaboration with a university or government laboratory, preferably located within the state, while technology commercialization projects did not require such collaboration. This distinction parallels that of the federal R&D grant program, where STTR grants require collaboration between the private and public sectors while SBIR grants do not. Applied research and technology commercialization projects were otherwise quite similar in scope. According to the RFP in 2006, applied research funds were for “testing, prototype development, pre-clinical trials, and clinical trials” and the “commercialization of the technology by a for-profit company in Michigan.” Similarly, technology commercialization funds were for tasks that support “the transition from research to the actions necessary to achieve market entry.”

As depicted in Figure 1, funds were allocated to projects and companies using a multi-staged selection process. In Round 1, proposals that met the RFP requirements were sent to external reviewers for initial scoring. From 2000 to 2006, technical experts from the American Association for the Advancement of Science (AAAS) evaluated the proposals. In 2008, individuals from the business and investment communities were added. Evaluators scored all proposals using four equal-weighted criteria: (1) scientific merit, (2) personnel expertise, (3) commercialization merit, and (4) the ability to leverage other funds. Proposals with above-cutoff scores in the first round proceeded to Round 2, where evaluators conducted a more intensive assessment, interviewed company representatives, and rescored the proposals as a panel. In a final stage, the MEDC performed additional due diligence on the projects recommended for funding and negotiated contract terms

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<sup>6</sup> According to the 2008 RFP, matching money must be “from a source other than personal funds, reinvested revenues, and/or funds received through other programs from the state of Michigan.” As discussed below, the ability to leverage external funds is an equal-weighted component of the proposal’s overall score.



with applicants on a confidential and one-on-one basis. Applicants could be dropped at this stage for two reasons. First, the state could rescind an award if the due diligence process revealed information that rendered an applicant ineligible (e.g., financial commitments from third parties had fallen through). Alternatively, the applicant could withdraw due to concerns about the contract terms or unrelated reasons (e.g., shifts in corporate priorities). Unfortunately we lack more detailed information on contract terms or withdrawal reasons due to confidentiality restrictions.

According to MEDC officials, the total funds in a competition were determined prior to the RFP and allocated based on rank-orderings of scores in Round 2. The minimum score was unknown to applicants, and reflected the total amount of funds available for disbursement and the quality and scale of other proposals. The highest-ranked projects in Round 2 were recommended for funding until the total budget was expended. As discussed more fully in Section 4, this institutional feature of the program is particularly useful from a research design perspective: total funding in a competition is not determined ex-post by the overall quality of the submissions.

The typical award provided entrepreneurs up to three years of credit at subsidized interest rates, with an option to convert to equity in future rounds of financing. Program managers saw advantages of this financial instrument (of convertible notes) over simple loans, which have limited upside potential, and pure-subsidy grants, which were viewed as more difficult to “sell” politically. Program managers also felt that the loans held applicants more accountable for the use of public funds than fully subsidized grants, since servicing debt typically requires a stable source of cash flow. In contrast, grants were sometimes referred to pejoratively as “free money.”

As shown in Figure 2, the average loan size was \$600,000 in 2002 and exceeded \$1.5 million in the 2006 and 2008 competitions. These amounts are an order of magnitude larger than Phase 1 grants of \$150,000 available through the federal SBIR program and parallel initiatives in other countries (Wang et al., 2017; Hünermund and Czarnitzki, 2019), and are more on par with the

million-dollar Phase 2 grants available to U.S. startups through the federal SBIR program (Lerner, 1999; Howell, 2017).

In addition to credit access, awardees received advice and oversight from an MEDC portfolio manager. Portfolio managers had business backgrounds and typically met with entrepreneurs on a monthly basis to advise and assist as needed.<sup>7</sup> They were also responsible for helping connect entrepreneurs with other resource providers and for featuring the companies in public events. To illustrate, one awardee mentioned that a portfolio manager helped him secure a prominent spot at a growth capital event for entrepreneurs and investors. In principle, the “local” nature of the policy experiment could enhance the effectiveness of these value-added services given the geographic proximity of portfolio managers to recipient firms (McDermott et al., 2009; Feldman et al., 2014). In contrast, federal R&D grants in the United States are often criticized for providing more distant, one-size-fits-all training (Cox Pahnke et al., 2015; Howell, 2017).

### **3. Implications for Entrepreneurial-firm Performance: Theory and Related Evidence**

The primary rationale for subsidizing the R&D projects of firms – whether through grants, loans, or equity-based levers – rests on conditions that lead the social returns to innovation to surpass the private returns to such investments (Hall and Lerner, 2010; Bloom et al., 2013; Brander et al., 2015). Firms underinvest in innovative activity relative to socially optimal levels for several reasons, including spillovers and market frictions.<sup>8</sup> As famously observed by Nelson (1959) and Arrow (1962), the output of R&D (“knowledge”) has a public goods component: use by one firm does not preclude use by another. In the presence of knowledge externalities, or “spillovers,” the

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<sup>7</sup> Of the three portfolio managers we interviewed, one had a law degree and had previously co-founded three technology startups, the second had a business degree and prior experience in commercial banking, and the third had an MBA degree and prior managerial roles at technology companies in the state.

<sup>8</sup> Hall and Lerner (2010) and Kerr and Nanda (2015) review the economic theory underpinning this underinvestment problem. Yao (1988) and Mahoney and Qian (2013) discuss the implications for firm performance.

socially optimal rate of R&D investment can exceed the private returns to such investment (Griliches, 1992).

Funding gaps also arise due to information-related frictions that increase the cost of external financing. These frictions, while challenging to observe directly, are widely assumed to be more severe for entrepreneurial firms (Hall and Lerner, 2010). As Booth and Smith (1986) establish, an entrepreneur is often better informed than outside parties about embryonic technologies under development. If the entrepreneur is unable to remove this information barrier, whether due to strategic concerns of disclosure or a lack of credible quality signals, financiers will charge a well-known “lemon’s premium” (Akerlof, 1970), thus increasing the costliness of external capital. When asymmetric information problems are severe or monitoring is costly, the capital required to develop risky projects will be rationed (Leland and Pyle, 1977; Stiglitz and Weiss, 1981). In turn, some “good” projects (i.e., those with positive net present values absent contracting frictions that now fall below the private returns hurdle) will face binding capital constraints and go unfunded.<sup>9</sup>

In theory, public R&D programs can transform the innovative pursuits of young companies into profitable investment opportunities by lowering capital costs, reducing market frictions, or both (Hall and Lerner, 2010). Subsidies directly reduce the “lemon’s premium” for early-stage investments through cost-sharing. If entrepreneurs use subsidized funds to move nascent technologies forward (e.g., through prototyping and testing), the projects could advance to a stage where frictions in private markets are less severe (Toole and Turvey, 2009; Howell, 2017). In this scenario, the subsidies could transform a project from negative to positive net present value in expectation and potentially stimulate funding from private sources in later stages of the development life cycle. For competition-based programs, the information gap could be narrowed further if award

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<sup>9</sup> Venture capitalists reduce this funding gap through staged investments, equity and control rights, and the active monitoring of young companies (e.g., Hellmann and Puri, 2002; Gompers and Lerner, 2004). VCs also provide quality signals that reduce information asymmetries with later-stage resource providers (Megginson and Weiss, 1991).

receipt sends a credible signal that helps “certify” the quality of the project or firm to other resource providers (Lerner, 1999; Feldman and Kelley, 2003; Lanahan and Armanios, 2018). Finally, public R&D programs could improve the performance of entrepreneurial firms in ways that span beyond the monetary value of the award. Examples include training services and preferential access to resource providers (Feldman and Zoller, 2011; Söderblom et al., 2015; Armanios, Eesley, Li and Eisenhardt, 2017). These channels are not mutually exclusive and are potentially inter-related. In combination, however, they suggest that public R&D programs should be particularly beneficial for entrepreneurial-firm projects when frictions in private resource markets are more severe.

Even if imperfections exist in private capital markets, it is not obvious that public R&D programs will reduce them. As Lerner (2009) notes, government R&D programs are notoriously difficult to design and manage. The U.S. SBIR program, for example, has been criticized for incentivizing rent-seeking behavior where “mill” companies remain in business simply by parlaying one government grant into many others.<sup>10</sup> Others voice similar concern that public R&D programs sub-optimally support “zombie” companies and “phantom” projects (Wang et al., 2017). In this scenario, public R&D funding could keep weak companies afloat without stimulating private-capital investments or bringing new technologies to market. Equally controversial, distortions can run in the opposite direction. To establish track records of success, program managers have incentives to pick projects that are likely to succeed, which could displace or even crowd out private sources of capital (David et al., 2000; Wallsten, 2000; Lach 2002; Czarnitzki and Lopes Bento, 2013). In this latter case, policy failure rests in the selection of projects likely to succeed absent the intervention—a counterfactual scenario that is difficult to discern with observational data.

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<sup>10</sup> An alternative “learning-by-doing” interpretation is that entrepreneurs learn from participating in one public R&D program in ways that lowers the cost of applying for funds from other government sources or increases the odds of success when doing so (Zúñiga-Vicente et al., 2014; Lanahan and Feldman, 2015, 2018).

Despite longstanding study, empirical evidence on whether and how public R&D programs shift the performance trajectories of entrepreneurial firms remains limited (Hall and Lerner, 2010; Becker 2015; Dimos and Pugh, 2016).<sup>11</sup> In addition to well-known measurement challenges when tracking startups, it is often difficult to observe which companies apply for but do not receive public R&D funding. Not surprisingly, government agencies are reluctant to reveal the identities of unsuccessful applicants. In light of this challenge, comparison groups are often assembled by matching award recipients to non-awardees based on observable characteristics (e.g., industrial sector and age). While useful, matching methods naturally raise questions about whether control group firms have private incentives to participate in the program or differ from award recipients in other unobservable ways likely to correlate with future outcomes (David et al., 2000; Hall and Lerner, 2010).<sup>12</sup>

Of particular relevance for our study, a small but growing stream of research leverages access to confidential data on entrepreneurial firms that apply for but do not necessarily win R&D subsidies in competition-based programs. Comparison groups of treated and untreated firms are compiled from the pool of applicants, thus ensuring that both groups are in the “risk pool” for funding. If available, proposal scores and finalist lists are used to control for quality differences among firms and projects. As discussed more fully in Section 4 and in Jaffe (2002), discontinuities in the awards allocation process can yield estimates of counterfactual outcomes if certain conditions are met. The main tradeoff is external validity: the findings may not generalize to broader populations of firms.

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<sup>11</sup> Much of the early research on public R&D programs focused on publicly traded firms that report R&D spending, thus tilting samples toward established firms. David et al. (2000), Klette et al. (2000), Jaffe (2002) review the early literature and discuss key measurement and methodological challenges. Hall and Lerner (2010), Zúñiga-Vicente et al. (2014), Becker (2015), and Dimos and Pugh (2016) review more recent studies and methodological advances.

<sup>12</sup> An alternative method exploits exogenous sources of variation in budget allocation rules within a program. Einiö (2014), for example, uses population-density rules to test the effects of R&D subsidies on Finnish firms. The median age of firms in his estimate sample is 12 years old. He finds a positive stimulus effect for firms on average, both for R&D spending and firm-level outcomes such employment and sales growth three years following the award. Also for a European program but using a different allocation rule, Hünermund and Czarnitzki (2019) reach a starkly different conclusion. They find that R&D grants to small and medium-sized companies fail to stimulate employment and sales growth except for projects at the upper tail of the quality distribution.

Table 1 lists recent studies that use applicant-pool data to test the effects of R&D programs on entrepreneurial firms in Italy (Bronzini and Iachini, 2014; Bronzini and Piselli, 2016), Sweden (Söderblom et al., 2015), the United States (Howell, 2017), and China (Wang et al., 2017). All of the studies feature national or regional R&D programs. Most of the programs subsidize projects only with grant-based levers. China’s Innofund is an exception. Although that program typically awards grants, it sometimes uses loan and equity-based levers (Wang et al., 2017).

The programs in Table 1 vary in terms of the amounts of funding that they provide and the types of firms and projects that they target. The per-project funding amount in the Italian and Chinese programs is comparable to the \$150,000 proof-of-concept (Phase 1) grants administered through the U.S. SBIR program. Similar to Michigan’s R&D loan program, the Italian program further requires cost-sharing and use of private funds to cover a portion of the project’s expense.<sup>13</sup> The Swedish Win Now program supports proof-of-concept projects, provides relatively little funding (a ~\$40,000 grant), and targets one-to-two year old companies. At the other extreme, Phase 2 grants in the U.S. SBIR program support later-staged technology development projects and provide up to \$1 million in funding. In the Howell (2017) study, the average company is 9.2 years old when it applies for SBIR funding. The age profile in China’s Innofund program is more comparable to that in our sample, with the average applicant-company ranging between 3 and 4 years old in the year of competition (Wang et al., 2017).

Despite common use of applicant-pool data and broad similarities in program objectives, the studies in Table 1 reach wide-ranging conclusions. For the regional Italian program, Bronzini and

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<sup>13</sup> The Italian program studied by Bronzini and Iachini (2014) and Bronzini and Piselli (2016) restricts participation to firms located in a particular region of the country. Although the program targets entrepreneurial ventures, established companies are eligible to participate. In Bronzini and Iachini (2014), the median age of applicant-companies is 17 years old. The other programs in Table 1 limit participation to small and medium-sized firms, and impose “place-based” restrictions at the national level. For example, the U.S. SBIR and China Innofund programs require that at least 50 percent of the equity stakes in an applicant company be owned by citizens of the respective countries.

Iachini (2014) find no evidence that award receipt improves the performance of firms on average. The lackluster finding masks, however, a large and significant boost to the employment and sales trajectories of smaller and younger firms. Using an expanded sample and a longer time period, Bronzini and Piselli (2016) report a significant treatment effect on patented output, particularly among smaller companies. Howell (2017) documents a similar pattern of heterogeneous effects for the SBIR program: Phase 1 grants lead to an uptick in innovative output as well as follow-on VC financing on average, particularly for firms that are younger, relatively inexperienced, or in less mature technology areas.<sup>14</sup> Howell attributes the effects to direct use of the funds for prototyping and product development (i.e., cost-sharing) rather than to quality certification. In contrast, Söderblom et al. (2015) attribute the positive effects of the Swedish Win Now program to a “halo effect” and quality certification, due in part to the small monetary value of the awards.<sup>15</sup>

At odds with the other studies in Table 1 and based on evidence from China’s Innofund program, Wang et al. (2017) fail to discern a significant effect of R&D subsidies on a wide range of firm-level outcome variables, both overall and for younger and smaller firms. This contrast is particularly striking given structural similarities with the Italian and U.S. programs. Wang and colleagues attribute the “non-findings” in part to the widespread availability of private capital in Beijing, where most of their applicant-companies are based. They further document, however, that the funding process is shaped by political connections, with some low-scoring projects of well-

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<sup>14</sup> These stimulus effects are consistent with the “added value” evidence in Lerner (1999) for earlier cohorts of SBIR winners but at odds with evidence in Wallsten (2000) that SBIR funding displaces private R&D investments. Howell (2017) also finds that Phase 1 awards increase the likelihood of business survival through 2016 by 12 to 14 percentage points on average. She finds much less salient effects of million-dollar Phase 2 awards on firm-level outcomes, which she attributes to a more onerous application process for the larger awards and the abilities of Phase 1 winners to secure superior sources of financing elsewhere.

<sup>15</sup> Söderblom et al. (2015) do not test the effects of award receipt on the likelihood of firm survival or patent-based outcome measures. All treated companies are very young and small. Intriguingly, the authors suggest that the “halo” effect can shape not only access to financial resources but also access to human capital through a recruitment channel.

connected entrepreneurs winning awards. This latter finding resonates with observations in Lerner (2009) that public R&D programs are difficult to manage and can give rise to rent-seeking behavior.

A priori, it is unclear how distinctive characteristics of the Michigan R&D loan program (e.g., a state-government rather than regional or national intervention; use of loans vs. grants as the main vehicle for financing) might affect the benefits that entrepreneurial firms derive from participation, if any. The program's overarching aims are similar to any R&D subsidy program: to lower capital costs for innovation-related projects or to reduce the frictions that entrepreneurial firms would otherwise face in private resource markets, albeit for companies doing business within the state. If the program succeeds in relaxing such constraints, its effects should mirror those expected for grant-based initiatives. The fact that the program is "local" and implemented in a geographic area with a relative lack of growth capital for startups could increase the likelihood of benefits relative to the counterfactual scenario of no intervention, provided that the applicant pool is sufficiently strong. Relative to national programs, the extra-financial services associated with the program could be better tailored and more effectively implemented due to closer proximity between program administrators and recipient firms. The "local" nature of the program could, however, intensify political forces and the type of rent-seeking behavior documented in Lerner (2009) and Wang et al. (2017). In this scenario, the program might keep languishing companies afloat with little impact on the mobilization of private capital typically required to develop and commercialize new technologies.

Whether and how the financing mechanism (loan versus grants) alters the benefits that firms derive from participating in the program is ambiguous from a theoretical perspective.<sup>16</sup> Although the

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<sup>16</sup> In Hall and Maffioli (2008), the predicted effects of both loan and grant R&D subsidies hinge on the severity of financial constraints in private markets. The main difference relates to an extensive margin unobservable to us: relative to loans, R&D grants should stimulate more entry even with cost-sharing. In line with that view, Huergo and Moreno (2017) find that public R&D grants in Spain attract a higher share of small-firm applicants relative to R&D loan programs in that country. Lach et al. (2017) model the optimal design of R&D loan programs from a social welfare perspective. Laudably, the authors examine how loan terms (interest rates, co-financing requirements) affect entrepreneurial incentives to exert costly effort and advance the project. The model assumes, however, that capital markets are competitive and focuses on contract terms unobservable in our study.



need for repayment could further incentivize entrepreneurs to move projects forward, it could also intensify financial pressures in the event of unexpected setbacks (Huergo and Moreno, 2017). If true, award receipt could lead to a temporary boost to survival, followed by accelerated rates of business failure when repayment is due. Relative to standard grants that do not require repayment, loans could also increase incentives to engage in near-term tasks likely to generate cash flows to service the loans, which could reduce risk-taking and experimentation relative to an equivalent cost-sharing subsidy administered through a grant-based lever.

In sum, empirical evidence on the effects of public R&D programs on entrepreneurial firms and their endeavors is mixed and wide-ranging—even among studies to date that test effects using applicant-pool data. We contribute new evidence based on a state-government intervention for science and technology startups in the United States and offer a rare glimpse inside a loan-based R&D program. Given ambiguities in how unique aspects of the program might differentially affect the benefits firms derive from participation and our lack of comparative data (i.e., from programs that fund similar projects with grants rather than loans), we treat the matter as an empirical question and investigate the effects from multiple angles.

#### **4. Empirical Approach**

Disentangling the effects of Michigan’s R&D loan program on entrepreneurial-firm outcomes is difficult, even with access to data on the applicant pool and their projects. Analysis requires time-varying data on privately held companies from multiple sectors. Key constructs such as funding gaps and information frictions are infeasible to observe directly. And the awards process is merit-based, raising concerns that performance differences between awardees and non-awardees ex-post stem from the selection of more promising projects ex-ante. This section describes our sample, data sources, and empirical approach with these challenges in mind.

#### *4.1. Sample Construction and Data Sources*

The MEDC archives revealed 264 entrepreneurial firms that applied for funding through the program between 2002 and 2008, including those that sought but failed to receive an award. Competitions were held each year during this period except in 2007. “Entrepreneurial firms” or “startups” are defined as for-profit entities founded within 15 years of the focal competition. This age filter eliminates 23 older companies but retains 92 percent of all for-profit applicants. Hellmann and Puri (2002) and Stuart et al. (1999) respectively use 11 and 12 years post-founding to classify “startups.” Since the Michigan program is administered during the 2000s, a decade that includes an economic recession and challenging market for IPO exits, we prefer a less restrictive 15-year threshold. The results are qualitatively unchanged if the sample is restricted to companies founded less than 11 or 12 years prior to the competition.

For each proposal, the archives indicated whether the project was in collaboration with a government research lab or university (“advanced research”) or not (“technology commercialization”), its stage of advancement in the competition, its average score from the external review panel, and the amount of funds awarded if any. The archives also provided basic information about the companies (name, primary sector, and headquarter location). As discussed more fully below, we compile added information about the companies from the following sources: the Michigan Department of Licensing and Regulatory Affairs (LARA) government registry of companies doing business in the state (for establishment years and business status), the Dow Jones VentureSource database (for VC investments), the Small Business Administration TECH-NET database (for federal SBIR and STTR grants), Google Maps (for geographic distance measures), Factiva (for media mentions), and Delphion (for patent information).

Thirteen companies (5%) submitted multiple applications to a competition. If the firm received funding in that competition, we omit its unfunded proposals from the control sample. For non-

awardees with multiple submissions, we retained only the top-ranked proposal in the control group to ensure greater comparability with awardee applications. The resulting sample comprises 297 proposals filed by 241 startups between 2002 and 2008. Of these proposals, roughly half (49%) were screened out in Round 1. The remaining half (51%) advanced to Round 2 in a competition.

#### 4.2. Main Outcome Variables

Our primary outcome variables include (a) whether a company remains in business in a given year (i.e., business survival) and (b) conditional on surviving, the extent to which a company succeeds in attracting follow-on financing from other external sources.<sup>17</sup> We track these outcomes for two years following a competition and for a longer four-year window. Table 2 lists the main outcome and control variables, with corresponding data sources.

The first outcome variable, *Survives*, equals one if the company is active and in good business standing in year  $t$  as reported in the Michigan LARA registry of companies doing business in the state. The LARA database lists five business status types (active, active but not in good standing, dissolved, withdrawn, and merged) and indicates when a firm switches type, if at all. For firms in categories other than “active,” we searched company websites and press releases to ensure that “dissolved” or “withdrawn” did not reflect a reorganization via a merger or acquisition or relocation. In ambiguous cases, we called the company to see if it was still in business. Of the 241 applicant startups, 23 (8 percent) had merged or been acquired by 2012. We treat these observations as having survived (not failed). The results do not change if we exclude merged or acquired startups from the estimation sample.

For follow-on financing, we distinguish between private (venture capital) and other government (federal SBIR) sources. The variable *#VC investments* measures the number of VC investments in the

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<sup>17</sup> In supplemental analyses, we track shifts in patenting and media proxies of funding and business development activity. We lack reliable time-varying information on R&D spending, employee counts, or revenues for these young companies.

company as listed in the Dow Jones VentureSource (VS) database.<sup>18</sup> In the Michigan program, the funding amount was negotiated on a case-by-case basis with applicant companies based on the project's scope and requirements. Loan size could therefore mechanically influence the amount of funds subsequently raised from equity investors. We therefore test the VC stimulus effect using the number of follow-on VC investments rather than the amount of subsequent VC funding. Funding amounts are also more sparsely reported.

A parallel variable, *# SBIR awards*, tallies the annual number of SBIR and STTR grants to the company as listed in the SBA TECH-Net database. SBIR/STTR grants are a relevant source of public R&D funding in all four sectors represented in our study. The young age profile of companies in our sample (averaging four years old up to a maximum of 15 years post-founding) also is well in line with that reported for SBIR recipients. Howell (2017), for example, finds an average age of 9.5 years for SBIR applicants in the energy sector. Lanahan and Armanios (2018) document an older profile (of 17 years on average) in all sectors but for companies located in a Southern U.S. region. We therefore assume, based on the age profiles and project types, that applicant companies are at risk of seeking funds from the federal SBIR/STTR program.<sup>19</sup>

It is important to distinguish between follow-on funding from private (VC) and other government (federal SBIR) sources for several reasons. First, if we find a positive stimulus effect only for follow-on financing from government sources, it raises concerns of potential rent-seeking behavior as documented in Lerner (2009) and Wang et al. (2017). An important litmus test and program aim is the mobilization of follow-on investment from private (non-government) sources.

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<sup>18</sup> We restrict attention to investments categorized as equity-based financing events. The results are robust to use of financing data from VentureXpert (VX), another leading VC database and unit of Thomson Reuters. We prefer use of the VS data because non-equity investments are coded in a more consistent manner. Kaplan et al. (2002) discuss commonalities and tradeoffs between the VX and VS databases in more detail.

<sup>19</sup> In a recent study of funds received by technology startups from different sources, Cox Pahnke et al. (2015, p. 624) report that the temporal ordering is indeed quite fluid: "some firms took government funding before turning to VCs and CVCs [Corporate Venture Capitalists], while others took VC funding and then turned to the government later... In all, we found that ventures pursued a variety of funding strategies."

At the same time, participation in the state-level program could increase a firm’s success in federal R&D grant competitions, whether due to quality certification (Lanahan and Feldman, 2018) or to learning-by-doing effects and training. Absent access to confidential SBIR/STTR applications data, we explore this possibility by tracking shifts in federal SBIR and STTR grants awarded to firms and testing for differential effects within the sample.

### 4.3. *Information-related Proxies*

Information frictions in entrepreneurial capital markets are unobservable. It is reasonable to assume, however, that more information about startups and the commercial potential of their endeavors is available for older (versus younger) companies and for those that have (versus have not) previously obtained external funding to develop their ideas.<sup>20</sup> We therefore use each company’s age and prior track record in fundraising as proxies likely to correlate with varying levels of financing frictions. The age-related variable, *Age in Application Year*, is defined as the year of the focal competition minus the company’s establishment year recorded in the LARA database. For prior fundraising activity, we use an indicator variable, *Has VC Funds or SBIR awards in prior 4 years*, set to one if the firm received at least one VC investment or SBIR/STTR grant in the four years prior to the MEDC competition. We obtain similar results based on counts of prior VC and SBIR funding, with separate variables for each funding source, and with counts from the first year of founding.

Our third information-related proxy leverages heterogeneity among firms in geographic location. As Sorenson and Stuart (2001) and Chatterji et al. (2014) suggest, co-location within a cluster of entrepreneurial activity can reduce ex-ante search costs for capital and support services. Such proximity can also reduce ex-post monitoring and coordination costs for resource providers such as banks or venture capital investors (Bernstein, Giroud, and Townsend, 2016). We therefore assume

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<sup>20</sup> In a similar spirit, smaller (larger) firms are often assumed to face more (less) severe information frictions in private capital markets. Unfortunately, we lack reliable employment data for these companies.

that, absent the policy intervention, information frictions in private resource markets will be less severe for startups located in an entrepreneurial cluster with funding sources nearby. In turn, if the program serves a friction-reducing role, its marginal impact on within-cluster firms should be lower.

Consistent with patterns reported across U.S. states, we find that venture capital and technology startup activity is spatially agglomerated in Michigan—with a dominant cluster near Ann Arbor, where the University of Michigan and most Michigan-based VCs are based.<sup>21</sup> We therefore define *Distance to Entrepreneurial Hub* as the distance (in miles) between Ann Arbor and each applicant’s headquarter location. The results are robust to designation of the Detroit-Ann Arbor metropolitan area as the hub location and use of alternative inside/outside hub indicator variables.

#### 4.4. Methodology

An ideal test of award receipt on firm-level outcomes would distribute funds to projects and companies on a random basis. Lacking that ideal, we use multiple approaches and samples. To provide a point of comparison, we start with a “naïve” (baseline) regression based on all entrepreneurial-firm applicants and control for observable characteristics. The baseline model is as follows:

$$Y_{it+1} = \Phi(\alpha \text{funded}_{it} + X_{it}\delta) \quad (1)$$

In equation (1),  $Y_{it+1}$  is the outcome variable of applicant  $i$  in the subsequent period  $t+1$ ,  $\text{funded}_{it}$  is a binary variable indicating whether the company receives R&D subsidies through the Michigan program in year  $t$  (1=funded; else=0), and  $X_{it}$  is a vector of controls for competition year, project, and applicant-level characteristics.

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<sup>21</sup> Based on VentureXpert data, VCs in the Detroit-Ann Arbor metropolitan area supplied roughly 85 percent of VC equity in Michigan startups between 2000 and 2008. Of 829 Michigan startups with VC financing in this period, 318 (38 percent) are based in Ann Arbor. The second-ranked locale is Detroit, with 124 (15 percent) of the companies.

An advantage of using applicant-pool data is the inclusion of startups that seek but do not necessarily receive funds through the program, thus revealing common intent that is difficult to establish from matches based on observable characteristics alone (David et al., 2000; Klette et al., 2000; Jaffe, 2002). The obvious drawback is that if applicants with superior projects receive awards, as seems plausible, the coefficient on *funded* will be biased upward if quality differences are insufficiently captured by the controls. In that scenario, the average treatment effect attributable to the program is overstated.

Refining the baseline (control for observables-only) regressions, our second approach restricts the sample to firms in Round 2 and uses their scores in that round to control for differences observable to the review panel but otherwise difficult for us to measure. Put differently, this approach focuses on finalist companies and assumes that project scores correlate with hard-to-measure quality differences among them.

Our third and preferred approach leverages information about the subset of companies with project scores near the threshold required for funding and tests effects using regression discontinuity-based methods (Jaffe, 2002; Lee and Lemieux, 2010). To identify “near-threshold” applicants, we create a narrow bandwidth surrounding the threshold score that (as shown below) provides covariate balance and a sufficient sample size for hypothesis testing. The bandwidth includes 103 applications in a 15-point region.<sup>22</sup> Intuitively, we assume that the degree of omitted variable bias declines as we focus on companies that win or fail by small margin. The main trade-off is that the estimates are “local” by design and may not generalize beyond the threshold region, as noted earlier. The decline in sample sizes also could reduce estimation precision. In robustness tests,

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<sup>22</sup> The results of power tests (available upon request) suggest that the sample size is sufficiently large for hypothesis testing. We nonetheless interpret a lack of statistical significance for coefficients with caution, and test the robustness of key findings with the expanded (but less comparable) 20-bandwidth and Round 2 samples.

we find similar results using a wider bandwidth of 127 applications within 20 points of the threshold score, albeit with a decline in covariate balance.

As Lee and Lemieux (2010) describe, a central assumption in regression discontinuity-based methods is there is an element of randomness or noise that (in our case) leads some firms to fall slightly below versus slightly above the threshold score for reasons that do not map one-to-one onto unobservable quality differences. If applicants successfully lobby to receive above-threshold scores, this assumption is violated. As noted earlier, the Michigan program is designed and managed in a way that makes score manipulation unlikely. In line with this observation, Figure 3 fails to reveal a “missing mass” of scores immediately below the breakpoint score. The score density function is smooth in the threshold region.<sup>23</sup>

Figure 4 shows that the probability of award receipt shifts discontinuously at the breakpoint score. Of particular importance and in contrast to Wang et al. (2017), we find no evidence that projects with below-threshold scores are funded. As noted earlier, however, an above-threshold score is not perfectly deterministic of award receipt in our sample since some above-threshold applications are withdrawn or rescinded.<sup>24</sup> Given this structure, we ideally would estimate effects using “fuzzy” regression discontinuity methods that use an above or below cutoff indicator to instrument for award receipt while controlling for scores (Lee and Lemieux, 2010). Unfortunately, we lack a sufficient sample size to implement such an approach with our outcome variables. Similar to Bronzini and Iachini (2014) and Kerr et al. (2014), we therefore estimate effects by comparing

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<sup>23</sup> Howell (2017) shows a smooth score density function in the cutoff region for SBIR energy projects. In contrast, Bronzini and colleagues show a “missing mass” of scores immediately below the cutoff in the northern Italy program, which raises concerns of score manipulation. Bronzini and Iachini (2014) and Bronzini and Piselli (2016) report that their results are robust to the omission of at-threshold companies from the estimation sample. For China’s Innofund program, Wang et al. (2017) report awards to below-threshold firms even without score manipulation.

<sup>24</sup> As noted earlier, we are unable to observe which applications withdrawn (e.g., due to an inability to reach agreement on terms of the loan or receipt of preferable sources of funding) versus rescinded. Non-awardees with above-threshold scores are, however, comparable on average with other near-threshold companies based on observable characteristics. In the regressions, non-awardees with above-threshold scores are included as control observations that are not treated.



subsidized and non-subsidized applicants that win or fail by small margin while controlling for observable characteristics and project scores. The results are similar but less precise when we remove the subset of untreated above-threshold companies from the estimation sample. Doing so eliminates 17 proposals from the 15-bandwidth region.

#### *4.5. Summary Statistics*

Table 3 reports summary statistics for the full sample of entrepreneurial firms that apply for funds through Michigan's R&D loan program between 2002 and 2008. The applicants are quite young in the year of the competition, as noted earlier, with a mean age of four years since founding. As expected given the program's history, the life sciences sector is heavily represented, with roughly half (49%) of the applications. Most of the submissions (77%) are for "technology commercialization" projects that do not include a university or government partner. Relatively few companies have SBIR grants (22%) or venture capital funding (7%) prior to the competition, which is not surprising given the age profile of the applicant companies. Out of 297 applications, 21 percent are selected to receive R&D subsidies through the program.

Table 4 reports similar statistics for two subsamples of applicant companies: (a) awardees and non-awardees that make it to the second round of the competition, and (b) the subset of Round 2 companies within 15 points of the threshold score required for funding. Mean values are reported, along with two-tailed t-tests for equality of means and Komogorov-Smirnov tests for equality of distributions.

For the near-threshold applicants, Columns 5-8 in Table 4 show that awardees are similar to non-awardees based on numerous observable characteristics, including the mean number of SBIR awards and VC investments in the four years prior to the competition. (The results are similar based on difference tests of median values.) The one exception is industry composition: life science projects are more heavily represented among awardees in the near-threshold sample. Sector controls

are therefore included in all regressions. As expected, Table 4 further reveals that awardees and non-awardees are more comparable to one another in the near-threshold region (Columns 5-8) than is true for all Round 2 competitors (Columns 1-4).

## 5. Results

Does receipt of state R&D funding shift the performance trajectories of technology startups? If so, do the awards benefit some companies more than others? We present three sets of analyses that inform these questions. The first estimates the effects of award receipt on firm survival. The second set tests whether, conditional on survival, award receipt tends to stimulate follow-on financing from other external sources either on average or for subsets of firms. The null hypothesis, that program participation does not significantly improve startup outcomes, could arise if equivalent or superior resources are available to advance the projects absent the intervention—a valid and important prediction (Lerner, 2009; Wang et al. 2017). In a final set of supplemental analyses, we investigate the robustness of our results to use of alternative media and patent-based outcome measures.

Table 5 reports bivariate correlations for the variables used in the main regressions and startup-applicants within 15 points of the threshold score. The outcome variables measured at two and four years post-competition are highly correlated, which is not surprising. As expected and shown earlier, Round 2 scores positively correlate with receipt of an award (“Funded”). The statistics are similar for the more expansive samples of all startup-applicants and all Round 2 competitors.

### 5.1 *Effects on startup survival*

Table 6 reports regression estimates of equation (1) with two time-periods of survival and the three estimation samples: all startup applicants (Columns 1 and 2), those making it to the second round of a competition (Columns 3 and 4), and those within 15 points of the threshold score (Columns 5 and 6). The dependent variable, *Survives*, is a binary indicator of whether the applicant remains active and in good business standing two or four years after the competition. Panel A

includes basic controls for application year, sector, and project category. Panel B adds controls for other observable firm-level characteristics related to each startup's age, prior funding, and geographic location. For the Round 2 and near-threshold (15 bandwidth) samples in Columns 3-6, Panel B also includes standardized Round 2 scores as an additional control for firm characteristics that are observable to external reviewers (e.g., through interviews with the entrepreneurs) but unobservable to us. The estimates are based on linear probability models with robust standard errors clustered at the applicant-firm level, and are robust to use of Cox proportional hazards models.<sup>25</sup>

Turning first to the full sample of entrepreneurial-firm applicants in Columns 1 and 2, the coefficient on the *Received award* indicator is positive and significant both in Panel A and in Panel B that includes a richer set of applicant-level controls. Importantly, in Panel B and with the full slate of controls, the *Received award* indicator remains positive and significant for the more comparable subset of Round 2 companies (in Columns 3 and 4) and those within 15 points of the threshold score (in Columns 5 and 6), albeit only for the four-year period.

The time pattern in Columns 3-6 of Table 6 is particularly striking. If the survival effect is merely due to keeping a company afloat through temporary access to credit, the magnitude of the effect should fade after three years, when repayment is typically due. At odds with this view, the *Received award* coefficients in Columns 4 and 6 for the four-year post-award period are larger in magnitude than those reported in Columns 3 and 5 for the shorter two-year window and are statistically significant at conventional levels. In Panel B with the added applicant-level controls, the coefficients in Columns 4 and 6 suggest that awardees are between 18.9 to 31.4 percent more likely to survive four years after the competition relative to similar applicants that seek but do not receive funding. As a robustness check, we estimate the survival effect with an extended six-year window. The

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<sup>25</sup> All unreported results and robustness checks are available upon request.

magnitudes and significance levels are comparable to those reported in Columns 4 and 6 for the four-year window.

## 5.2 *Effects on follow-on financing conditional on survival*

It is possible, of course, that R&D subsidies keep companies alive without having a meaningful effect on their abilities to mobilize other external resources required to develop and commercialize their projects. On one hand, recipients of R&D subsidies from one government program could gain experience that makes them more likely to succeed in other public R&D competitions, a learning effect that could create linkages across multiple levels of innovation programs (Zúñiga-Vicente et al., 2014; Lanahan and Feldman, 2018). On the other hand, and more troublesome from a policy perspective, firms could use R&D subsidies from multiple government sources to keep weak or “zombie” projects alive (Lerner, 2009; Wang et al., 2017). We therefore investigate whether award receipt stimulates follow-on financing not just from other government (federal SBIR) sources but also from more selective venture capital investors.

Table 7 reports Poisson quasi-maximum likelihood estimates for two finance-related outcome variables: *# VC investments*, and *# SBIR awards*.<sup>26</sup> As before, we use robust standard errors clustered at the applicant-firm level, report results for two- and four-year windows, and include application year, project category, and sector fixed effects in all regressions. Panel A reports results for all startups that remain in business in the relevant time window. Panel B shows parallel estimates for near-threshold companies, while Panel C tests the sensitivity of those results to the inclusion of the full slate of firm-level and score controls.<sup>27</sup> For brevity, we report results for near-threshold

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<sup>26</sup> Poisson QMLE outperforms OLS when dependent variables are non-negative and skewed, allows for over-dispersion in the data, and produces unbiased estimates under less stringent assumptions than negative binomial estimators (Cameron and Trivedi, 2013; Santos and Tenreiro, 2006, 2011). Our main findings are robust to use of negative binomial estimators, also with robust standard errors clustered at the applicant-firm level.

<sup>27</sup> Appendix Table A1 provides more detailed output for Panels B and C, including coefficients and standard errors on the main control variables.

applicants based on the 15-bandwidth sample here and below. The results are qualitatively similar for the less comparable set of all Round 2 companies.

For follow-on VC investments, the estimates in Columns 1 and 2 of Table 7 are generally indicative of a positive stimulus effect on average. In the most stringent specification in Panel C of near-threshold firms with added firm- and score-level controls, the *Received Award* coefficient is large in magnitude and significant at conventional levels in both time windows. To interpret, the coefficients on the *Received Award* indicator in Columns 1 and 2 of Panel C suggest that awardees receive between 5.4 ( $=\exp(1.680)$ ) and 4.9 ( $=\exp(1.582)$ ) more VC investments two to four years after the competition than non-awardees in the threshold region. These estimates are consistent with the VC stimulus effects documented for the federal SBIR program (Howell, 2017) and for the R&D grant program in Sweden that targets very young firms (Söderblom et al., 2015). The findings conflict, however, with evidence from China's Innofund Program (Wang et al., 2017).

Turning to follow-on SBIR funding and Columns 3 and 4, the coefficient on *Received Award* is positive and significant only for the full applicant sample in Panel A. For more comparable near-threshold firms and with more stringent controls, the average effect is insignificant at conventional levels. While recipients of funds through the Michigan R&D loan program receive more follow-on SBIR and STTR grants on average, the effect dissipates and is indiscernible from zero for the more comparable subsamples and with added controls.

Taken together, the evidence in Table 7 is inconsistent with a simple rent-seeking explanation for the survival findings. We find no evidence that receipt of funds through the Michigan program stimulates financing only from other government (federal SBIR) sources. Rather, for near-threshold firms on average and with stringent controls, award receipt predicts a significant increase in follow-on funding from private (venture capital) sources but not from the federal SBIR/STTR program.

The lackluster average effect on follow-on SBIR funding could, however, mask substantive differences within the sample—a possibility that we turn to below.

### 5.3 Heterogeneity among startups in the magnitude of the effects

If the Michigan R&D loan program serves a meaningful friction-reducing role, it should “matter more” for firms likely to face greater challenges sourcing entrepreneurial resources absent the intervention. To investigate this possibility, we sequentially interact the *Received Award* indicator the three proxies likely to correlate with wider information gaps between entrepreneurs firms and external resource providers: (1) *Has prior VC or SBIR funding*, (2) *Age in application year*, and (3) *Distance to entrepreneurial hub*. The first variable, on prior fundraising experience, is a binary (yes/no) indicator. The age and distance variables are continuous measures. *Distance to entrepreneurial hub* is log-transformed to mitigate the potential effects of outlier observations.

To test for heterogenous effects, we add each interaction term in turn to the preferred specification reported earlier in Panel C of Table 7, of near-threshold companies with the full slate of applicant and project controls. Appendix Tables A1 and A2 (columns 2 and 7) reproduce this specification for the VC and SBIR outcome variables respectively. For brevity, we report results only for applicants within 15 points of the threshold score required for funding. As before, use of slightly expanded samples (of applicants within 20 points of the threshold score or all Round 2 companies) produces similar findings. To elaborate, the coefficient on the *Received Award* (“Funded”) variable in Column 2 of Appendix Table A1 corresponds to that reported in Panel C of Table 7 (Column 1) for the same two-year window. Table A1 also reports the coefficients and significance levels of the main control variables in the specification that are not reported in Table 7 for sake of brevity. Columns 3 through 5 of Appendix Table A1 add the three interaction terms in turn. A parallel structure is used in Columns 8 through 10 of Appendix Table A1 for VC funding over the longer four-year window, and in Appendix Table A2 for SBIR funding during equivalent time windows.

For non-linear models such as Poisson, interpretation of interaction terms requires the computation of conditional effects at different points in the distribution (Long and Freese, 2006; Hoetker, 2007). To determine the magnitude and significance of the heterogeneous effects in the appendix tables, we therefore compute the conditional effects of award receipt at different points in the distribution. If the coefficient of *Received award* is  $A$ , the coefficient of the interaction term is  $B$  in a Poisson model, and  $X$  is the independent variable of interest, the conditional effect of *Received award* would therefore equal  $A+B*X$ . Following the method in Hilbe (2008), we obtain the variance-covariance matrix of  $A$  and  $B$  and calculate the standard errors (SEs) of the conditional effects as follows:

$$SEs = \sqrt{Var(A) + X^2 Var(B) + 2XCov(A, B)} \quad (2)$$

Table 8 reports the conditional effects of award receipt on follow-on VC investments and SBIR funding for the respective two and four-year windows. As noted earlier, Appendix Tables A1 and A2 report the baseline models and the addition of each interaction term in turn. To interpret the interaction terms with the continuous distance and age-related variables, we use Equation (2) to compute the magnitude and significance levels at different points in the within-sample distribution.<sup>28</sup> The corresponding estimates are reported in Panels B and C of Table 8. For simplicity, the distance estimates in Panel B are computed at consistent 50-mile intervals.

The results in Table 8 reveal a clear and consistent pattern: award receipt tends to have a stronger stimulus effect on follow-on financing when near-threshold startups lack prior VC or SBIR funding (Panel A), are less proximate to the state's dominant hub of entrepreneurial activity (Panel B), or are younger (Panel C).

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<sup>28</sup> For the t+2 estimation sample, 56 percent of the applicants are located in the entrepreneurial hub and 60 percent are three years or younger in the year of the competition. The distribution is similar in the t+4 estimation sample.

The pattern is particularly visible for the VC estimates in Columns 1 and 2 of Table 8. In Panel A, the estimates suggest that award receipt leads to a significant and large boost in subsequent VC investments for near-threshold startups that lack prior VC or SBIR funding in both the two and four-year windows. Among those that successfully secured funds from VC or SBIR sources prior to the competition, however, the predicted effect is much smaller in magnitude and statistically indistinguishable from zero.

The estimates in Columns 1 and 2 of Table 8 similarly suggest that award receipt “matters more” as a stimulus to follow-on VC investments when near-threshold applicants are less proximate to the predominant entrepreneurial hub within the state (Panel B) or are younger (Panel C). Put differently, the estimated magnitude of the effect is larger for applicants that are not located inside the entrepreneurial hub (Panel B) and for firms that are younger in the competition year (Panel C), particularly in shorter time window after the competition.

Columns 3 and 4 report parallel estimates when the outcome variable is redefined as the number of follow-on SBIR grants. The pattern is similar, except in Panel A, where award receipt fails to have a statistically discernible effect on applicants that lack prior success in VC or SBIR fundraising. Consistent with the VC-related findings in Columns 1 and 2, however, the estimated impact of award receipt on follow-on SBIR funding varies markedly among firms based on their ages and geographic location. Indeed, the estimates in Table 8 suggest that award receipt significantly boosts follow-on SBIR awards only for near-threshold companies headquartered outside the hub of entrepreneurial activity within the state (Panel B, Columns 3 and 4) and for very young firms less than three years old in the competition year (Panel C, Column 3).

The conditional effects reported in Table 8 are robust to numerous supplemental tests, including (a) re-estimation based on startups in the wider 20-point region, (b) winsorizing the sample to omit outlier observations, and (c) removing companies that receive unusually large loans (top 5% of the



loan size distribution) from the estimation sample. The results are also robust to use of alternative measures for fundraising track records that separate VC and SBIR sources, and to use of categorical (versus continuous) distance measures.

#### *5.4 Supplemental analyses using media and patent-based outcome measures*

The results in Tables 6-8 suggest that receipt of funds through the Michigan R&D program increased the likelihood that near-threshold companies remained in business four years following the competition. They further suggest that award receipt disproportionately stimulated follow-on VC financing for subsets of companies that were very young, relatively inexperienced in external fundraising, or headquartered outside the state's dominant hub of entrepreneurial activity. Among otherwise comparable near-threshold firms, we also find a positive stimulus effect on follow-on R&D funding from other government (federal SBIR) sources, but only for very young firms and those located outside the dominant hub of entrepreneurial activity within the state.

From a policy perspective, it is natural to question whether the program has a meaningful effect on the productivity of recipient firms beyond their abilities to remain in business and secure funds from outside sources. Lacking a reliable panel of employment or balance sheet data for these young companies, we conduct supplemental tests using media and patent-based outcome measures. For the media-based outcomes, we start by testing the robustness of our follow-on financing results to use of funding events reported in press releases and news articles. Media outlets are likely to follow awardee companies more closely in the post-award period, leading to an upward reporting bias for this subset of firms. We therefore view the media-based analysis as supplemental and focus primarily on differences among firms in the relative magnitude of the effects.

As described more fully in Appendix B, we compiled news articles and press releases (i.e., "media mentions") by searching applicant-company names in the Factiva database, downloading all media mentions of those names through 2012, and screening out false hits (e.g., news about former

employees). In total, we identified 8,721 media mentions about the applicant startups. Based on a manual review of article titles and abstracts, we eliminated 2,044 articles that pertained to the focal program (e.g., announced winners in the Michigan-based competition) or were generic business directories or conference/trade show listings.

Of the remaining 6,677 articles, 3,897 (58 percent) announced receipt of external financing from sources other than the Michigan R&D loan program. An additional 2,018 articles (30 percent) primarily reported updates about commercialization progress or business expansion. In the latter case, articles were considered as primarily related to business development activity if they featured updates about the company’s business alliances or acquisitions, product development and testing (including inventions filed or approved for patent protection), sales milestones or contracts, employment growth, or the expansion of physical facilities (new offices, labs, or locations). The remaining 12 percent of the 6,677 articles ( $n=762$ ) fell in the general “exposure” and “other” categories in Appendix B and were omitted from both the financing and business development/expansion proxies. To give higher weight to more important announcements, we retained “duplicative listings” in multiple Factiva media outlets. The findings are robust to the omission of both duplicate news listings and 52 articles reporting “bad news” about the companies (e.g., layoffs; setbacks in product development or testing).

Reassuringly, Columns 1 and 2 in Table 9 reveal—using the alternative media-based measure for follow-on financing activity—a pattern similar to that shown earlier in Table 8 using VC and SBIR data.<sup>29</sup> As before, award receipt has an amplified effect on follow-on financing for near-threshold firms that are relatively inexperienced in external fundraising (Panel A), more distant from the

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<sup>29</sup> As in Table 8, Table 9 reports conditional effects at different points in the distribution as required for the interpretation of interaction effects in non-linear models. Columns 1 and 2 of Table 9 report conditional effects derived from specifications in Appendix Table A3, for the media proxy of financing activity. Similarly using Equation (2) reported in the text, Columns 3 and 4 in Table 9 are derived from specifications in Appendix Table A4, for the media-based proxy of business development-related activity.

dominant hub of entrepreneurial activity within the state (Panel B), or younger in the year of the competition (Panel C).

Equally important, Columns 3 and 4 in Table 9 reveal that this consistent pattern of heterogeneous effects remains visible for media-based measures that track shifts in the business development activities of near-threshold companies. In all three panels, award receipt predicts a greater upward shift in business development activities two-to-four years following the competition when companies are relatively inexperienced in external fundraising (Panel A), are located farther away from the entrepreneurial hub (Panel B) or are younger (Panel C). In contrast to evidence based on finance-related outcome measures, however, we also find a positive and significant effect of award receipt on follow-on business-development activity even among subsets of relatively “advantaged” companies. This finding could arise from an increased proclivity of news outlets to report news about award winners.<sup>30</sup> It is also consistent, however, with qualitative evidence in Söderblom et al. (2015) that award winners benefit from the added visibility and exposure.

Taken together, the patterns revealed in Table 9 again suggest that public R&D funding is particularly beneficial for companies likely to face heightened challenges in private markets for entrepreneurial resources. Importantly, we find that the effect is not only due to differential effects on business survival and follow-on financing but is also reflected in proxies that capture shifts in the business development and expansion.

Finally, in a battery of supplemental tests, we investigated the effects of award receipt on patent-based productivity measures both overall and for subsets of firms. At odds with the patterns

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<sup>30</sup>A related concern is reverse causality. More promising discoveries could ignite a surge in news coverage prior to the competition, potentially increasing the likelihood that a firm will receive an award. In this event, the relationship between award receipt and public exposure could run in reverse and correlate with quality differences insufficiently captured by the controls. At odds with this view, in placebo tests failed to reveal that award receipt predicted a boost in public exposure one to two years prior to the focal competition either overall or disproportionately for these subsets of firms.

revealed through our direct (SBIR, VC) and indirect (media-based) outcome measures for surviving companies, we failed to discern a significant effect of award receipt on standard patent productivity measures, including new patent filings (as in Bronzini and Piselli, 2016) or citation-weighted output of patented inventions (as in Howell, 2017).<sup>31</sup> This “non-finding” could be an artifact of our sample, which includes young companies in several sectors (e.g., security software) that do not traditionally rely on patents to profit from their investments (e.g., see Graham et al., 2009). State-level R&D programs could also support commercialization-related tasks (e.g., the building of testing or pilot manufacturing facilities or the ramping up of clinical trials required for product launch) less likely to shift inventive output than R&D grants administered at the national level (Lanahan and Armanios, 2018). An alternative possibility, which we are unable to rule out, is that the need to repay the loan could redirect attention to shorter-term tasks likely to generate cash flow. In this last scenario, loan and grant-based programs could give rise to divergent outcomes ex post even if they target identical types of projects ex ante.

Our inability to discern a significant effect on patent productivity stands in contrast to recent evidence for federal R&D grant programs in the United States (Howell, 2017) and for regional programs in Europe (Bronzini and Piselli, 2016). This discrepancy invites systematic analysis on how different mechanisms for subsidizing R&D endogenously shape the innovative activity that follows.

## **6. Discussion and Conclusion**

New science and technology companies spawn from universities, research labs, and established firms distributed throughout the United States, including the Great Lakes region. Yet the resources that such firms typically require for product development and commercialization remain concentrated in bicoastal regions of the country. Not surprisingly, this resource gap has led to

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<sup>31</sup> Appendix Table A5 reports results using the citation-weighted count of follow-on patents as the outcome variable. Use of unweighted patent counts as the outcome variable produces similar findings.

increased activism among state governments seeking to develop ecosystems of technology startups within their borders and to reduce historic dependencies on traditional manufacturing industries. Despite growing calls for policy intervention—whether through strengthening ties between public institutions and the private sector (Safford 2009) or allocating more federal R&D dollars to entities outside the dominant bicoastal regions (Gruber and Johnson, 2019)—little is known about the effects of state-level R&D programs on entrepreneurial firms and their endeavors.

This study provides new evidence based on a competitive R&D loan program in the state of Michigan. Leveraging access to proprietary data on startups that seek but do not necessarily receive credit access and support services through the program, we find a large and enduring effect of award receipt on business survival. This survival effect extends beyond the typical payback period for the loans and does not seem to be due to simple rent-seeking or selection bias. We interpret this evidence as indicative of binding capital constraints: Absent receipt of public R&D funding, otherwise comparable startups with project scores near the funding threshold are less likely to obtain the resources required to develop their projects and remain in business. This evidence is consistent with the view that financing frictions constrain entrepreneurial activity even in advanced economies such as the United States.

We also show that, conditional on surviving, near-threshold firms likely to face more severe informational frictions in private markets reap disproportionate benefits from the program. This distinctive pattern of heterogeneous effects holds for multiple indicators of follow-on financing as well as a media-based proxy of shifts in business development and expansion. Although rent-seeking behavior is a valid concern for public R&D programs (Lerner, 2009; Wang et al., 2017), we find no evidence that funds were allocated to below-threshold companies or that award receipt stimulated follow-on fundraising from government sources alone.

In combination, these findings underscore the importance of moving beyond the analysis of average effects in evaluations of public R&D programs: the magnitude of effects can vary substantially within the same program (Einiö 2014; Hünermund P, Czarnitzki D. 2019). Growing evidence from national and regional R&D programs shows amplified effects of award receipt for relatively young, inexperienced, or small firms (e.g., Lach, 2002; Bronzini and Iachini, 2014; Howell, 2017). We document heterogeneous effects even within a sample of relatively young firms, and further show that geographic proximity to a cluster of entrepreneurial activity also plays a role.

Limitations in the study set a natural stage for future research. By design, the study is conditioned on entrepreneurial firms that opt to compete for funds in one state's R&D program. We take the quality of the applicant pool and program characteristics as given, and focus on subsets of projects with scores near the threshold required for funding to improve the internal validity of the findings. Despite this specificity, our findings of heterogeneous effects resonate closely with those from other studies—suggesting that the results are not unique to this program or time period. In principle, however, the exact same program could be implemented in another context and yield different outcomes. As Lerner (2009) makes clear, public R&D programs are difficult to design and manage. Insufficient safeguards against unmeritorious awards or onerous requirements for applicant-companies could undermine the efficacy of an otherwise equivalent program.

Another potential boundary condition is the quality of the applicant pool. The state of Michigan houses top-tier research institutions and universities, which no doubt shapes the quality of applications that flow into the program. Indeed, this historic strength is featured in Gruber and Johnson's (2019) call to disperse more federal R&D funding into mid-tier cities in states such as Michigan with strong universities and human capital. From a policy perspective, however, little is known about the minimum levels of institutional and human capital strength required to warrant such policy intervention and how such initiatives are best governed. Future research on this topic

could leverage recent advances in the measurement of geographic clusters (e.g., Delgado and Stern, 2014), and investigate the trade-offs of alternative governance models more fully.

Even if states with suitable conditions opt to subsidize R&D projects for entrepreneurial firms within their borders, it remains unclear whether doing so through credit access and support services is the optimal policy lever. Grant-based programs are less costly to administer and could pull more nascent projects and smaller companies into the applicant pool (Hall and Maffoli, 2008). Future research could provide a much-needed comparative perspective by accessing archival data for R&D competitions administered in other states. Examples include the Third Frontier Program in the adjacent state of Ohio and the USTAR program in Utah. Recent research combining tax and R&D grant data for British companies illustrates the added insights that can be gleaned from a comparative analysis (Pless, 2019).

From a firm strategy perspective, it is important to move beyond *whether* public R&D programs affect entrepreneurial firms to a clearer understanding of *why* and *how* they do so. Although our evidence suggests that the Michigan program served a meaningful friction-reducing role in entrepreneurial resource markets, the mechanism underpinning this effect remains unclear. As in Howell (2017), the effect could arise due to simple cost-sharing: the subsidies could enable entrepreneurs to move technology projects forward (e.g., through prototyping and testing) to a stage where imperfections in private markets are less severe. We cannot rule out, however, that firms derive added benefits from “certification” effects long-studied in the program evaluation literature or from the bundle of support services and training provided through the program. Understanding these conceptually distinctive channels and their relative importance for entrepreneurial firms could inform private-sector decisions of whether and when to pursue government sources of funding. Relatedly, more research on the restrictions imposed by “place-based” R&D programs and the

extent to which they *constrain* entrepreneurial and innovative activity is needed. Recent work by Conti (2019) is a laudable step in that direction.

From a policy perspective, models of economic growth show that R&D subsidies are more fruitfully invested in entrepreneurial ventures than incumbent firms (e.g., Acemoglu et al., 2018), echoing consensus in the empirical literature (Hall and Lerner, 2010; Becker, 2015). On the one hand, interventions such as the Michigan R&D loan program could stimulate entry by entrepreneurial firms in ways beyond the scope of our study, potentially giving rise to more vibrant clusters of innovative activity across U.S. states and regions (Feldman et al., 2005; Agrawal et al., 2014).<sup>32</sup> On the other hand, competition among states to fund and retain innovative companies could give rise to a “beggar thy neighbor” dynamic, with minimal or even deleterious effects on social welfare and productivity at the more aggregate level (Wilson, 2009; Kline and Moretti, 2014). In light of this concern, recent proposals call for state governments to coordinate R&D and entrepreneurship-related policies at a regional or national level. Examples include Vey, Austin and Bradley (2010), Atkinson, Muro and Whiton (2019), and Gruber and Johnson (2019).

In conclusion, this study investigates the effects of a competitive R&D loan program administered in the state of Michigan during the decade of the 2000s. Our findings suggest that the program reduced capital constraints for entrepreneurial-firm projects, and was particularly beneficial for firms that were very young, lacked prior track records of external fundraising, and based outside the dominant hub of entrepreneurial activity. The study adds to growing evidence that the effects of R&D programs on entrepreneurial-firm outcomes vary substantially even within the same program.

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<sup>32</sup> The tradeoffs with alternative R&D tax levers are, however, important to consider (Hall and Lerner, 2010; Moretti and Wilson, 2017).



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Figure 1. The multi-staged selection process

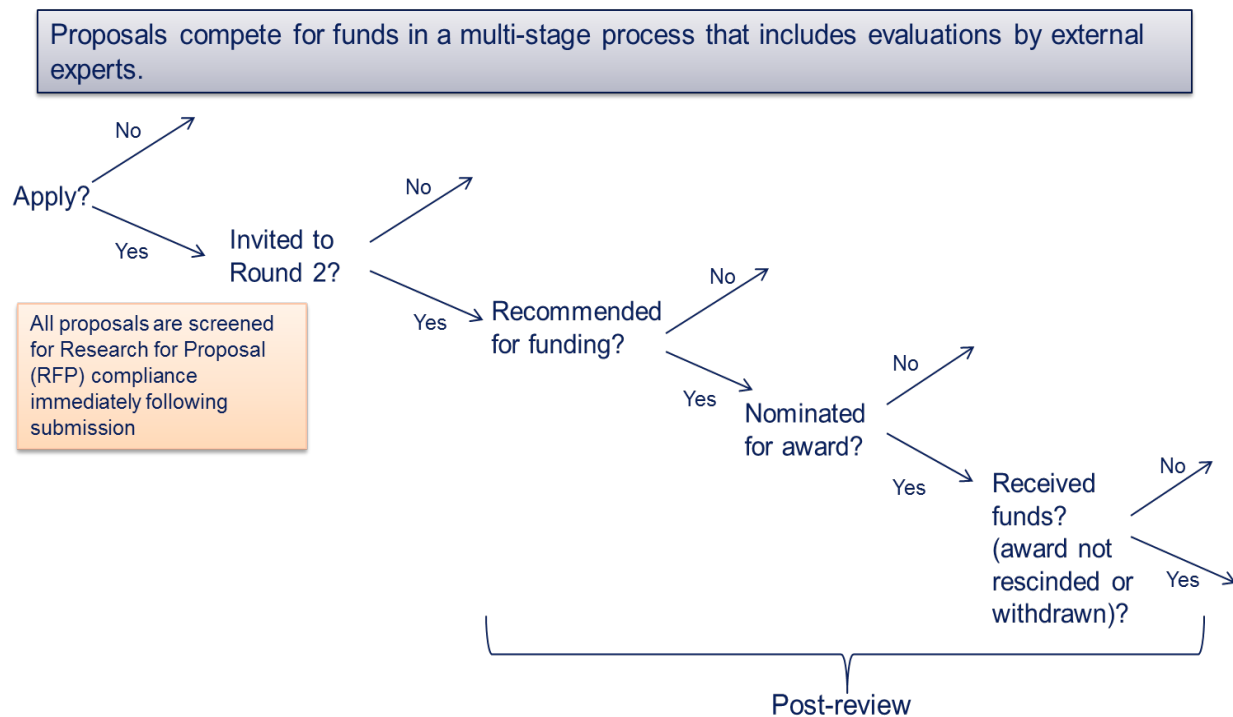
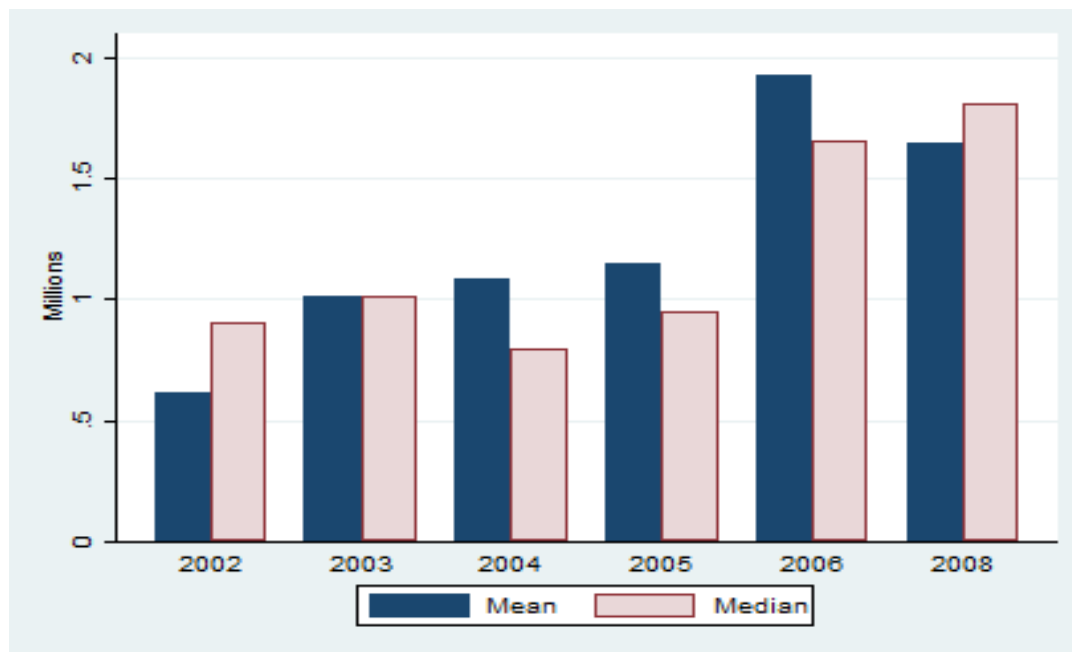
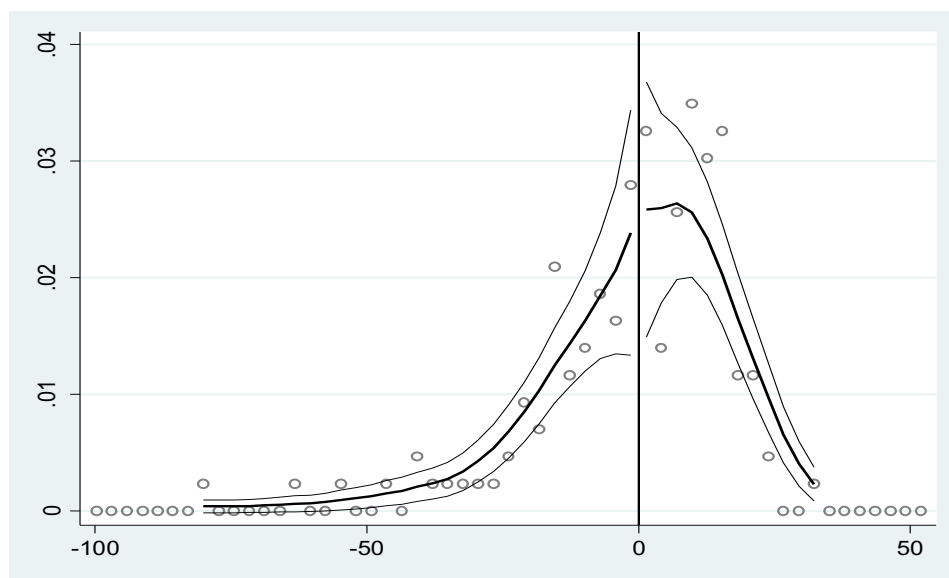


Figure 2. Average size of R&D loans awarded in the Michigan program from 2002 to 2008

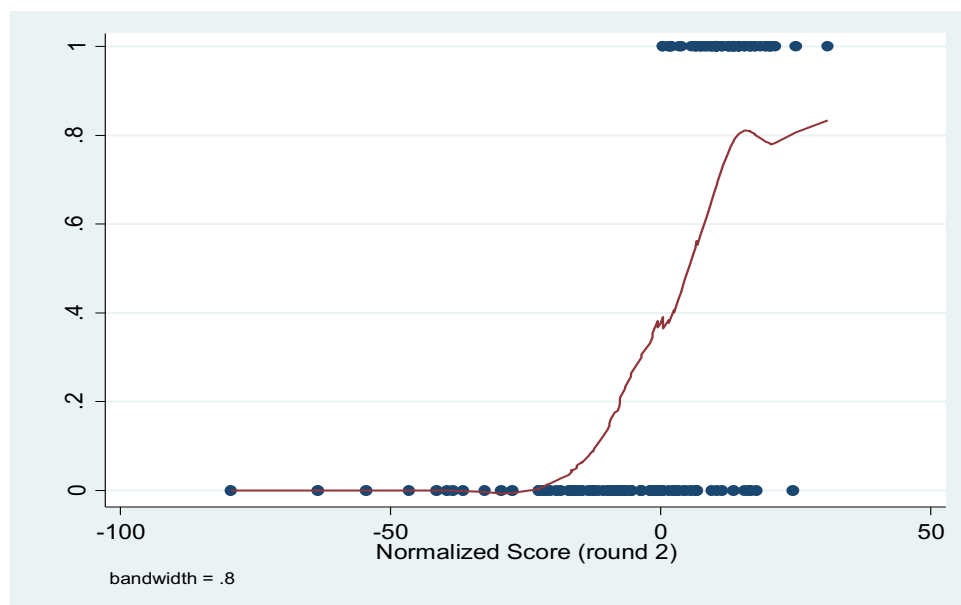


**Figure 3. Density of applicant scores above and below the funding threshold**



Note: This figure presents a visualization of the McCrary (2008) test for the continuity of normalized score density relative to the threshold score. The y-axis indicates the estimated density with 95 percent confidence intervals. The discontinuity estimation (log difference in height) is not statistically significant.

**Figure 4. Effect of evaluator score on the probability of receiving funding**



Note: This figure plots the relation between the probability of receiving funds and normalized scores. The x-axis indicates the normalized score, defined as the Round 2 score of company  $i$  in application category  $j$  in year  $t$  minus the minimum score required for funding. The y-axis shows the lowess smoother of funding probability with bandwidth 0.8.

**Table 1: Recent studies using applicant-pool data to test the effects of public R&D subsidies on entrepreneurial firms**

Authors	Country – govt. level	Program Overview	Applicant Profile & Time Period	Funding Type	Amount (est, current US\$)	Outcome Variables	Main Findings
Bronzini and Iachini (2014)	Italy - regional	“Regional Program for Industrial Research, Innovation and Technology Transfer” of the Emilia-Romagna region; Funds up to 60% costs of research and technology development projects for firms in region. Targets 1-2 yr. projects < €250,000.	468 firms from competitions in 2004 and 2005 with balance-sheet data (median firm age is 17 years)	grant	~\$200,000	balance sheet investments t+2 (total, tangible, intangible), # employees t+2	insignif. overall; +, signif. effects only for relatively small and young firms
Bronzini and Piselli (2016)	Italy - regional	see above	612 firms from competitions in 2004 and 2005, with an expanded sample of small firms and startups	grant	see above	patent productivity t+6	+, signif. effects on prob (patenting) and patent counts for both larger and smaller firms, but amplified for smaller firms (below-median sales)
Söderblom, Samuelsson, Wiklund and Sandberg (2015)	Sweden - national	"Win Now" program; funds up to 24 very young startups from country each year. Targets proof of concept projects seeking to expand.	1102 firms founded between 2002 and 2008, of which 284 make it to final evaluation stage. Analysis compares 130 awardees with 154 non-awardees from final stage of the competition. (all firms = very young, ~1-2 years old in competition year)	grant	~\$40,000	equity financing t+1; employment growth t+1; longer term sales growth up to 7 yrs	+, signif. effects
Howell (2017)	United States - national	SBIR program for proof-of-concept (Phase 1) and later staged tech. development projects (Phase 2). Targets US-based companies with fewer than 500 employees	4,545 firms that apply for SBIR grants from the US Department of Energy, 1995-2013 (mean firm age is 9.5 years)	grant	\$150,000 (Phase 1), up to \$1 million (Phase 2)	survival by 2016; patent productivity (cite-weighted patents), private VC financing, revenue by 2016	insignif. effects of larger Phase 2 grants. +, signif effects of smaller Phase 1 grants on most outcomes, particularly for young, inexperienced firms and in emerging sectors.
Wang, Li and Furman (2017)	China - national (regional branch)	China's Innovation Fund for Technology-Based Small and Medium-Sized Companies (Innofund). For Chinese companies with fewer than 500 employees. Evidence = from a high-tech cluster near Beijing	1,086 applications from firms less than 8 years old with less than 500 employees, 2005-2010. (mean firm age is 3-4 years old).	primarily grants; some loans + equity	~\$80,000 to \$161,000 grant + 50 to 100% match from local government	survival by 2015, follow-on equity investments from private (VC/PE), follow-on funding from state owned or community enterprises (SOE/COE), patent productivity	Analysis of applicants vs non-applicants (n=974): + signif effect only on survival & follow-on \$ from SOE/COE; insignif. effects on private financing or patent filings. Analysis of near-threshold firms (n=321): insignif. effects on all outcome variables

**Table 2. Main variables and data sources**

	Definition	Data Source
<b>Dependent Variables</b>		
<i>Survives<sub>i,(t+2, t+4)</sub></i>	Indicator set to 1 if a startup is still active and in good standing 2 (4) years after the competition	Michigan Department of Licensing and Regulatory Affairs (LARA) database
<i># SBIR awards<sub>i,(t+2, t+4)</sub></i>	# SBIR and STTR grants a startup receives 2 (4) years after the competition	Small Business Administration (SBA) TECH-Net database
<i># VC investments<sub>i,(t+2, t+4)</sub></i>	# VC investments a startup receives 2 (4) years after the competition	VentureSource, company website, and Zephyr
<b>Independent Variables and Controls</b>		
<i>Funded<sub>j</sub></i>	Indicator set to 1 if a startup receives a Michigan R&D award in competition j	Michigan Economic Development Corporation (MEDC) records
<i>Age in application year</i>	Application year minus the startup's year of incorporation	LARA database, MEDC records
<i>Has VC or SBIR funding prior 1-4 years</i>	Indicator set to 1 if a startup receives venture capital or SBIR/STTR grants four years prior to the competition.	Small Business Administration (SBA) TECH-Net database, VentureSource, company website, and Zephyr
<i>Log distance to entrepreneurial hub (miles)</i>	Distance in miles from the startup headquarter city to the dominant hub of entrepreneurial investment activity in the state (Ann Arbor) plus one, in logs	MEDC records, Google maps
<i>Application category</i>	Indicator for project type: applied research or technology commercialization project	MEDC records
<i>Application year</i>	Indicator for competition year in which the application was submitted	MEDC records
<i>Industrial sector</i>	Indicator for startup's primary sector: life science, advanced manufacturing/materials, alternative energy, or homeland security	MEDC records



**Table 3. Summary statistics - all startup applicants**

	Obs	Mean	Std. Dev.	Min	Max
<b>Basic characteristics</b>					
Age in application year (in years)	297	4.29	4.03	0.00	15.00
Distance from entrepreneurial hub (100s miles)	297	0.46	0.66	0.00	5.69
Primary sector (mean = %)					
Life science	297	0.49	0.50	0.00	1.00
Advanced auto	297	0.29	0.46	0.00	1.00
Alternative energy	297	0.08	0.28	0.00	1.00
Homeland security	297	0.13	0.34	0.00	1.00
Application category (mean = %)					
Applied research	297	0.23	0.42	0.00	1.00
Commercialization	297	0.77	0.42	0.00	1.00
<b>Pre-award outcomes as indicators (mean = %)</b>					
Has SBIR award prior 4 years	297	0.22	0.41	0.00	1.00
Has VC funding prior 4 years	297	0.07	0.25	0.00	1.00
Has VC or SBIR funding prior 4 years	297	0.28	0.45	0.00	1.00
<b>Pre-award outcomes as counts</b>					
# SBIR awards prior 4 years	297	0.76	2.33	0.00	21.00
# VC investments prior 4 years	297	0.28	1.15	0.00	12.00
<b>Competition Variables</b>					
Normalized score (1st Round)	297	-4.46	19.04	-58.50	32.00
Normalized score (2nd Round)	152	-0.63	17.39	-79.50	31.00
Received state R&D funding (%)	297	0.21	0.41	0.00	1.00
<b>Post-award Outcome variables</b>					
survives, t+2	297	0.89	0.31	0.00	1.00
survives, t+4	297	0.79	0.40	0.00	1.00
# VC investments, t+2	297	0.28	1.08	0.00	10.00
# VC investments, t+4	297	0.50	1.98	0.00	18.00
# SBIR awards, t+2	297	0.57	1.43	0.00	10.00
# SBIR awards, t+4	297	1.10	2.67	0.00	17.00
# of financing news, t+2	297	0.78	2.35	0.00	17.00
# of financing news, t+4	297	1.58	5.78	0.00	68.00
# of business development-related news, t+2	297	4.64	16.17	0.00	159.00
# of business development-related news, t+4	297	8.20	27.16	0.00	260.00

**Table 4. Summary statistics – subsamples of startup-applicants in Round 2 overall and with scores near the threshold required for funding**

	Startups in Round 2				Startups within 15 points of threshold score			
	Non- awardees	Awardees	Two-tailed <i>t</i> -test for equality of means	KS equality- of- distributions test	Non- awardees	Awardees	Two-tailed <i>t</i> -test for equality of means	KS equality- of- distributions test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>A. Basic Characteristics</b>	Mean	Mean	P-value	P-value	Mean	Mean	P-value	P-value
Age in application year (in years)	4.19	3.87	0.64	0.97	3.93	3.32	0.40	0.64
Distance from entrepreneurial hub (100s miles)	0.48	0.29	0.09	0.06	0.47	0.33	0.38	0.60
Primary sector (%)								
Life science	0.53	0.66	0.12	1.00	0.51	0.67	0.09	0.99
Advanced auto	0.21	0.16	0.45	1.00	0.26	0.17	0.28	1.00
Alternative energy	0.56	0.81	0.54	0.83	0.04	0.07	0.48	0.94
Homeland security	0.2	0.1	0.09	0.59	0.19	0.09	0.13	0.49
Application category (%)								
Applied research	0.24	0.24	0.97	1.00	0.21	0.20	0.85	1.00
Commercialization	0.76	0.76	0.97	1.00	0.79	0.80	0.85	1.00
<b>B. Pre-award outcomes as indicators (mean= %)</b>								
Has SBIR award prior 4 years	0.22	0.4	0.02	0.18	0.23	0.37	0.12	0.69
Has VC funding prior 4 years	0.11	0.15	0.54	1.00	0.12	0.17	0.47	1.00
Has VC or SBIR funding prior 4 years	0.30	0.50	0.01	0.11	0.32	0.48	0.10	0.51
<b>C. Pre-award outcomes as counts</b>								
# SBIR awards prior 4 years	1.09	1.24	0.76	0.18	1.18	1.09	0.89	0.69
# VC investments prior 4 years	0.41	0.35	0.80	1.00	0.49	0.43	0.85	1.00
<b>D. Competition Variables</b>								
Normalized score (Round 2)	-9.33	11.9			-2.83	9.21		
Observations	90	62			57	46		

Notes: This table shows ex-ante traits of startup applicants near the threshold score. Panel A reports applicant characteristics in the year of the focal competition. Panels B and C report applicant outcomes in the 4-year window prior to the competition, as (0,1) indicators (Panel B) and as counts (Panel C). Panel D reports normalized scores from Round 2 of the competition. Columns 3 and 6 report the equality of means for non-awardees and awardees in the respective groups. Columns 4 and 8 report the Komogorov-Smirnov (KS) test for equality of distributions.

**Table 5. Correlation matrix and summary statistics: Startups within 15 points of threshold score**

	Variable	Mean	Std. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Survival, t+2	0.92	0.27	1.000							
(2)	Survival, t+4	0.85	0.35	0.703	1.000						
(3)	# of VC investments, t+2	0.67	1.71	0.109	0.155	1.000					
(4)	# of VC investments, t+4	1.33	3.27	0.102	0.144	0.903	1.000				
(5)	# of SBIR Awards, t+2	0.86	1.87	0.135	0.192	-0.036	-0.090	1.000			
(6)	# of SBIR Awards, t+4	1.66	3.31	0.146	0.208	-0.033	-0.086	0.947	1.000		
(7)	# of financing news, t+2	1.20	2.81	0.125	0.129	0.183	0.038	0.327	0.300	1.000	
(8)	# of financing news, t+4	2.14	4.32	0.144	0.173	0.178	0.029	0.370	0.349	0.853	1.000
(9)	# of business development-related news, t+2	7.09	17.04	0.121	0.164	-0.034	-0.071	0.074	0.048	0.478	0.462
(10)	# of business development-related news, t+4	12.60	32.19	0.113	0.157	-0.002	-0.049	0.211	0.177	0.363	0.524
(11)	Funded	0.45	0.50	0.188	0.316	0.151	0.125	0.003	0.063	0.221	0.226
(12)	Has a SBIR or VC in the prior 4 years	0.39	0.49	0.157	0.216	-0.012	-0.061	0.315	0.306	0.263	0.243
(13)	Distance from entrepreneurial hub (log)	1.92	2.17	-0.129	-0.131	-0.142	-0.167	-0.178	-0.248	0.034	0.040
(14)	Age	3.66	3.57	0.095	0.123	-0.097	-0.126	0.349	0.330	0.009	-0.061
(15)	Sector 1 (Adv Auto, Mfg, Materials)	0.22	0.42	-0.106	-0.175	0.028	0.005	-0.136	-0.129	-0.006	-0.077
(16)	Sector 2 (Alternative Energy)	0.05	0.22	0.066	0.093	-0.051	0.011	0.187	0.133	0.016	-0.039
(17)	Sector 3 (Homeland Security)	0.15	0.35	0.017	-0.064	-0.134	-0.126	0.134	0.193	-0.109	-0.058
(18)	Category 1 (Applied Research)	0.20	0.40	0.147	0.141	-0.099	-0.018	0.154	0.140	0.041	0.051
(19)	Round 2 Score	2.55	8.28	0.120	0.136	0.147	0.106	-0.108	-0.070	0.132	0.081

		(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(9)	# of business development-related news, t+2	1.000									
(10)	# of business development-related news, t+4	0.832	1.000								
(11)	Funded	0.348	0.300	1.000							
(12)	Has a SBIR or VC in the prior 4 years	-0.042	-0.032	0.166	1.000						
(13)	Distance from entrepreneurial hub (log)	0.173	0.189	-0.106	-0.211	1.000					
(14)	Age	-0.158	-0.155	-0.085	0.374	-0.162	1.000				
(15)	Sector 1 (Adv Auto, Mfg, Materials)	-0.153	-0.149	-0.107	-0.188	0.157	-0.159	1.000			
(16)	Sector 2 (Alternative Energy)	-0.068	-0.054	0.070	0.098	0.024	0.085	-0.121	1.000		
(17)	Sector 3 (Homeland Security)	-0.038	-0.034	-0.149	0.066	-0.089	0.226	-0.221	-0.093	1.000	
(18)	Category 1 (Applied Research)	0.283	0.251	-0.018	-0.008	-0.244	0.116	-0.214	-0.114	-0.072	1.000
(19)	Round 2 Score	0.207	0.135	0.726	0.116	-0.046	-0.021	-0.178	-0.010	-0.161	-0.140

**Table 6. Effect of state R&D award on startup survival**

	All startup applicants		Startups in Round 2		Startups within 15 points of the threshold score	
	survives, $t+2$	survives, $t+4$	survives, $t+2$	survives, $t+4$	survives, $t+2$	survives, $t+4$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Base regression, with application year, category, and sector fixed effects						
Received award (“Funded”)	0.120*** (0.028)	0.206*** (0.035)	0.132*** (0.050)	0.206*** (0.056)	0.134** (0.058)	0.220*** (0.064)
Panel B: Panel A, with added controls for applicant-level characteristics						
Received award (“Funded”)	0.118*** (0.032)	0.195*** (0.038)	0.091 (0.074)	0.189** (0.076)	0.118 (0.106)	0.314*** (0.118)
Observations	297	297	152	152	103	103

Notes: This table reports linear probability estimates of the effect of award receipt on venture survival. Columns 1 and 2 report results for all applicant-startups. Columns 3-6 report results for the subsample of round 2 and near-threshold applicants. *Received award* equals one if the applicant receives R&D funding through the competition; else, it equals zero. The outcome variable, survival, indicates whether the applicant-company is in operation and in good business standing two years (columns 1, 3, and 5) or four years (columns 2, 4, and 6) following the competition. The regressions in Panel A include application-year, application category (applied research or commercialization project), and sector fixed effects. The regressions in Panel B include controls for other applicant characteristics, including age in application year, prior receipt of VC funds and/or SBIR grants, and geographic proximity to the entrepreneurial hub within the state. For subsamples of round 2 and within bandwidth startups, standardized scores are also included as an additional control for unobservable applicant characteristics in Panel B. Table 2 describes the variables in more detail.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

**Table 7. Average effect of state R&D award on follow-up financing:  
All startup applicants vs. those within 15 points of the threshold score**

	# VC investments		# SBIR awards	
	<i>t</i> +2 (1)	<i>t</i> +4 (2)	<i>t</i> +2 (3)	<i>t</i> +4 (4)
Panel A: All Applicants, with application year, category, and sector fixed effects				
Received award (“Funded”)	1.010** (0.396)	0.972** (0.442)	0.789*** (0.214)	0.809*** (0.263)
# Observations	264	236	264	236
Panel B: Near-threshold subsample, with application year, category, and sector fixed effects				
Received award (“Funded”)	0.974* (0.537)	0.575 (0.562)	-0.055 (0.347)	0.172 (0.315)
# Observations	95	88	95	88
Panel C: Near-threshold subsample, with added controls for applicant-level characteristics				
Received award (“Funded”)	1.680** (0.738)	1.582** (0.673)	0.770 (0.546)	0.449 (0.460)
# observations	95	88	95	88

Notes: This table reports Poisson quasi-maximum likelihood estimates of the average effect of state R&D award receipt on startup performance, conditioned on survival. Panel A includes all applicants that survive in the time window, while Panels B and C focus on applicants within 15 points of the threshold score. Application-year, application category (applied research or commercialization project), and sector fixed effects are included in the regressions for all three Panels. The regressions in Panel C also include controls for other applicant characteristics, including age in application year, prior receipt of VC funds and/or SBIR grants, geographic distance to the entrepreneurial hub within the state, and standardized external review scores. Table 2 describes the controls and outcome variables in more detail. Appendix Tables A1 and A2 report detailed regression output, including control variable results, for the near-threshold subsamples in Panels B and C and the VC and SBIR outcome variables respectively.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

**Table 8. Conditional effects of state R&D award on VC and SBIR funding: applicants within 15 points of the threshold score**

	# VC Investments				# SBIR Awards			
	t+2		t+4		t+2		t+4	
	(1)		(2)		(3)		(4)	
<b>Panel A: Has VC or SBIR funding prior 4 years</b>								
Yes	0.332	(0.800)	0.448	(0.750)	0.744	(0.571)	0.396	(0.499)
No	2.202***	(0.663)	1.805***	(0.569)	0.844	(0.754)	0.582	(0.653)
<b>Panel B: Log Distance to entrepreneurial hub</b>								
Distance = 0	1.573*	(0.844)	1.467*	(0.761)	0.239	(0.512)	0.126	(0.436)
Distance = 50 miles	1.950**	(0.921)	2.029**	(0.975)	2.096***	(0.753)	1.426**	(0.699)
Distance = 100 miles	2.015*	(1.041)	2.126*	(1.111)	2.419***	(0.856)	1.652**	(0.797)
Distance = 150 miles	2.053*	(1.118)	2.184*	(1.197)	2.609***	(0.920)	1.785**	(0.858)
Distance = 200 miles	2.082*	(1.175)	2.225*	(1.260)	2.744***	(0.966)	1.879**	(0.902)
<b>Panel C: Age in application year</b>								
Age = 0	2.010***	(0.714)	1.677**	(0.722)	1.258*	(0.713)	0.749	(0.601)
Age = 1	1.851***	(0.704)	1.627**	(0.688)	1.170*	(0.675)	0.693	(0.567)
Age = 2	1.692**	(0.714)	1.576**	(0.672)	1.082*	(0.645)	0.638	(0.539)
Age = 3	1.533**	(0.744)	1.526**	(0.677)	0.995	(0.623)	0.583	(0.518)
Age = 4	1.374*	(0.792)	1.476**	(0.702)	0.907	(0.611)	0.528	(0.504)
Age = 5	1.215	(0.854)	1.425*	(0.745)	0.820	(0.610)	0.472	(0.500)

Notes: This table reports the estimated conditional effects of receipt of state R&D funding on applicants within 15 points of the threshold score. Panel A presents the heterogeneous effects of award receipt conditional on whether the focal firm has prior VC or SBIR awards. Panel B and C report the heterogeneous effects conditional on the focal firm's location (i.e., distance to entrepreneurial hub) and age in application year. The magnitude and significance of the conditional effects are computed based on the coefficients reported in Table A1 (for # VC investments) and Table A2 (for # SBIR/STTR awards) using formulas in Hilbe (2008). Details are reported in the text.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

**Table 9. Conditional effects of state R&D award on media measures of follow-on financing and business development activity: applicants within 15 points of the threshold score**

	# Finance-Related Articles				# Business Development-Related Articles			
	t+2		t+4		t+2		t+4	
	(1)		(2)		(3)		(4)	
<b>Panel A: Has VC or SBIR funding prior 4 years</b>								
Yes	0.954	(0.763)	0.937	(0.626)	2.508**	(1.051)	1.820**	(0.776)
No	2.266**	(0.951)	2.528***	(0.778)	3.354***	(0.878)	2.335***	(0.614)
<b>Panel B: Log Distance to entrepreneurial hub</b>								
Distance = 0	0.767	(0.743)	0.817	(0.589)	2.703***	(1.012)	2.038***	(0.719)
Distance = 50 miles	1.701**	(0.838)	1.858***	(0.688)	2.991***	(0.816)	2.080***	(0.588)
Distance = 100 miles	1.863**	(0.923)	2.039***	(0.778)	3.041***	(0.833)	2.087***	(0.615)
Distance = 150 miles	1.959**	(0.978)	2.145**	(0.835)	3.070***	(0.850)	2.091***	(0.638)
Distance = 200 miles	2.207**	(1.019)	2.221**	(0.877)	3.091***	(0.865)	2.094***	(0.657)
<b>Panel C: Age in application year</b>								
Age = 0	2.318**	(1.049)	1.740**	(0.832)	3.529***	(0.937)	2.302***	(0.622)
Age = 1	2.087**	(0.961)	1.626**	(0.751)	3.343***	(0.919)	2.231***	(0.604)
Age = 2	1.856**	(0.888)	1.513**	(0.682)	3.157***	(0.911)	2.160***	(0.599)
Age = 3	1.625*	(0.833)	1.399**	(0.630)	2.970***	(0.913)	2.089***	(0.608)
Age = 4	1.394*	(0.802)	1.285**	(0.600)	2.785***	(0.925)	2.017***	(0.631)
Age = 5	1.162	(0.795)	1.171**	(0.594)	2.599***	(0.946)	1.946***	(0.665)

Notes: This table reports the estimated conditional effects of receipt of state R&D funding on applicants within 15 points of the threshold score. Panel A presents the heterogeneous effects of award receipt conditional on whether the focal firm has prior VC or SBIR awards. Panel B and C report the heterogeneous effects conditional on the focal firm's location (i.e., distance to entrepreneurial hub) and age in application year. The magnitude and significance of the conditional effects are computed based on the coefficients reported in Table A3 (for # Finance-Related News Articles) and Table A4 (for # Business Development-Related News Articles) using formulas in Hilbe (2008). Details are reported in the text.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

## **Appendix A:**

### Supplemental Output Tables



**Table A1. Effect of state R&D award on follow-on receipt of VC financing: applicants within 15 points of the threshold score**

	# VC investments, $t+2$					# VC investments, $t+4$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Received state R&D funding ("Funded")	0.974*	1.680**	2.202***	1.573*	2.010***	0.575	1.582**	1.805***	1.467*	1.677**
	(0.537)	(0.738)	(0.663)	(0.844)	(0.714)	(0.562)	(0.673)	(0.569)	(0.761)	(0.722)
Funded * Has VC or SBIR funding prior 4 years			-1.870**					-1.357*		
			(0.909)					(0.801)		
Funded * Log distance to entrepreneurial hub				0.096					0.143	
				(0.258)					(0.264)	
Funded * Age in application year					-0.159					-0.051
					(0.122)					(0.117)
Has VC or SBIR funding prior 4 years		-0.316	0.894	-0.313	-0.252		-0.662	0.204	-0.656	-0.644
		(0.502)	(0.703)	(0.505)	(0.489)		(0.520)	(0.598)	(0.525)	(0.523)
Log distance to entrepreneurial hub		-0.288*	-0.294*	-0.346**	-0.311**		-0.431**	-0.438**	-0.527***	-0.438**
		(0.156)	(0.157)	(0.165)	(0.154)		(0.176)	(0.180)	(0.181)	(0.177)
Age in application year		-0.102*	-0.082	-0.094	-0.005		-0.162**	-0.149**	-0.152**	-0.133*
		(0.059)	(0.059)	(0.071)	(0.087)		(0.068)	(0.068)	(0.077)	(0.077)
Score Control?	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Application-Year Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project Category Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.314	0.496	0.061	0.540	0.329	0.506	1.602***	1.368***	1.639***	1.557***
	(0.468)	(0.533)	(0.682)	(0.509)	(0.471)	(0.421)	(0.443)	(0.478)	(0.412)	(0.442)
Observations	95	95	95	95	95	88	88	88	88	88
Log-likelihood	-91.42	-82.77	-78.30	-82.62	-81.87	-191.6	-155.4	-151.0	-154.9	-155.2

Notes: This table reports Poisson quasi-maximum likelihood estimates of the effects of state R&D awards on follow-on receipt of VC financing. The estimation sample includes applicant-startups within 15 points of the threshold score required for funding. The outcome variable is the number of VC investments the startup receives two years (columns 1-5) to four (columns 6-10) years after the competition.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

**Table A2. Effect of state R&D award on follow-on receipt of SBIR awards: applicants within 15 points of the threshold score**

	# SBIR awards, $t+2$					# SBIR awards, $t+4$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Received state R&D funding ("Funded")	-0.055 (0.347)	0.770 (0.546)	0.844 (0.754)	0.239 (0.512)	1.258* (0.713)	0.172 (0.315)	0.449 (0.460)	0.582 (0.653)	0.126 (0.436)	0.749 (0.601)
Funded * Has VC or SBIR funding prior 4 years			-0.100 (0.696)					-0.186 (0.650)		
Funded * Log distance to entrepreneurial hub				0.472** (0.189)					0.331* (0.174)	
Funded * Age in application year					-0.088 (0.080)					-0.055 (0.066)
Has VC or SBIR funding prior 4 years		0.840* (0.496)	0.881 (0.611)	0.847* (0.454)	0.863* (0.483)		0.641 (0.481)	0.724 (0.628)	0.624 (0.462)	0.651 (0.475)
Log distance to entrepreneurial hub		-0.102 (0.108)	-0.105 (0.109)	-0.359*** (0.136)	-0.125 (0.116)		-0.185* (0.104)	-0.190* (0.103)	-0.373*** (0.133)	-0.197* (0.107)
Age in application year		0.104* (0.062)	0.105* (0.062)	0.135** (0.057)	0.144** (0.072)		0.054 (0.058)	0.056 (0.059)	0.071 (0.056)	0.081 (0.063)
Score Control?	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Application-Year Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project Category Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.969** (0.482)	-1.613*** (0.545)	-1.633*** (0.562)	-1.388*** (0.480)	-1.745*** (0.558)	-0.509 (0.467)	-0.712 (0.499)	-0.758 (0.513)	-0.524 (0.459)	-0.811 (0.516)
Observations	95	95	95	95	95	88	88	88	88	88
Log-likelihood	-131.9	-113.7	-113.6	-108.3	-112.8	-201.2	-176.1	-176.0	-171.3	-175.3

Notes: This table reports Poisson quasi-maximum likelihood estimates of the effects of state R&D awards on follow-on receipt of SBIR/STTR grants. The estimation sample includes applicant-startups within 15 points of the threshold score required for funding. The outcome variable is the number of SBIR or STTR grants the startup receives two (columns 1-5) to four (columns 6-10) years after the competition.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

**Table A3. Effect of state R&D award on media evidence of financing activity: applicants within 15 points of the threshold score**

	# Finance-Related News Articles, $t+2$					# Finance-Related News Articles, $t+4$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Received state R&D funding ("Funded")	0.838*	1.217*	1.846**	0.966	1.967**	0.666*	1.235**	2.528***	0.817	1.740**
	(0.442)	(0.699)	(0.933)	(0.757)	(0.996)	(0.387)	(0.569)	(0.778)	(0.589)	(0.832)
Funded * Has VC or SBIR funding prior 4 years			-0.846					-1.591**		
			(0.866)					(0.789)		
Funded * Log distance to entrepreneurial hub				0.127					0.265	
				(0.203)					(0.186)	
Funded * Age in application year					-0.165					-0.114
					(0.151)					(0.123)
Has VC or SBIR funding prior 4 years		1.294***	1.829***	1.294***	1.289***		1.177***	2.250***	1.143***	1.177***
		(0.435)	(0.621)	(0.437)	(0.436)		(0.442)	(0.663)	(0.430)	(0.442)
Log distance to entrepreneurial hub		0.164*	0.148	0.079	0.128		0.133	0.118	-0.045	0.114
		(0.096)	(0.103)	(0.157)	(0.097)		(0.100)	(0.109)	(0.168)	(0.096)
Age in application year		0.030	0.033	0.045	0.133		-0.048	-0.040	-0.014	0.017
		(0.078)	(0.076)	(0.082)	(0.102)		(0.071)	(0.067)	(0.065)	(0.088)
Score Control?	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Application-Year Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project Category Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.113	-1.053*	-1.357*	-0.884	-1.332*	0.714*	-0.111	-0.838	0.159	-0.294
	(0.408)	(0.604)	(0.700)	(0.599)	(0.684)	(0.376)	(0.475)	(0.514)	(0.477)	(0.479)
Observations	95	95	95	95	95	88	88	88	88	88
Log-likelihood	-205.7	-179.5	-177.6	-178.8	-176.8	-304.4	-267.3	-256.5	-261.7	-265.3

Notes: This table reports Poisson quasi-maximum likelihood estimates of the effects of state R&D award on media evidence of financing activity. The estimation sample includes applicant-startups within 15 points of the threshold score required for funding. The outcome variable is the number of financing-related media mentions the startup receives two (columns 1-5) to four (columns 6-10) after the competition.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

**Table A4. Effect of state R&D award on media evidence of business development activity: applicants within 15 points of the threshold score**

	# Business Development-related News Articles, $t+2$					# Business Development-related News Articles, $t+4$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Received state R&D funding ("Funded")	1.849*** (0.329)	2.864*** (0.859)	3.355*** (0.878)	2.703*** (1.012)	3.529*** (0.937)	1.636*** (0.326)	2.060*** (0.594)	2.335*** (0.614)	2.038*** (0.719)	2.302*** (0.622)
Funded * Has VC or SBIR \$ prior 4 years			-0.956 (0.820)					-0.515 (0.726)		
Funded * Log distance to entrepreneurial hub				0.073 (0.169)					0.011 (0.142)	
Funded * Age in application year					-0.186* (0.095)					-0.071 (0.091)
Has VC or SBIR \$ prior 4 years		0.131 (0.336)	0.880 (0.763)	0.116 (0.325)	0.203 (0.329)		0.240 (0.352)	0.619 (0.655)	0.238 (0.342)	0.251 (0.349)
Log distance to entrepreneurial hub		0.316*** (0.078)	0.312*** (0.080)	0.257 (0.165)	0.294*** (0.079)		0.253*** (0.065)	0.248*** (0.067)	0.245** (0.123)	0.242*** (0.068)
Age in application year		-0.060 (0.073)	-0.052 (0.071)	-0.052 (0.064)	0.057 (0.076)		-0.111* (0.066)	-0.110* (0.067)	-0.110* (0.056)	-0.071 (0.070)
Score Control?	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Application-Year Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project Category Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.101 (0.648)	-0.153 (0.647)	0.246 (0.787)	-0.220 (0.683)	0.101 (0.648)	1.781*** (0.309)	1.332*** (0.464)	1.211*** (0.455)	1.349** (0.535)	1.235*** (0.457)
Observations	95	95	95	95	95	88	88	88	88	88
Log-likelihood	-506.6	-498.2	-505.6	-492.5	-506.6	-1054	-811.2	-806.2	-811.2	-807.6

Notes: This table reports Poisson quasi-maximum likelihood estimates of the effects of state R&D award on media evidence of non-financing business activity. The estimation sample includes applicant-startups within 15 points of the threshold score required for funding. The outcome variable is the number of business-related media mentions the startup receives two (columns 1-5) to four (columns 6-10) after the competition. Media mentions related to the Michigan R&D loan program or other fund-raising events (e.g., receipt of VC or SBIR funding) are omitted from the outcome measure.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

**Table A5. Average effect of state R&D award on patenting:  
All startup applicants vs. those within 15 points of the threshold score**

	Citation weighted Patents Numbers (log)	
	$t+2$	$t+4$
	(1)	(2)
Panel A: All Applicants, with application year, category, and sector fixed effects		
Received award (“Funded”)	-0.005	-0.012
	(0.015)	(0.019)
# Observations	264	236
Panel B: Near-threshold subsample, with application year, category, and sector fixed effects		
Received award (“Funded”)	-0.030	-0.032
	(0.030)	(0.031)
# Observations	95	88
Panel C: Near-threshold subsample, with added controls for applicant-level characteristics		
Received award (“Funded”)	-0.050	-0.057
	(0.052)	(0.055)
# observations	95	88

Notes: This table reports log linear estimates of the average effect of state R&D award receipt on citation weighted patent applications, conditioned on survival. Panel A includes all applicants that survive in the time window, while Panels B and C focus on applicants within 15 points of the threshold score. Application-year, application category (applied research or commercialization project), and sector fixed effects are included in the regressions for all three Panels. The regressions in Panel C also include controls for other applicant characteristics, including age in application year, prior receipt of VC funds and/or SBIR grants, geographic distance to the entrepreneurial hub within the state, and standardized external review scores. Table 2 describes the controls variables in more detail.

Robust standard errors, clustered at the applicant-firm level, are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; two-tailed tests.

## **Appendix B: Process used to Construct the Media-Based Measures**

This appendix describes the method used to compile, clean, and categorize news articles about the financing and business development/expansion activities of applicant companies.

As discussed in Section 5.4 of the paper, our primary objective is to test the effects of award receipt on firm performance beyond the ability to raise funds and remain in business. Ideally, we would test this effect with time-varying indicators such as employment counts, commercialization milestones, or revenue growth. We lack a reliable panel of such data for companies in our sample, which are from multiple sectors and are often very young and privately held in the competition year. As an alternative but imperfect proxy, we track changes in media mentions of business activity. An obvious drawback is that media outlets are likely to follow awardee companies more closely in the post-award period, leading to an upward reporting bias for this subset of firms. Indeed, the evidence in Table 9 of the manuscript is consistent with an overall “publicity boost” for award recipients on average. We therefore view the media-based analysis as supplemental and focus primarily on differences among firms in the relative magnitude of the effects. Separately, we use the media proxy for follow-on financing to test the robustness of our findings based on measures compiled from venture capital (VC) and SBIR databases. The media proxy of follow-on financing yields a pattern that is consistent with the VC and SBIR findings in Table 8 of the paper, which is reassuring.

To compile the news articles, we first searched the Factiva news database and downloaded all articles and press releases that match the names of companies in our sample. For companies with generic names (e.g., “GeneGo”), company-related terms were added to help filter out false positives (e.g., “GeneGo Incorporated” or “GeneGo Inc”). We downloaded all news articles about the focal company, including “duplicative listings” that Factiva defines as news articles with the same title that appear in different media outlets. Using summary output from Factiva, we compiled a spreadsheet with each article represented as a row that reported each company’s name, its unique ID, the article

title, the publication year, and an identifier for duplicate listings. Based on an iterative reading of the full text of the articles, we created the classification scheme listed below.

**Table B.1. Classification Scheme for Article Content**

Category	Subcategory	Description
Financing	Private: VC <sup>1</sup>	Investment from independent or corporate venture capitalist
	Public: SBIR <sup>1</sup>	SBIR/STTR grant
	Public: MEDC	Received award through our focal MEDC R&D loan program
	Other Public <sup>1</sup>	Funding from other university or government sources
	Other Private <sup>1</sup>	Funding from private sources other than VCs (e.g., angels)
Business Development and Expansion	Alliance <sup>2</sup>	License, R&D, co-development and/or distribution deals
	Product development and testing <sup>2</sup>	Clinical trials, beta testing, new product announcements
	Sales contracts or milestones <sup>2</sup>	Procurement contracts, purchase agreements, sales milestones
	Hiring <sup>2</sup>	New employees hired (does not include rotations or promotions of existing employees)
	New Facility <sup>2</sup>	New plants or offices
	Acquisition <sup>2</sup>	Acquired or merged with another company
	Publication <sup>2</sup>	Scientific or technical publication
	Patent <sup>2</sup>	Patent application or grant
	Other <sup>2</sup>	Other evidence of business growth and expansion (e.g., creation of scientific board, trademark registrations)
Exposure	Conference	Participation in professional conferences and trade shows
	News feature	Features about the company that are not primarily about a new financing event or development milestone (e.g., company histories and profiles)
	Honor	Awards and accolades for the company or executive team (e.g., entrepreneur of the year award, a top 50 company to watch)
Other	False hit	Article is not about the focal company (e.g., unaffiliated company of same name in a different country; news about career moves of former employees)
	Generic directory listing	Generic lists of companies covered in analyst and consulting reports
	Bad news	Layoffs, company dissolution
	Other	Other articles unrelated to financing, business development/exposure (e.g., internal promotions and reorganizations)

Notes:

<sup>1</sup> Included in media proxy for financing activity

<sup>2</sup> Included in media proxy for business development activity

The scheme includes four broad categories, which are coded as mutually exclusive. Specifically, we assess whether the primary focus of an article pertains to one of the following categories: 1. Receipt of external funding, included but not limited to VC investments and SBIR grants; 2. Updates about product development and business expansion (e.g., the formation of new alliances,

product development milestones, or the opening of new plants or facilities); 3. General information about the company or its current employees (e.g., news features; conference participation); and 4. Other articles that include “false hits” (e.g., news about former employees), generic listings of the firm’s name in directories or events, “bad news” events such as layoffs, and other updates about the company that do not primarily pertain to either fund-raising or business development activity (e.g., reorganizations or internal promotions). We initially expected to use automated text analysis tools to categorize the articles. Given the relatively small sample size and ambiguity in which terms should be used to parse the articles into the different categories based on primary focus, we opted to manually code the articles instead by reading the title, abstract and (if necessary) the full text of the article.

In total, we identified 8,721 media mentions of applicant companies. Of these, we eliminated 2,044 articles that either pertained to the focal Michigan R&D loan program or were generic listings of the firm in directories or conference/trade show events. Of the remaining 6,677 articles, 3,897 articles (58 percent) announced receipt of external financing from sources other than the Michigan R&D loan program. An additional 2,018 articles (30 percent) primarily reported updates about commercialization and business expansion. The remaining 12 percent of the 6,677 articles ( $n=762$ ) fell in the general “exposure” and “other” categories and were not included in our financing and business development/expansion proxies.

As discussed in the manuscript, our media-based proxies retain duplicate listings from Factiva. Doing so gives higher weight to more important announcements. Findings in the manuscript are robust to the omission of such listings. As reported in Table B.1, we omit “bad news” articles reporting setbacks at the company (e.g., layoffs or problems in product development or testing) in the proxy for business development and expansion. “Bad news” articles are relatively uncommon ( $n=52$ ) for firms in our sample. Example articles for the “financing” and “business development/expansion” categories are reported below.



## Example Article 1: "Financing" category

### **Rubicon Genomics , Inc. Completes \$3.5 Million Series B Financing**

534 words

1 October 2002

08:02 AM

PR Newswire

PRN

English

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-Funding To Facilitate Continuing Commercialization of OmniPlex(TM)  
Technology-

ANN ARBOR, Mich., Oct. 1 /PRNewswire/ -- **Rubicon Genomics, Inc.**, today announced it has completed its Series B round of financing raising \$3.5 million. The round was lead by ARCH Development Partners, with participation from Duchossois TECnology Partners, Sloan Ventures and individual investors. **Rubicon Genomics** is fundamentally advancing genome-wide genetic analysis with its OmniPlex(TM) technology, a novel strategy for amplifying, archiving and analyzing DNA to improve the diagnosis and treatment of disease. Teri F. Willey, managing partner of ARCH Development Partners has joined Rubicon's Board of Directors. Rubicon was first funded in May 2000 and has raised \$7.22 million to date.

"This funding will allow Rubicon to commercialize OmniPlex technology and help us reach our goal of expanding our technological base and commercial offerings," said Fred G. Beyerlein, newly appointed chief executive officer of Rubicon Genomics. "Our Whole Genome Amplification (WGA) OmniPlex technology, provides a robust means to achieve high degrees of amplification and accurate representation of DNA from extremely small samples."

"Rubicon has already made important progress in developing OmniPlex as a fundamental tool to facilitate drug discovery, pharmacogenomics, companion diagnostics and ultimately individualized medicine," said Teri F. Willey, managing partner of ARCH Development Partners. "We believe this technology will become the industry standard, providing an integrated front-end solution."

## Example Article 2: “Business Development and Expansion” category

### **Rubicon Genomics , Inc. Announces Technical Breakthrough In Whole Genome Amplification for Drug Development**

685 words

7 June 2002

08:00 AM

PR Newswire

PRN

English

(Copyright (c) 2002, PR Newswire)

ANN ARBOR, Mich., June 7 /PRNewswire/ -- **Rubicon Genomics, Inc.**, today announced it has achieved a pivotal technical breakthrough with its **OmniPlex**(TM) technology for whole genome amplification (WGA) that enables large-scale **pharmacogenomics** and drug target discovery projects to be conducted utilizing less than a single drop of blood from each clinical subject.

"Rubicon **OmniPlex** WGA will change the structure of population studies and clinical trials, decreasing the cost and time for drug development," stated Thomas A. Collet, President and CEO of **Rubicon Genomics**. "Many of the large-scale population and clinical single nucleotide polymorphism (SNP) studies have encountered hurdles due to the lack of sufficient DNA to score hundreds of thousands, or millions, of SNPs from subjects. However, Rubicon now has the capability of solving this problem, through our latest application of **OmniPlex** to WGA."

Rubicon WGA has been reproducible and controllable over the course of processing over one hundred human samples. Greater than a million-fold amplification has been achieved from 1 **ng** aliquots of human **OmniPlex** DNA. Quantification of more than one hundred human coding and non-coding sites after thousand-fold amplification of 5 **ng** showed that one hundred percent were successfully amplified, and more than ninety percent of the sites were amplified within a factor of two of the mean. SNPs were successfully scored on an automated platform using the amplified **OmniPlex** DNA.

These results open the door to comprehensive SNP studies from very small amounts of blood, buccal swabs, **mouthwashings**, or archived tissue from clinical records for drug discovery. External validation of **OmniPlex** WGA has begun at several pharmaceutical and biotechnology companies.

"We are proud of the many technical achievements we have made to date with **OmniPlex** and excited to commercialize **OmniPlex** to whole genome amplification. Rubicon's objective is to make **OmniPlex** the industry standard for the collection, storage, and amplification of DNA for gene-based drug discovery and delivery," added Collet.

**OmniPlex** is an integrated technology platform for drug target discovery, **pharmacogenomics**, and diagnostics that can archive, amplify, and analyze DNA. **OmniPlex** WGA is fifty to one hundred times faster than conventional in vivo techniques and fifty times more representative of the entire genome than conventional in vitro techniques of WGA. In addition to WGA, the complimentary **OmniPlex** molecular **haplotyping** application gives pharmaceutical companies the ability to discover associations between genes and drug efficacy in a more precise and cost-efficient manner. These processes can aid in the acceleration and development of safer and more efficacious drugs to cure diseases.