THE EFFECTS OF STATE INNOVATION PROGRAMS ON ENTREPRENEURIAL FIRMS: THREE ESSAYS

by

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DEDICATION

To My Family

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CHAPTER 1

INTRODUCTION

With the belief that entrepreneurship is a key driver of economic growth and job creation, many U.S. states have launched ambitious programs aimed at stimulating entrepreneurial activity within their borders. Not surprisingly, most of these programs target the science and technology-related sectors. Despite state government enthusiasm for such programs, systematic evidence regarding the effects on these programs on entrepreneurial firms remains lacking (Brander, Du, & Hellmann, 2011; Lerner, 2009). Unlike federal initiatives, such as the Small Business Innovation Research (SBIR) program (Lerner, 1999; Wallsten, 2000), information about state innovation programs is fragmented and thus challenging to assemble. Teasing apart the causal impact of these initiatives is further complicated by the absence of viable comparison baselines.

My dissertation provides new evidence on the effects of state innovation programs on entrepreneurial science and technology companies in the Great Lakes region. To do so, I assemble novel databases and use multiple research methods to address the effects in a series of studies. My first essay examines the extent to which, if at all, competitive R&D awards from Michigan innovation programs enhance the performance of participating ventures relative to startups that seek but fail to receive an award. I then expand the scope of my inquiries to other states in the Great Lakes region and investigate the broader implications of large-scale programs on entrepreneurial activity, including patterns of entry and survival (Essay 2) and the retention of innovation-oriented startups within a state (Essay 3).

The Great Lakes region[1] is a particularly useful context in which to investigate the interplay between state policies and entrepreneurial-firm behavior and performance. First, the ideas and human capital needed to launch new science and technology companies are geographically distributed across this region, which houses numerous top-ranked universities and research institutions (Austin & Affolter-Caine, 2006). However, despite the favorable innovation environment in the Great Lakes region, the venture capital and support services typically required for high-growth startups are tightly agglomerated elsewhere, specifically in the coastal states of Massachusetts and California (Chen, Gompers, Kovner, & Lerner, 2010; Samila & Sorenson, 2011b). Between 1995 and 2009, for example, 16.1 percent of the doctorates in life sciences were awarded by research institutions in the Great Lakes region, while 15.9 percent were awarded in California and Massachusetts. In the same period, however, startups headquartered in the Great Lakes states received only 3.9 percent of U.S. venture capital (VC) investments in the life sciences, while California and Massachusetts-based ventures received 56.2 percent.[2] While arguments exist for and against public efforts to boost local entrepreneurial activity, evidence on the effects of these initiatives remains scarce (Chatterji, Glaeser, & Kerr, 2013; Lerner, 2009; Samuel, 2010).

To fill this gap in understanding, my dissertation contributes new evidence on the impact of state innovation programs on entrepreneur firms in three related and complementary studies. The first study, joint with Rosemarie Ziedonis, uses a unique database of R&D award competition applicants and recipients in Michigan from 2002 through 2008 to study the impact of state awards on firm performance. The data, drawn primarily from state government archives, provide pre-treatment characteristics and external

[1] The Bureau of Economic Analysis (BEA) defines the Great Lakes region to include Illinois, Indiana, Michigan, Ohio, and Wisconsin.
[2] Authors' calculation using National Science Foundation (NSF) WebCASPAR and VentureXpert data.

reviewer scores for all award applicants, including firms that sought but did not receive state R&D funding. Using regression discontinuity design methods (Lee & Lemieux, 2010), we find strong and compelling evidence that state R&D funding enhances the commercial viability (i.e., survival) of recipient firms, suggesting that receiving an award eases a firm's financial constraints. In particular, among firms with scores near the discontinuous funding threshold, awardees were more likely to survive three years after the competition than otherwise comparable applicants that sought but did not receive an award. We also find that receipt of state R&D funding enhances the follow-on financing for new ventures, but only for those with more onerous information challenges in entrepreneurial capital markets.

The second study broadens my scope to the impact of state innovation programs in other states in the Great Lakes region, including Illinois, Indiana, Ohio, and Wisconsin. Prior studies in strategy and economics show that initial founding conditions can affect the post-entry performance of entrepreneurial firms (e.g., Audretsch, 1995; Geroski, Mata, & Portugal, 2010; Mata, Portugal, & Guimarães, 1995). Other studies explore the difficulties firms face in their attempts to transition between idea discovery and the launch of successful products, or what is termed the "valley of death" (Kerr & Nanda, 2009b). Whether state initiatives can improve the entrepreneurial founding environment and help new ventures bridge the valley of death in the early stages of their development is a matter of ongoing academic debate (Lerner, 2009). To address this question, my study assesses the extent to which state innovation programs increase the survival prospects for life sciences startups in the Great Lakes region. Based on the post-entry performance of new ventures, my evidence suggests that new ventures formed when an innovation program is present have significantly higher survival rates than new ventures formed without the presence of such a program. I also find that program effects on firm survival diminish over time and that they are more pronounced for firms in sub-sectors with greater resource requirements for commercialization.

Finally, in my third essay, I investigate the effects of state innovation programs on the location decisions of high technology companies in the life sciences and information technology industries. For new science and technology companies, the decision to migrate to other regions often involves a difficult set of trade-offs. Prior research suggests that staying local allows entrepreneurs to leverage interpersonal networks and existing organizational ties (e.g., with universities or other research institutions) while avoiding the disruptions and costs of relocation (Dahl & Sorenson, 2012; Feldman, 2004). On the other hand, failure to re-locate near entrepreneurial sources could make it more difficult to secure expansion capital, management talent, or business services, thus limiting the upside potential of these ventures (Chen, Gompers, Kovner, & Lerner, 2010; Hochberg, Ljungqvist, & Lu, 2007; Porter & Stern, 2001). In this study, I present evidence of the effect of state innovation programs on firm relocation decisions by tracking the geographic location changes of life sciences and information technology companies initially established in the Great Lakes region. Specifically, I find that the startups with greater needs for external financing and support services in the commercialization process are more likely to leave their home states. Importantly, I further document that, for relatively young firms, the baseline proclivity of firms to stay local increases with the presence of a state innovation program.

All three essays in my dissertation benefit from 25 semi-structured interviews I conducted with entrepreneurs, investors, and government officials in the Great Lakes states. These interviews deepened my understanding of the role of state innovation programs and helped me identify and better interpret my data sources. They also enabled me to understand the perceived effects of specific programs as well as the viewpoints of entrepreneurs and investors not participating in such programs.

Overall, my dissertation contributes to five main strands of literature. First, it contributes to a burgeoning literature in strategic management, finance, and economics on the performance implications of alternative sources of entrepreneurial financing. Prior work has investigated the various effects of corporate funding (Dushnitsky & Shaver, 2009; Katila, Rosenberger, & Eisenhardt, 2008; Park & Steensma, 2012), venture capital (Fitza, Matusik, & Mosakowski, 2009; Hellmann & Puri, 2002; Hsu, 2004), and federal government monetary support (Brander *et al.*, 2011; Lerner, 2010) on the success of new ventures. However, the extent to which public efforts at the state level can affect entrepreneurial-firm performance has received little attention, a gap that my dissertation addresses.

Second, my research contributes to a growing literature on how institutional and policy reforms affect entrepreneurial firms and whether public sector intervention can reduce new venture market failures (Eesley, 2010; Kerr & Nanda, 2009b). In doing so, it fills a gap in management research and could thus contribute to debates on public policy issues related to entrepreneur and economic development (Adler & Jermier, 2005; Kochan, Guillen, Hunter, & O'Mahony, 2009).

Third, my research is salient to the literature on the association between a firm's founding environment and its post-entry performance (Eisenhardt & Schoonhoven, 1990; Geroski *et al.*, 2010). Specifically, it provides systematic and cross-state evidence on whether changes in the entrepreneurial founding environment created by state initiatives can affect new venture post-entry performance, and as a consequence, survival.

Fourth, my research extends current work on economic geography, industry agglomeration and firm location decisions by introducing a dynamic view of firm location decisions. Although previous studies in international business and industrial agglomeration have identified institutional-, industrial- and firm-level factors that may affect firm location decisions, most of these studies focus on existing industry clusters and the initial location decisions of in-country or global ventures (Alcacer & Chung, 2007; Glaeser & Kerr, 2009; Wheeler & Mody, 1992).

Finally, within strategic management, my dissertation contributes to the ongoing search for ways to tease apart the consequences associated with non-random actions using observational data, a methodological challenge that continues to garner widespread attention in the field (Durand & Vaara, 2009; Hamilton & Nickerson, 2003; Shaver, 1998a).

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CHAPTER 2

STATE GOVERNMENTS AS FINANCIERS OF TECHNOLOGY STARTUPS: IMPLICATIONS FOR FIRM PERFORMANCE[1]

2.1 Introduction

Faced with an eroding base of traditional manufacturing industries, U.S. state governments have assumed a more prominent role as financiers of new science and technology companies. In 2002, for example, Ohio launched a $1.6 billion Ohio Third Frontier (OTF) initiative to support technology-based economic development within the state. The program is credited with helping create and finance over 571 Ohio-based companies since its inception (SRI, 2009). Also aimed at stimulating entrepreneurial innovation inside its borders, the state of Utah established a Science Technology and Research (USTAR) program in 2006. In addition to funding research at Utah-based universities, USTAR subsidizes the commercialization activities of technology startups within the state (Duran, 2010).

Despite large-scale policy experimentation, little is known about the effects of state innovation programs on the performance of participating ventures. Relative to federal

[1] We thank representatives from the Michigan Economic Development Corporation (MEDC) for providing access to archives and for answering our many questions, and Matt Justice, Meng Lu, Karina Mann and Anastasia Strader for excellent research assistance. Financial support from the Ewing Marion Kauffman Foundation is gratefully acknowledged. We are also grateful to suggestions from Janet Berkovitz, Ha Hoang, Jenny Kuan, Francine Lafontaine, Marvin Lieberman, David Mowery, Ramana Nanda, Joanne Oxley, Mike Roach, Robert Seamans, Jagadeesh Sivadasan, Heidi Williams, Brian Wu, Arvids Ziedonis and participants in seminars and conferences at UC Berkeley, UCLA, Georgia State University, the University of Maryland, the University of Michigan, NBER, Northwestern University, the University of Oregon, the University of Pennsylvania, and Stanford University.

initiatives in the United States like the Small Business Investment Research (SBIR) program, information about state-level R&D programs is fragmented and cumbersome to assemble. Empirical research on this topic is further plagued by methodological problems. Absent appropriate baselines for comparison, it is difficult to discern whether state funds causally improve firm performance or whether more promising companies are simply chosen for awards. Given the pervasiveness of state-level R&D programs (Coburn & Berglund, 1995; Feldman & Lanahan, 2010), distinguishing between these interpretations is vital both from an academic and practical (managerial/public policy) perspective.

This study provides new evidence based on innovation programs launched since 1999 in the state of Michigan. Like many states in the Great Lakes region, Michigan has been battered for decades by declining health in its manufacturing sectors and an outmigration of high-skilled labor (Samuel, 2010). To diversify its tax base and re-kindle economic growth within the state, the Michigan Life Science Corridor (MLSC) program was launched in 1999 through a $1 billion legal settlement from the tobacco industry. Similar to the later Ohio and Utah initiatives, the MLSC and its affiliated programs offer R&D financing to startups through a competitive awards process.

To test whether state R&D awards enhance the performance of participating ventures, we compile a novel database from Michigan government archives on all for-profit participants in competitions held from 2002 through 2008. Importantly, these data enable us to observe both pre-treatment characteristics and external reviewer scores for the entire applicant pool, including firms that sought but failed to receive an award. Also useful from a methodological perspective, these data reveal discontinuous cut-offs in the distribution of reviewer scores that correspond to receipt of funding. This artifact of the selections process enables us to use regression discontinuity design (RDD) methods to compile more comparable sets of participating and non-participating ventures than is typically possible for innovation scholars. Increasingly common in economics (e.g., Black, 1999; Lee & Lemieux, 2010), RDD-related approaches remain under-utilized in the strategic management and entrepreneurial finance literatures.[2]

The results of our analyses are quite striking. On one hand, we find strong and compelling evidence that program participation bolstered the commercial viability of Michigan-based technology companies: funded firms are 12-13% more likely to survive 2 years and 21-23% more likely to survive 4 years after the competition. The results hold in subsamples of firms proximate to the funding cut-off and do not appear to be driven purely by the selection of "better" companies for the awards. This evidence is consistent with the view that the program helped ameliorate imperfections in the market for entrepreneurial financing: absent R&D awards from the state, companies of comparable quality were less likely to remain in business.

The effects of program participation on other aspects of entrepreneurial-firm performance—including patent productivity and receipt of follow-on financing—are more ambiguous. Surprisingly, we find no discernable effect of award receipt on patent productivity. Our analysis reveals, however, that state R&D funding stimulates follow-on financing from other government (SBIR) and VC sources when capital-market imperfections are more severe. We interpret this latter evidence as consistent with the view that competition-based R&D awards help reduce informational inefficiencies in markets for entrepreneurial financing (Hall & Lerner, 2010; Lerner, 1999).

This study contributes to three main strands of literature. First, it contributes to a burgeoning literature in strategic management, finance and economics on the performance

[2] See Kerr, Lerner, and Schoar (2011) for a recent exception in entrepreneurial finance.

implications of alternative sources of entrepreneurial financing. Prior work has investigated the effects on new ventures of financial backing from corporations (Dushnitsky & Shaver, 2009; Katila, Rosenberger, & Eisenhardt, 2008; Park & Steensma, 2012), independent venture capitalists (Fitza, Matusik, & Mosakowski, 2009; Hellmann & Puri, 2002; Hsu, 2004) and national government agencies (Brander *et al.*, 2010; Cox & Katila, 2010; Kortum & Lerner, 2000). The extent to which, if at all, R&D financing from state-government sources affects new venture performance has received little attention in this literature, a gap that our study helps fill.

Within strategic management, the study also is salient to an ongoing search for ways to tease apart the consequences associated with non-random actions using observational data, a methodological challenge that continues to garner widespread attention in the field (Durand & Vaara, 2009; Hamilton & Nickerson, 2003; Shaver, 1998). Our study not only underscores the importance of taking into account the underlying selection process, but also illustrates how discontinuities that result from that process can be fruitfully exploited.

Finally, we contribute to a more targeted line of inquiry on R&D program evaluation (Jaffe 2002; Klette, Møen, & Griliches, 2000). Even though governments aim to alleviate sources of market failure through R&D policy intervention, they often fail to do so due to design and implementation problems (Lerner 2009; Wallsten, 2000). Empirical evidence on this topic nonetheless remains inconclusive and is sparse in state-government contexts. We provide new evidence with an approach that could be used to evaluate the private returns of other R&D programs, both within the United States and in other countries. Although providing limited guidance on whether public R&D programs are justified from a social welfare perspective (see Klette *et al.*, 2000), such evidence would deepen extant understanding on the extent to which government R&D awards boost the performance of award recipients above and beyond what otherwise would be predicted.

2.2 Rationale for Government R&D Awards and Prior Empirical Evidence

Why should governments subsidize R&D projects in the private sector?[3] The answer rests on theoretical concerns about market failure. One concern is that, absent policy intervention, the private sector will under-invest in R&D relative to socially optimum levels (Griliches, 1992; Hall, 1996; Jaffe, 2002). 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 socially optimal rate of R&D investment can exceed the private returns to such investments.

A second and related concern is that capital markets function imperfectly, further eroding R&D incentives in the private sector (Hall and Lerner, 2010). For young science and technology companies, the development and commercialization of new products typically requires financial backing from third parties. Discerning the value and commercial promise of embryonic technologies nonetheless can be difficult for outsiders. As Hall and Lerner (2010) point out, when investors find it challenging to sort good projects from bad due to imperfect information, financial backing can be more costly or difficult to secure. If financial intermediaries like banks, angel investors, and venture capitalists are unable to fully mitigate this problem, entrepreneurs may be unable to secure sufficient capital through market mechanisms alone (Lerner & Kegler, 2000).

[3] In addition to allocating R&D funds directly to companies, governments can reduce the costs of industrial R&D through tax-based incentives. Wilson (2009) and Hall and Lerner (2010) discuss alternative policy levers used to stimulate innovation in the private sector and key trade-offs among them.

In addition, state governments pursue more parochial interests: to stimulate economic growth inside geographic borders and to diversify the tax base (Acs *et al*., 2008). Not surprisingly, eligibility in state-run R&D and commercialization programs is therefore restricted to companies with headquarters or major R&D facilities within the state. A more specific concern is that entrepreneurs within the state may find it difficult to secure "expansion" capital without re-locating to a major hub of venture capital activity. Despite syndicated deals through investor networks, the U.S. venture capital (VC) industry remains tightly agglomerated in the bicoastal states of California and Massachusetts (Sorenson and Stuart, 2001). From 1995-2009, for example, only 25.8 percent of biomedical research dollars from the National Institutes of Health (NIH) flowed to California and Massachusetts-based institutions. That same year, however, over 56.2 percent of U.S. venture capital to biomedical startups originated from these two states.[4] To facilitate interactions with entrepreneurs and to lower monitoring costs, venture capitalists typically require portfolio companies to locate key operations and personnel nearby, including top managers and core development teams (Chen, Gompers, Kovner, & Lerner, 2010). By providing entrepreneurs with an alternative source of R&D financing, state governments may be able to retain more promising ventures and, in doing so, stimulate the development of an indigenous investment community.

Empirical evidence on the "treatment" effects of government R&D funding on participating (versus non-participating) remains largely based on national programs. Within the United States context, the SBIR program and a similar subsidy-based Advanced Technology Project (ATP) initiative have received the lion's share of analytical attention.[5]

[4] Authors' calculations based on NIH and VentureXpert data.
[5] Lerner (2009) and Brander, Du, and Hellmann (2011) review the evidence from national programs outside the United States. For brevity, we restrict attention below to evidence on U.S.-based programs.

Even then, prior studies fail to reach consensus on the effects of these long-standing programs on participant-firm performance.

Consider evidence from the SBIR program. Comparing SBIR awardees with matched samples of entrepreneurial companies, Lerner (1999) finds that SBIR recipients are more successful in securing follow-on VC financing relative to non-recipients. This evidence is consistent with the view that winning a public R&D awards can help "certify" the quality of new technology companies to outside investors, thus reducing information problems in markets for entrepreneurial financing. Feldman and Kelley (2003) report a similar "halo" effect in the ATP program. Based on survey evidence, Audretsch, Link and Scott (2002) further suggest that SBIR awards enable the commercialization of research that would not have been undertaken absent policy intervention.

Wallsten (2000) and Cox and Katilla (2010) offer a less sanguine view of the relationship between SBIR funding and new venture performance. Taking into account the SBIR selection process, Wallsten (2000) fails to discern that the awards stimulate employment growth among young companies, an effect attributed to the "cherry-picking" of more-promising applicants for the awards. More troublesome, Wallsten suggests that the SBIR program fails to address capital-market imperfections, crowding out R&D funds from private sources on a dollar-for-dollar basis. Also troublesome, Cox and Katila (2010) suggest that SBIR funding *undermines* the innovative and commercial productivity of technology ventures, based on comparisons between VC-backed companies that did (versus did not) receive such awards. As mentioned earlier, systematic evidence on the performance implications of state-government programs remains lacking.

2.3 Michigan's Innovation Programs[6]

2.3.1 *Overview*

To investigate the effects of state-government R&D funding on new-venture performance, we focus on three innovation programs introduced since 1999 in Michigan, a state that houses top-tier medical and research institutions despite well-known challenges in traditional manufacturing industries (Samuel, 2010). The Michigan Life Science Corridor was the state's first large-scale innovation program. When the program was announced in 1999, its billion-dollar size was unprecedented among state R&D initiatives. The MLSC aimed to position Michigan among the top five U.S. states in the life science sector within twenty years, in part by stimulating a more vibrant base of entrepreneurial companies. The annual budget anticipated for the program was $50 million, much of which was initially directed toward university research.

After gubernatorial turnover and lobbying from non-life-science industries, the MLSC was modified in 2004 to include advanced automotive technologies, alternative energy and homeland security technologies. Reflecting this shift, the program was renamed the Michigan Technology Tri-corridor (MTTC). Soon thereafter, the MLSC and MTTC activities were subsumed under a new 21st Century Jobs Fund (21CJF) program. From 2000 through 2003, the total program budget ranged from $32 to $50 million per year. In the ensuing years, annual budgets fluctuated from $10 million in 2004-2005 and $200 million in 2006-2007, to $75 million in 2008.

Under this umbrella of programs, Michigan-based companies could apply for R&D awards to help defray product development and commercialization expenses in eligible

[6] This section draws on conversations with program managers during 2010-2011, annual Battelle/BIO State Bioscience Initiatives reports, archived minutes from Michigan Strategic Fund Board meetings, and government reports (e.g., MEDC, 2010).

sectors, with preference given to young and small companies. Relative to other sources of government R&D funds for technology ventures, the sums available from the state are non-trivial. As shown in Figure 2.1 Average Size of MEDC Program Funding to Awardees, the mean award per firm was $600,000 in 2002 and exceeded $1.5 million in the 2006 and 2008 competitions. By comparison, SBIR technology development and commercialization awards in this period averaged around $500,000 but included a per-firm limit of $1 million (Wessner, 2007).[7]

Across all incarnations of Michigan's innovation programs—from the MLSC and MTTC to the ongoing 21st Century Jobs Fund—one agency was responsible for overseeing and managing the state's R&D awards to for-profit companies. This quasi-governmental agency, the Michigan Economic Development Corporation (MEDC), is responsible for economic development in the state. According to MEDC officials, state R&D awards are typically structured as repayable debt or "convertible loans" that can switch to equity if certain milestones are met.[8] Although contract terms are confidential, program managers report that loans are offered at competitive rates and typically allow firms to defer payment for a two-to-three year period. Program managers saw some advantages of this financial instrument over pure loans, which have limited upside potential, and grants, which as subsidies offer less means for accountability and are more difficult to "sell" politically.

In addition to awarding R&D funds to technology startups, the state of Michigan plays a more passive role in entrepreneurial capital markets through its "fund-of-funds" program. In this initiative, the state invests in venture capital funds that support Michigan-

[7] Statistics are based "Phase II" SBIR awards administered through the National Science Foundation. As Wessner (2007) reports, the Small Business Administration (SBA) increased the per-firm limit of SBIR Phase II grants from $750,000 to $1 million in 2003.
[8] Both parties must agree to the conversion. From an entrepreneur's perspective, the conversion trades off loan repayment with the sale of private equity in the company. See Lerner (2009) for more detailed discussion of alternative financing vehicles.

based companies in hopes of increasing the supply of expansion capital within the state. The state has sponsored two such funds to date, one in 2006 with $95 million and another in 2011 with $120 million.[9] Unfortunately it is premature to assess the impact of these fund-of-fund investments, either overall or relative to direct models of R&D financing. We therefore restrict attention below to R&D awards directly allocated to technology startups through the combined set of MLSC, MTTC and 21CJF programs.

2.3.2 *The selection process*

To receive R&D funding from the state, entrepreneurs must submit an application through a competitive awards process. As depicted in Figure 2.2. The Selection Process (Decision Tree), proposals are first screened for Request for Proposal (RFP) compliance. All proposals that meet the RFP requirements proceed through a competitive evaluation and review process. In Round 1, proposals are sent to an external panel of peer reviewers for evaluation and scoring.[10] The proposals are scored based on four equal-weighted criteria specified in the RFP: (1) Scientific Merit, (2) Personnel expertise, (3) Commercialization Merit and (4) Ability to Leverage Additional Funds. Based on Round 1 scores, top-ranked proposals are invited to proceed to Round 2. Lower-ranked proposals are omitted from consideration.

In Round 2, additional input is gleaned from interviews with representatives from applicant companies and proposals are re-scored based on the RFP criteria. Following this second evaluation, the external review panel recommends proposals for funding and provides the state information about each proposal's ranking, score, and budget. A

[9] For more information, see http://www.venturemichigan.com (last visited Jan 03, 2012).

[10] From 2002 through 2006, technical experts from the American Association for the Advancement of Science (AAAS) evaluated the proposals. In 2008, the review process was altered to include individuals with business and/or entrepreneurial investment experience.

governing board, the Strategic Economic Investment and Commercialization (SEIC) Board, then selects the highest-ranked projects recommended for funding until the total budget allocated for the competition is expended. According to MEDC officials, the total budget amount for a competition round is largely pre-determined prior to a solicitation for proposals. Funding decisions are final and not subject to appeal.

The final stage is "due diligence" and contract negotiation. At this stage, projects can be dropped for two main reasons. First, the state may choose to rescind an award if new information revealed through due diligence renders an applicant ineligible (e.g., financial commitments from third parties have fallen through). Alternatively, the applicant may choose to withdraw from consideration due to concerns about the terms or cost of financing or unrelated reasons (e.g., a shift in corporate priorities).

Of the 297 entrepreneurial-firm proposals in our estimation sample described below, roughly half (49%) were screened out in Round 1 of the selection process while the remainder (51%) proceeded to Round 2. Of those invited to Round 2, less than half (41%) received R&D funds. In total, 21% of all entrepreneurial-firm applicants from 2002 through 2008 received financial assistance through these state-run R&D programs, and 7% were either rescinded or withdrawn.[11]

2.4 Data

2.4.1 *Sample construction*

Applicants for R&D financing through Michigan's competition-based programs were identified with archival data from the Michigan Economic Development Corporation. For

[11] In contrast, Wessner (2007, p. 55) reports NSF acceptance rates of SBIR proposals between 40 and 60 percent from 1997 through 2005. For the federal ATP initiative, Feldman and Kelley (2003, p. 155) document that "fewer than 20 percent of proposed projects [submitted between 1990 and 1999] actually receive funding" 1990 and 1999."

each proposal, these data report information about the principle investigator (name, title, department), organization (name, address), project type (applied research or commercialization), industry sector, and funds requested. In addition, these data reveal project-specific information generated during the evaluation process, including the firm's aggregate external reviewer score, stage of advancement through the competition, and how much funding was recommended and dispersed, if any.

To identify "entrepreneurial-firm" applicants, we first restricted attention to proposals from for-profit companies, thus omitting awards to universities and non-profits. Based on a state business registry (described below), we then identified the founding years and selected the subset of for-profit applicants that were 15 years or younger as of the application year.[12] This age filter eliminated 23 older firms from the estimation sample, but retained 92 percent of all for-profit applicants. As a robustness check, we re-ran the regressions below with the entire company-applicant sample and obtained similar results.

Finally, thirteen (13) firms filed multiple applications in a given round of competition. If a firm with multiple applications received R&D funds in a single round, we omitted unfunded proposals of the company from the control-group sample. For non-winners with multiple submissions, we retained only the applicant's top-ranked proposal in the control group to yield greater comparability with the awardee sample.

In combination, these criteria resulted in 297 applications filed by 241 entrepreneurial firms from 2002 through 2008.

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[12] Hellmann and Puri (2002) define "startups" as firms less than 11 years old while Stuart et al. (1999) report that the maximum age of venture-backed biotechnology firms with IPOs in the 1980s to mid-1990s is 12 years since founding. Since our data span the decade of the 2000s, a period that includes a prolonged and severe economic downturn, we prefer a less restrictive 15-year threshold.

2.4.2 *Startup characteristics and outcome variables*

Empirical studies on entrepreneurial firms face notorious data-collection challenges. Unlike older and publicly traded companies, information about entrepreneurial firms is more scattered and difficult to obtain. In light of this challenge, we integrate data from multiple sources. Key sources include the MEDC archives (for applicant-level information and reviewer scores), the Michigan Department of Licensing and Regulatory Affairs database (for commercial viability), VenturXpert (for follow-on VC financing), SBIR awardee lists (for SBIR awards), and Delphion (for successful applications of U.S. patents). We supplement these data with searches of company websites, press releases, and news articles as needed.

Information from these sources is used to compile three time-varying indicators of new venture performance: (1) whether the firm remains in business (i.e., "survives") by time *t*; (2) its ability to secure financing from other third parties; and (3) its productivity in generating patents. Unfortunately, we lack reliable firm-level data on annual R&D expenditures and employment growth.

Our first outcome variable, *Survival*, is based on the current status of companies listed in the Michigan Department of Licensing and Regulatory Affairs (LARA) database. Five main status types are listed: (1) active; (2) active but not in good standing; (3) dissolved; (4) withdrawn; and (5) merged. Fortunately, the database also indicates the date on which a firm switches type, if at all. For firms listed in categories other than "active," we conducted supplemental searches of company websites and press release. This process helps ensure that a "dissolved" or "withdrawn" status does not simply reflect movement from the state or a re-organization via merger or acquisition. In ambiguous cases, we called the company to determine whether it was still in business. The LARA database also reports incorporation dates for Michigan-based companies, which we used to determine the ages of applicant-firms in our sample.

A second outcome variable pertains to follow-on financing, and is used to test the "certification" hypothesis (Lerner, 1999; Wallsten, 2000)—that winning a competitive R&D award casts a positive signal to other investors, thus making it easier to attract other sources of financing. Young science and technology companies seek financial capital from numerous sources. Prominent among those capital sources are grants from the SBIR and investments from VCs. To identify SBIR awards to applicant-companies, we searched the Small Business Administration (SBA) TECH-Net database by company names, using company locations to ensure a match. We then compiled the number of SBA awards to each applicant company, including both Phrase I and Phrase II awards. For VC investments, we conducted similar searches of VentureXpert, a venture capital database commonly used in empirical research (e.g., Dushnitsky and Lenox, 2005; Park and Steensma, 2012), company websites, and Zephyr, which includes news articles about VC deals since 1997. Since funding amounts were sparsely reported, our proxy for follow-on VC financing is based on the number of VC investment rounds, if any, listed for each firm.

A third outcome variable, *Patent Productivity*, captures whether state R&D funding enhances the innovative productivity of participating firms. Although an imperfect measure of innovative output, patent counts capture the extent to which these startups succeed in producing novel and patent-worthy inventions from their R&D activities. By searching company names in the Delphion database, we assemble all U.S. patents awarded to these companies through 2012. The annual patent productivity of each company is based on the dates that issued patents are filed rather than granted, as is conventional practice in the literature.

Table 2.1 reports summary statistics for the entrepreneurial applicant-firm sample. On average, sample firms are quite young in the focal year of competition, at 4 years post-founding. As expected from the program's history, the life science sector represents the largest component of the applicant pool, filing almost half (49%) of all requests for funding. Roughly 21 percent of the applicants ceased operations due to business failure within four years of the competition year, which could reflect the liquidity constraints faced by Michigan-based companies in the recessionary period of the 2000s.

2.5 Estimation Method

Establishing a causal relationship between state R&D financing and the subsequent performance of new ventures poses well-known methodological challenges (David, Hall, & Toole, 2000; Klette *et al.*, 2000). In light of that challenge, we employ multiple empirical approaches and estimation samples. First, we estimate "naïve regressions" that use the entire applicant-pool sample but control for observable characteristics of the firms pre-treatment. Then we use regression discontinuity design (RDD) methods to estimate effects with subsets of firms proximate to the cut-off in scores that determine the allocation of funding. Intuitively, we assume that omitted variable problems fall as more restrictions are imposed on the sample. The trade-off, of course, is that a corresponding decline in sample sizes, which could reduce estimation precision. We therefore report results using multiple methods and samples and assess patterns among them.

2.5.1 *Controlling for observables*

Equation (1) represents our baseline model:

$$Y_{it+1} = \Phi(\alpha funded_{it} + X_{it}\delta) \tag{1}$$

Y_{it+1} is the outcome variable of applicant i in subsequent period *t+1*. $funded_{it}$ is a binary variable that indicates whether the company was funded (1=funded; else=0). X_{it} is a vector of applicant-level covariates that include the age of the firm in the competition year, the industrial sector, the application category (applied research vs. commercialization project), and competition-year fixed effects. Controlling for these observable firm-level characteristics, we estimate effects with the entire pool of entrepreneurial-firm applicants, including firms that sought but failed to receive an award.

When the dependent variable is a binary variable such as an indicator of survival, where $Y_{it+1} = P(\lambda_{it+1} = 1|Z_{it})$ and λ is the binary indicator, we use linear probability estimation with robust standard errors. Probit estimation is also used as a robustness check. When the dependent variable is a count (i.e., number of SBA awards, patents, or VC investments), we use a Poisson quasi-maximum likelihood estimator, again with robust standard errors. As Gourieroux, Monfort, and Trognon (1984) and Santos, Silvam, and Tenreyo (2006) report, Poisson QMLE outperforms OLS in terms of fit and robustness when dependent variables are non-negative and skewed.

2.5.2 *Estimation near the discontinuity border*

The second approach exploits the discontinuous breakpoint between external reviewer scores and funding probabilities more fully by invoking regression discontinuity design (RDD) methods widely used in labor and education economics (Lee & Lemieux, 2010). Black, Galdo, and Smith (2007), for example, use discontinuities in treatment status to evaluate the effects of government training services on individuals in search of re-employment. Implementing RDD in an instrumental variable framework, Jacob and Lefgren (2004) test the causal effects of educational remedial programs on the scholastic achievement of students. A separate body of research, more closely related to this study, uses RDD methods to discern how government R&D grants affect the career trajectories and productivity of individual scientists (Arora & Gambardella, 2005; Carter, Winkler, & Biddle-Zehnder, 1987; Chudnovsky, López, Rossi, & Ubfal, 2008; Ubfal and Maffioli, 2011).

In this study, we restrict attention to more comparable Round 2 applicants and define cutoff c_{jt} as the score above which companies are recommended for funding. We then subtract the cutoff from the second-round score of company *i* in application category *j* in year *t,* defined as p_{ijt}. This process yields a normalized score for each applicant, defined as $n_{it} = p_{ijt} - c_{jt}$.

Intuitively, RDD methods let us compare the performance of companies that lie slightly above a discontinuity border with that of entities falling slightly below that border. We assume that companies within certain bandwidths of the cut-off border are more similar to one another (both on observable and unobserved characteristics) than they are to firms located at more distant points in the distribution (Lee & Lemieux, 2010). Put differently, we assume that two companies with normalized scores of +50 and -50 (i.e., positive and negative outliers) are less comparable than two companies with normalized scores of +1 and -1, where both firms have scores close to the funding breakpoint.

To infer causality using RDD methods in this setting, three assumptions must be met: (1) the cut-off score cannot be pre-determined and subject to manipulation by applicants; (2) the relationship between the score and the probability of funding must be non-linear (i.e., a breakpoint must exist); (3) applicant characteristics (both observed and unobserved) must be comparable in the cutoff region (Lee & Lemieux, 2010).

As discussed earlier, an independent panel of external reviewers scores each funding proposal. The cut-off score is unknown to applicants in advance and can change across competitions: it is largely driven by the total funds allocated to a competition in advance of solicitations for proposals and the amount of funds requested by high-ranked submissions. Therefore, assumption (1) is satisfied.

Figure 2.3a and 2.3b suggest that assumption (2) is satisfied: the probability of receiving state R&D funding shifts discontinuously with external reviewer scores. Figure 2.3a is a lowess smoother with bandwidth 0.8. Figure 2.3b plots the mean of the binary variable "funded" over constant 10-unit intervals. Both figures reveal a visible and discontinuous pattern.

Table 2.2 evaluates the comparability of firms just below and above the discontinuity border based on observable characteristics. Panel A of Table 2.2 reports mean values of applicant characteristics within 20-points of the discontinuous cutoff. Panel B reports similar statistics for the narrower 15-point bandwidth. Based on two-tailed t tests, the average pre-treatment characteristics of the groups are statistically indistinguishable within 20-points bandwidth. The only exception is on the measure of whether the focal firms have VC fund or SBA award in year 1-2 prior to application, which is marginally significant with p value of 0.07. When the sample is further narrowed down to 15-point bandwidth, the sample firms become more comparable since all pre-treatment characteristics are statistically indistinguishable. Despite the evidence in Table 2.2, it is possible of course that firms near the funding cutoff differ in *unobserved* ways likely to affect future performance. Lacking a direct test, we must assume that this latter requirement—of comparability in unobserved traits—is met (Lee & Lemieux, 2010).

2.6 Findings

To what extent, if at all, does receipt of state R&D financing improve the performance of technology startups? Does state R&D financing help mitigate imperfections in entrepreneurial capital markets? To shed empirical light on these questions, we present three sets of analyses that correspond to each outcome variable. The first set estimates the effects of state R&D awards on a crucial outcome variable for young technology companies: survival. A second set tests for "certification" effects on follow-on financing, both for SBA awards and VC investments. A final set tests whether state R&D financing bolsters the patent productivity of new ventures.

2.6.1 *Effects on firm survival*

Table 2.3 reports regression estimates of equations (1) with two time-periods of survival and the three applicant-firm samples discussed above. The dependent variable in Panel A and B is a binary indicator of whether an applicant is active (i.e., not in poor standing or disbanded) 2 and 4 years after the competition respectively. All regressions include year, sector and project category dummies as control variables.

The results in Table 2.3 are quite striking. Regardless of the survival period or estimation sample, applicants that receive state R&D financing are significantly more likely to survive than those that do not. Importantly, we find no evidence that this result is a simple artifact of the selection process. Even after the sample is narrowed to more comparable sets of firms (those proximate to the funding cutoff), Table 2.3 suggests that awardees are 12% to 13% more likely to survive 2 years and 21% to 23% more likely to survive 4 years following the competition than firms seeking but failing to receive such awards. The results are robust to the exclusion of 27 applicants with merger/acquisition exits and to the Probit regression estimations.

We interpret this evidence as consistent with the view that state R&D financing relaxed the financial constraints for these companies: absent R&D funds from the state, otherwise-comparable companies were less likely to remain in business. It is also interesting to find that the magnitude of the R&D financing effect on survival is larger in the longer period (4-year vs. 2-year). It implies that the state funding may not just solve the short-term liquidity constraint of entrepreneurial firms, but could "add value" to recipient firms and increase their commercial viability in the long-run. To test this hypothesis more directly, we move to the second set of analyses.

2.6.2 *Effects on follow-on financing*

The second set of analyses tests the "certification hypothesis" that, by certifying new venture quality, state R&D awards reduce informational problems in markets for entrepreneurial capital and thereby stimulate the subsequent financing activities of young companies (Lerner, 1999; Feldman and Kenney, 2003). Table 2.4 reports the estimated effect of state R&D awards on follow-on financing from SBA and VC sources. Tables 2.5-2.8 test for heterogeneous effects within the sample: If state R&D awards certify quality to external capital providers, their effects should be more pronounced for startups with greater informational challenges in such markets.

Turning first to Columns (1), (4), (7) and (10) of Table 2.4 and the full entrepreneurial-applicant sample, the estimates suggest that conditional on survival, funded startups receive significantly more SBA awards and VC investments in the two years and four years following the competition.

To disentangle certification from a potential "cherry-picking" effect, Table 2.4 restricts the sample to more comparable subsets of firms near the discontinuity border in the remaining columns. Once the estimation sample is restricted to more comparable firms, we fail to discern a significant effect of the awards on follow-on financing activities from government/SBA (Cols. 2, 3, 5 and 6). For the follow-on financing from private/VC (Panel B) sources, Columns (8) and (9) show that awardees secure more VC funding than comparable non-awardees in the following two years. As shown in Columns (11) and (12), however, the difference disappears when we extend the observation period to four years. Although suggestive of a certification effect, this significant effect on VC investments in the two-year period following the competition could be due to the process used to select applicants for funding. As noted earlier, the ability to secure third-party financial commitments is among the criteria used in the selection process. From the evidence in Table 2.4 alone, it is therefore difficult to discern whether the "cherry-picking" of firms with greater financing prospects for the awards or a "certifying" effect of award recipient to external sources of financing drives the results.

If state R&D awards reduce informational problems in entrepreneurial capital markets (via certification), however, we should expect heterogeneous treatment effects within the sample. More specifically, the awards should "matter more" to new ventures facing wider the information gaps with potential capital providers.

To test the certification hypothesis more fully, we therefore identify three sources of firm-level variation likely to correlate with information asymmetry levels within the context of our study. Absent R&D financing from the state, startups with prior VC-backing or SBA awards should be better able than their unfunded counterparts to convey quality to external capital providers. If state R&D awards serve a quality-certification function, we therefore should expect their effects on follow-on financing to be more pronounced among startups *lacking* prior VC-backing or SBA awards. Similarly, the awards should be especially important for younger (versus older) startups given the relative lack of observable track records with which to convey performance-potential.

On a related point, Sorenson and Stuart (2001) and others suggest that (a) hubs of entrepreneurial activity house rich information about entrepreneurs and the resources for building new companies and that (b) such information transfers imperfectly across geographic distances. If true, we should expect less efficient ("thinner") entrepreneurial capital markets farther away from hubs of entrepreneurial activity, therefore amplifying the certification value of R&D awards from the state.

To operationalize this final location-based test, we identify the headquarter location of applicants from MEDC documents and use VC investments reported in VentureXpert to measure hubs of entrepreneurial activity within the state. Consistent with patterns reported across U.S. states (Sorenson and Stuart 2001), VC investments are spatially agglomerated within Michigan—with a dominant cluster near Ann Arbor, where the University of Michigan and most Michigan-based VCs are based. We therefore define *Driving Distance to VC hub* as the number of miles (in 100s) between Ann Arbor and each applicant-firm's headquarter location. As a robustness check, we categorize the VC hub as the greater Ann Arbor-Detroit Metro Area and use of indicator variables (inside/outside VC hub) and obtain similar findings.

Tables 2.5-2.8 report results that sequentially interact *Funded* with the three variables discussed above: (1) *Has Prior VC or SBA Award*, (2) *Startup Age*, and (3) *Driving Distance to VC Hub*. For simplicity, we show results based on two estimation samples: (a) all entrepreneurial-applicants (i.e., the "full sample") and (b) firms 15 or fewer points surrounding the normalized funding cutoff. We show results for the 2-year period following the competition (t+2) and list them separately for SBA awards (in Table 2.5) and follow-on rounds of VC investment (in Table 2.6). Results on SBA awards for the 4-year period following the competition (t+4) are listed in Table 2.7 and results on VC investment for the same observation period are listed in Table 2.8.

To synthesize key findings from Tables 2.5-2.8, Table 2.9 reports the estimated conditional effect of state R&D awards on follow-on financing for our most comparable subsample of firms—those closest to the funding threshold (i.e., the "15 bandwidth" companies). Standard errors and confidence intervals are computed with formulas reported in Hilbe (2008), given the non-linearity of the estimator.

Turning first to Panel A of Table 2.9, the estimates suggest that receipt of state R&D financing significantly boosts the predicted levels of follow-on financing for entrepreneurial firms *lacking* prior VC-backing or SBA awards: among this subset of relatively disadvantaged companies, awardees received 3.78 times (=exp(1.33)) more follow-on SBA awards in the 4-year period after the competition and 4.76 times (=exp(1.56)) more rounds of VC financing in the following 2 years, relative to otherwise comparable applicants that sought but failed to receive an award.

As depicted in Figure 2.4a and Figure 2.5a, we fail to discern a significant effect of state R&D awards on the follow-on financing of applicants with prior VC or SBA funding, suggesting that the marginal effect of being "certified" by the state is negligible for such companies.

In Panel B of Table 2.9, we expected to find that the conditional effect of state R&D awards would grow larger as distance from the VC hub increases. The evidence is only partially supportive of this view. Similar to the findings in Panel A, Panel B suggests that the "certification" value of state

R&D awards is negligible for startups located in better-developed markets for entrepreneurial capital (i.e., inside a hub of VC activity). For those located outside the VC hub, however, the conditional effect of state R&D award on follow-on financing is statistically significant and increasing in distance—for other government (SBA) sources in both observation periods, but only for private (VC) sources in the short-term.

More specifically, the point estimates in Panel B of Table 2.9 suggest that effect of state R&D financing on the securement of future SBA awards in the following two years is roughly 7 times (=exp(3.30)/exp(1.40)) larger for firms located 100 miles from the VC hub than it is for firms located only 50 miles from the hub. The corresponding effect is around 5 times in the following four years. A similar effect on VC investment arises in the two-year period after the competition. The results show that effect of state R&D financing on the VC investment in the following two years is roughly 2 times (=exp(1.79)/exp(1.05)) larger for firms located 100 miles from the VC hub than it is for firms located only 50 miles from the hub. Although the magnitude of the effect also is increasing in distance for follow-on VC financing in four-year period (reported in the fourth column of Table 2.9, Panel B), the estimated effect is not statistically significant at conventional levels. Figure 2.4b and Figure 2.5b plot these effects.

Panel C of Table 2.9 similarly reveals partial evidence that state R&D awards "matter more" to the follow-on financing activities of younger companies. Here, however, the effect is statistically significant for private/VC but not for government/SBA sources. As shown in Figure 2.4c, receipt of a state R&D award significantly boosts the number of VC financing otherwise predicted for young firms in years 1-2 after the competition. The magnitude of the effect decreases with age, however, and becomes insignificant when the firm is more than 3 years old.

Although the evidence in Tables 2.5-2.9 suggests that the effects of state R&D awards on follow-on financing can differ markedly for government/SBA and private/VC sources, it is generally consistent with the view that the "certification value" of the awards is higher in the presence of greater informational imperfections in external markets for entrepreneurial capital.

2.6.3 *Effects on patent productivity*

A final set of analyses in Table 2.10 investigates the effects of state R&D funding on patent productivity. Aided by funds from the state, startups should be able to proceed with R&D and commercialization activities more aggressively than otherwise possible. If true, receipt of state-government financing should enable awardees to yield more innovative output from their endeavors. To investigate this potential productivity effect, we test whether receipt of state-government financing increases the annual production of patented inventions by new ventures.

Table 2.10 reports the patent productivity estimates using Poisson QMLE methods and the estimation samples defined earlier. Panel A estimates effects in the 2-year period following the competition, while Panel B allows for a longer 4-year window.

In Columns (1) and (4) of Table 2.8, the *Funded* coefficient is a positive predictor of patent productivity but the effect is statistically indistinguishable from zero. This result is surprising since it is based on the entire applicant pool. As noted earlier, scientific merit is one of the criteria used to score proposals include scientific merit. Assuming that such merit correlates with patenting potential, we should expect a positive and significant *Funded* coefficient simply as an artifact of the selection process. We fail, however, to discern this effect. The effect is not driven by differential survival rates of funded and unfunded companies. As a robustness check, we retained failed companies in the sample (with post-exit patenting output coded as zero) and obtained similar results. Not surprisingly, the coefficient on *Funded* remains statistically insignificant in other columns of Table 2.10**,** where the estimation sample comprises more comparable firms.

One explanation for this "non-finding" is measurement error. Small firms often submit provisional filings a year in advance of formal patent applications, which could make it more difficult to discern a near-term effect. As a robustness check, we re-estimated effects using the earliest date associated with each patented invention (including the date of provisional filings if any). The results were qualitatively unchanged.

Similarly, it is logical to assume that many applicant-firms are commercializing technologies from Michigan-based universities. Since universities typically retain title to inventions originating from their labs, this could impose a downward bias on our patent-based output measures. To investigate this possibility, we use supplemental information from press releases and news articles to identify applicants (~36% of the full sample) founded by university faculty or formed to commercialize university inventions. In supplemental analyses, we find no evidence that this source of measurement error explains the patent-related non-finding.

A final, more plausible explanation is that the funds allocated by the state are used primarily to accelerate time-to-market rather than to discover and develop new products. In this event, patent-based estimates could underestimate the true productivity effects associated with the awards. Unfortunately, we lack reliable time-to-market indicators with which to investigate this issue further.

2.7 Discussion and Conclusion

This study investigates whether R&D financing from state-government sources improves the performance of technology startups. Using novel data on Michigan-based programs, we test for causal linkages between state R&D financing and new venture performance with multiple outcome variables and methods, including regression discontinuity design. Increasingly common within the field of economics (e.g., Black, 1999; Lee & Lemieux 2010), RDD methods remain under-utilized in the strategic management and entrepreneurial finance literatures.

We present new and compelling evidence that these state-run R&D awards increased the commercial viability (i.e., survival) of award recipients relative to startups that sought but failed to receive such awards. We find little evidence that this survival effect is driven solely by the selection of "better" companies into awards. Proximate to the funding threshold, recipients and non-recipients are comparable based on observable pre-treatment characteristics. Nonetheless, state funding remains a positive and significant predictor of survival among these otherwise-comparable applicants. This evidence is consistent with the view that public R&D financing helps ameliorate imperfections in capital markets for entrepreneurial companies: absent R&D financing from the state, our findings suggest that otherwise comparable ventures were less likely to remain in business.

The effects of state R&D awards on other salient outcomes for technology ventures—the production of patents and the securement of other third-party financing—are more ambiguous in the context of this study. Surprisingly, we find no evidence that state funds bolstered the patent productivity of recipient companies, an effect that could reflect the more applied and commercialization-focused orientation of the program.

We do, however, find more nuanced effects on follow-on financing. In regressions that include all applicants in the estimation sample, receipt of state R&D financing correlates with greater follow-on financing activity in both the two-year and four-year periods following the award, from both public (SBA) and private (venture capital) sources. At first blush, this finding appears to confirm the "certification effect" shown in empirical studies of federal R&D programs (Feldman & Kelley, 2003; Lerner, 1999): winning public R&D competitions can cast a positive signal that helps attract additional sources of financing. We show, however that the overall effect dissipates in more comparable pre-treatment samples. This finding underscores the importance of taking into account potential "cherry picking" in the provision of entrepreneurial capital, a topic widely discussed in the program evaluation literature (Klette *et al.*, 2000; Wallsten, 2000): firms likely to attract other sources of financing typically receive higher scores and are more likely to receive funding.

More consistent with the view that state R&D awards help certify the value of young companies to other capital providers, we observe heterogeneous treatment effects within the sample. In general, we find that state R&D awards "matter more" to the follow-on financing activities of firms that lack prior VC funding or SBA awards, are younger, and are located farther away from spatial hubs of entrepreneurial activities. Assuming that these firm-level traits correlate with greater inefficiencies in securing access to financial resources, this evidence is consistent with the view that public R&D financing can help ameliorate imperfections that arise in markets for entrepreneurial financing.

This study is limited in ways that build a natural the stage for further research. Of particular note, our analysis is based on R&D awards from a single state in the decade of the 2000s, when technology ventures faced tighter capital constraints than was true in the boom years of the late-1990s. From a policy perspective, this timing of the Michigan-based programs was fortuitous: it increased the odds of capital-market imperfections that public monies could help address (Lerner, 2009). If similar data were compiled for more longstanding government programs, future studies could investigate how the magnitude of private-sector outcomes associated with public R&D financing are altered by macroeconomic conditions.

Future research also could probe more deeply into how the design of public R&D programs affects outcomes realized by program participations. In this respect, Michigan's recent switch from a direct (provision of R&D financing) to an indirect (subsidization of private equity) model of entrepreneurial financing is particularly intriguing. Understanding the trade-offs of alternative vehicles for financing entrepreneurial-firm innovation, both within the United States and in other countries, remains a fruitful avenue for further investigation.

Finally, while this study provides evidence on the private returns to state R&D awards, answers to larger policy-related questions remain unclear: Is it optimal—from a social welfare perspective—to extend the survival period of new science and technology companies or to enhance the abilities of such companies to secure funds from other government and private sources? Do these benefits outweigh the direct and indirect costs of the program? In general, our evidence suggests that Michigan's competitive R&D awards involved more than simply "picking winners." To investigate whether the intervention was justified from a policy perspective, a host of factors beyond the scope of our study must be considered.

To conclude, although state governments are active financiers of new science and technology companies, little is known about their effects on new venture performance. Based on novel data for Michigan-based innovation programs, we find that state R&D

financing increased the survival prospects of new ventures and helped stimulate the follow-on financing of firms with wider information gaps in markets for entrepreneurial capital.

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Figure 2.1 Average Size of MEDC Program Funding to Awardees

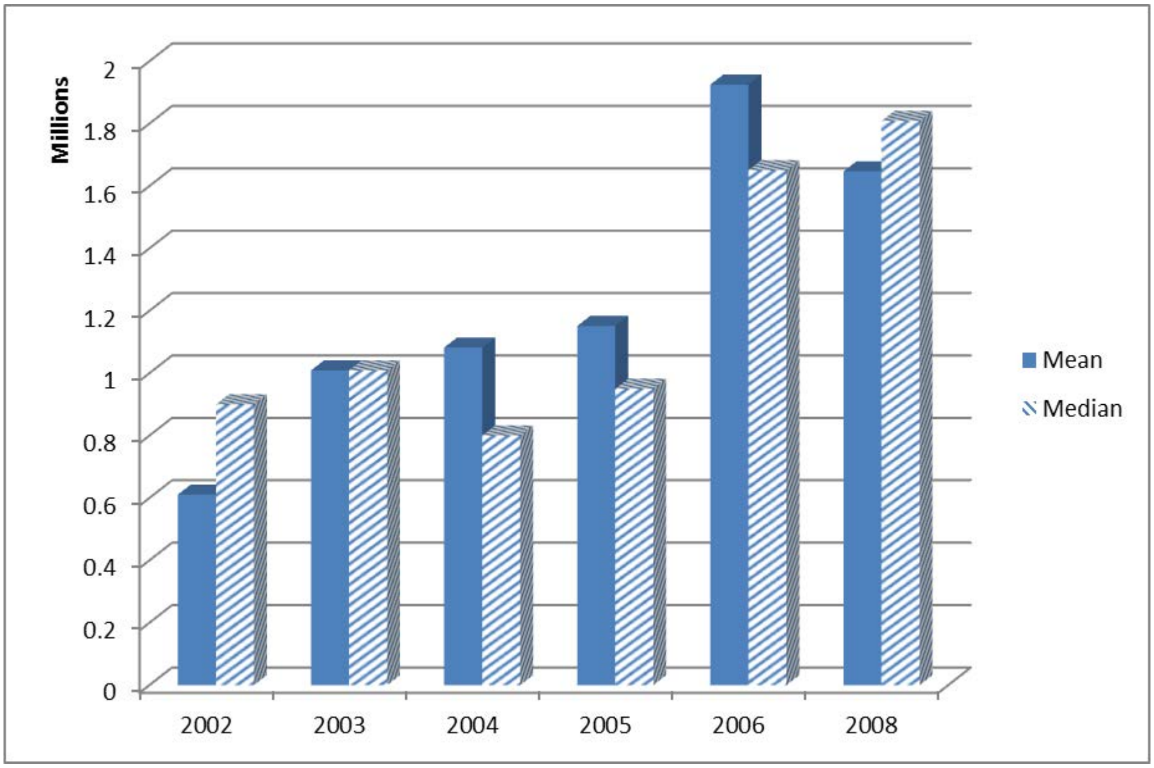


Figure 2.2 The Selection Process (Decision Tree)

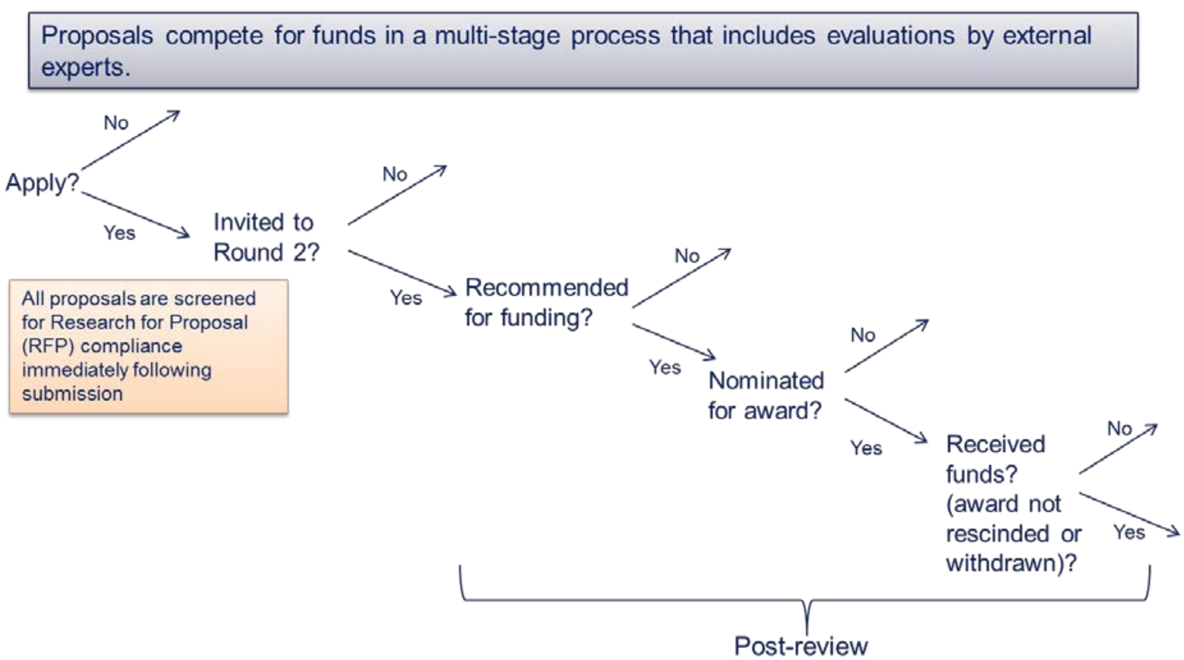
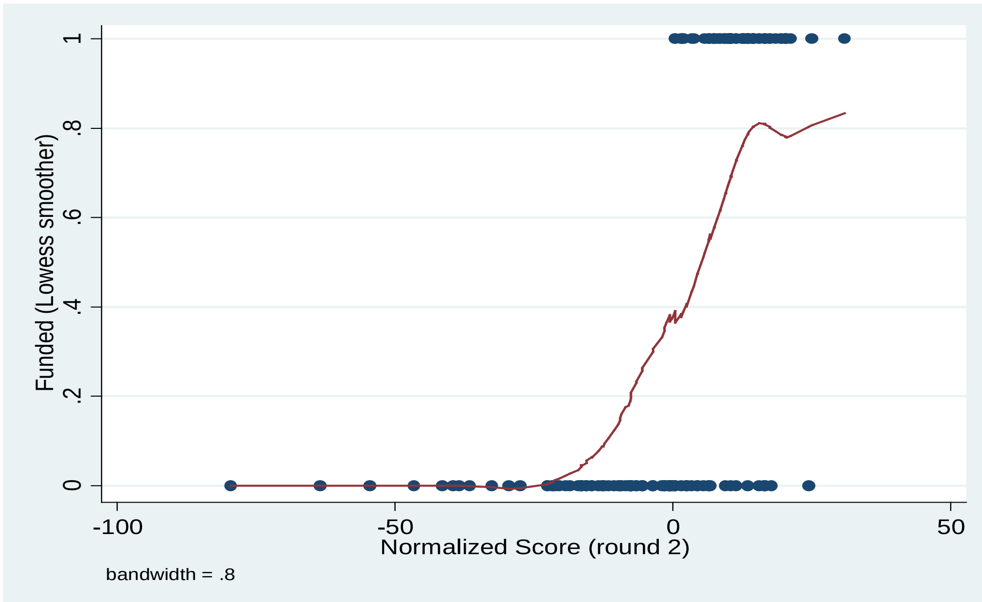


Figure 2.3 Effect of Peer Review Score on Probability of Receiving Funds

2.3a Calculated with Lowess smoother (bandwidth 0.8)



2.3b Calculated at mean of binary "funded" variable over constant 10-unit intervals

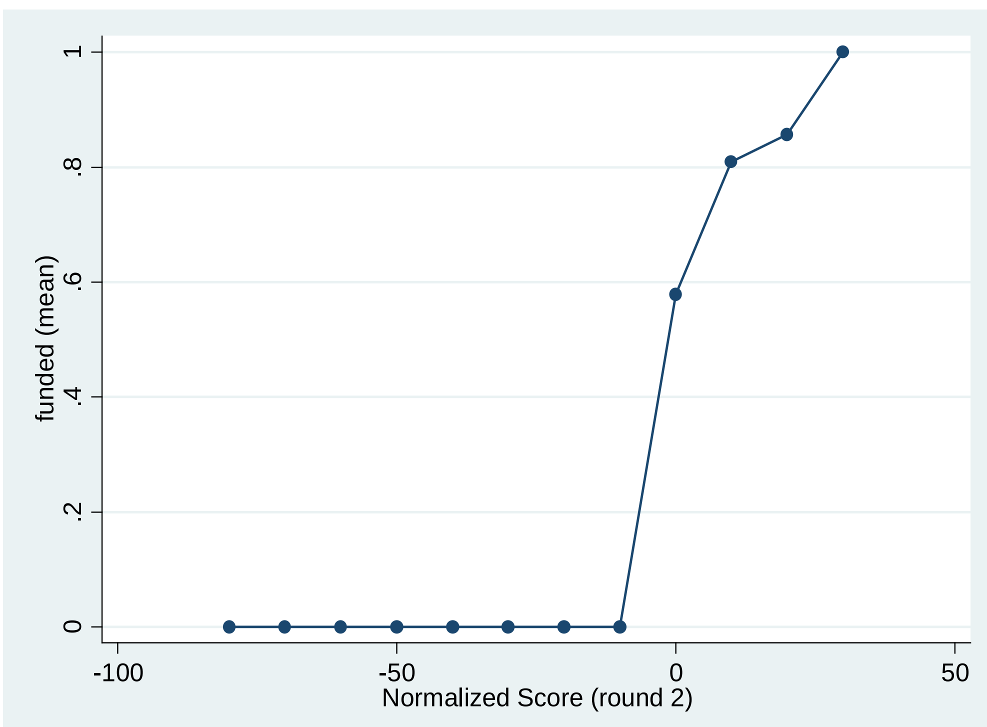
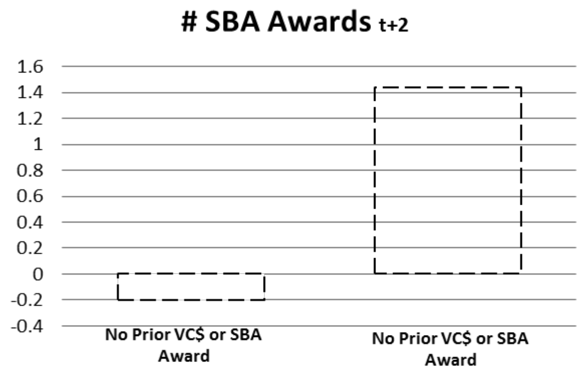
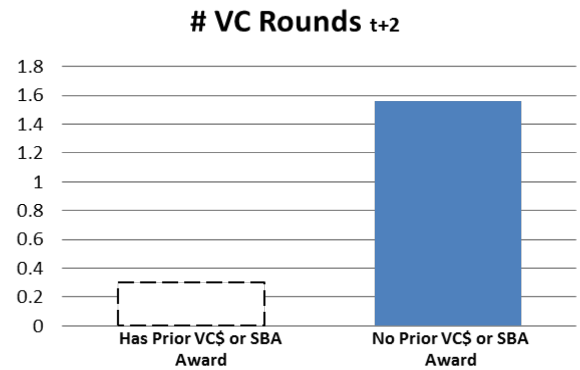


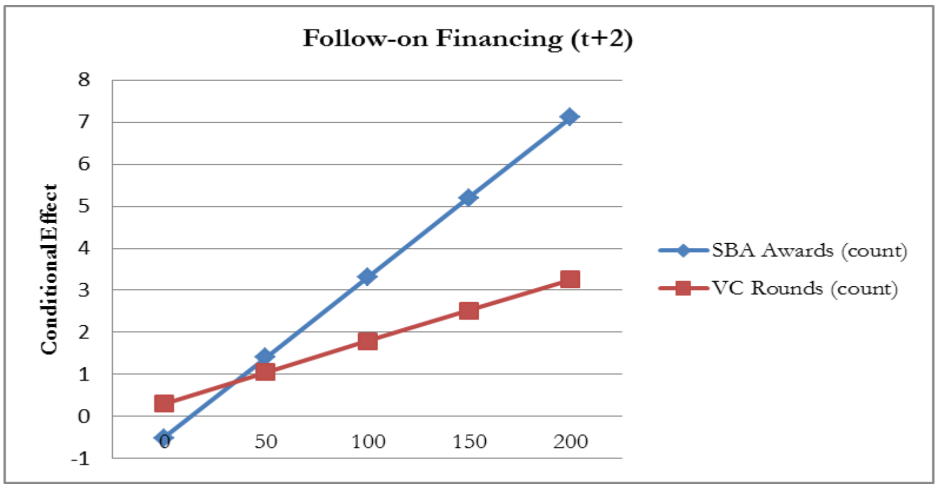
Figure 2.4 Conditional Effects of State R&D Awards on Follow-on Financing (t+2)[13]

2.4a: Startup has (vs does not have) Prior VC$ or SBA Award

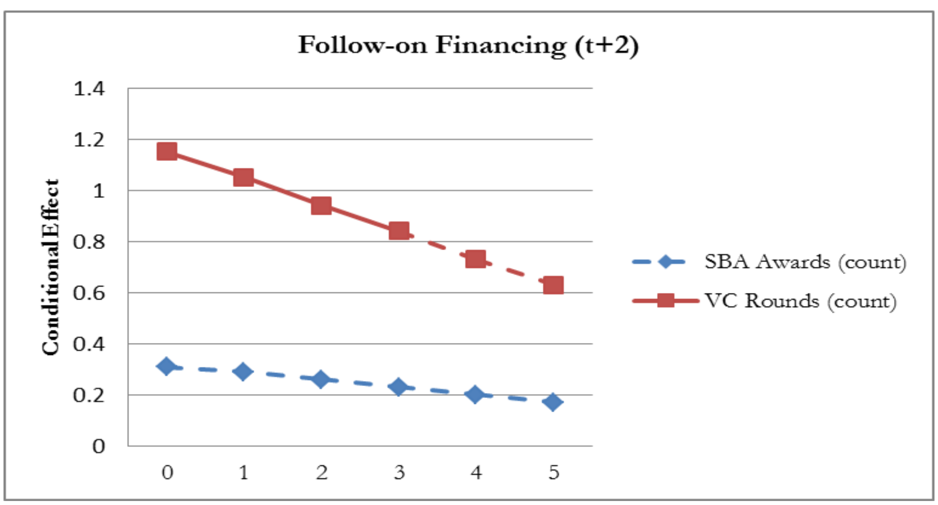




2.4b Startup Distance from VC Hub within the State (in miles)



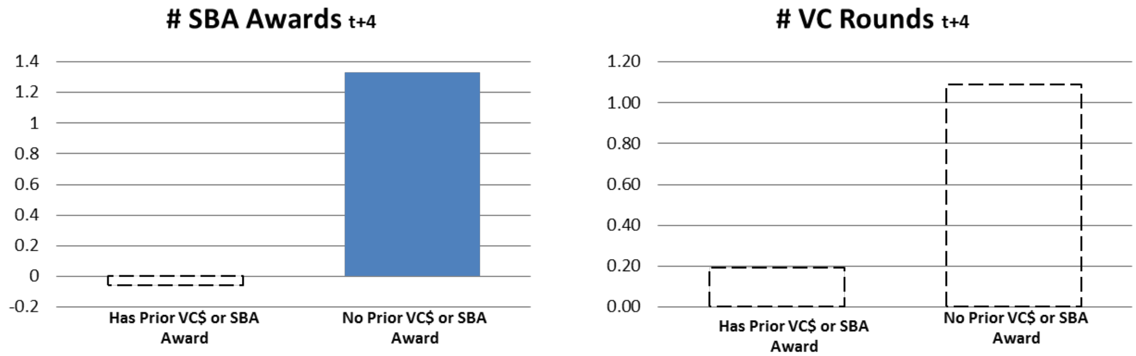
2.4c Startup Age in Years (Application Year minus Founding Year)



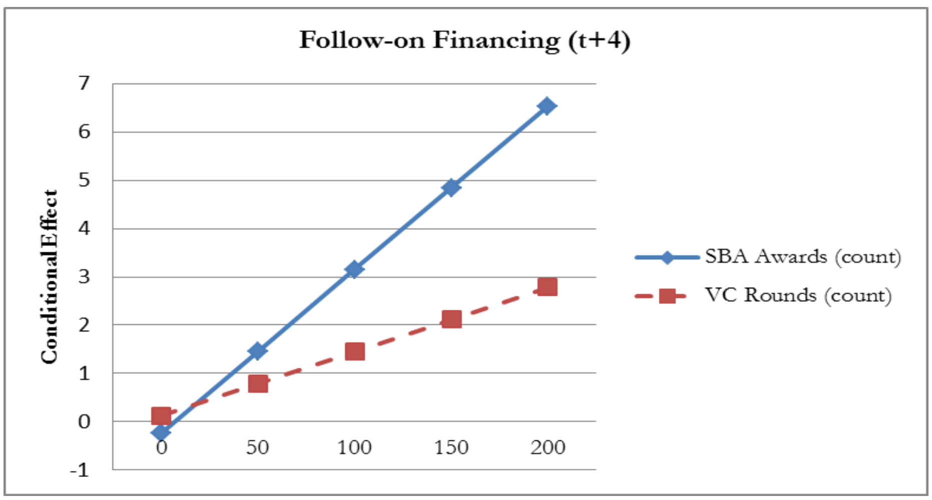
[13] Dashed lines indicate that the conditional effect is statistically insignificant.

Figure 2.5 Conditional Effects of State R&D Awards on Follow-on Financing (t+4)[14]

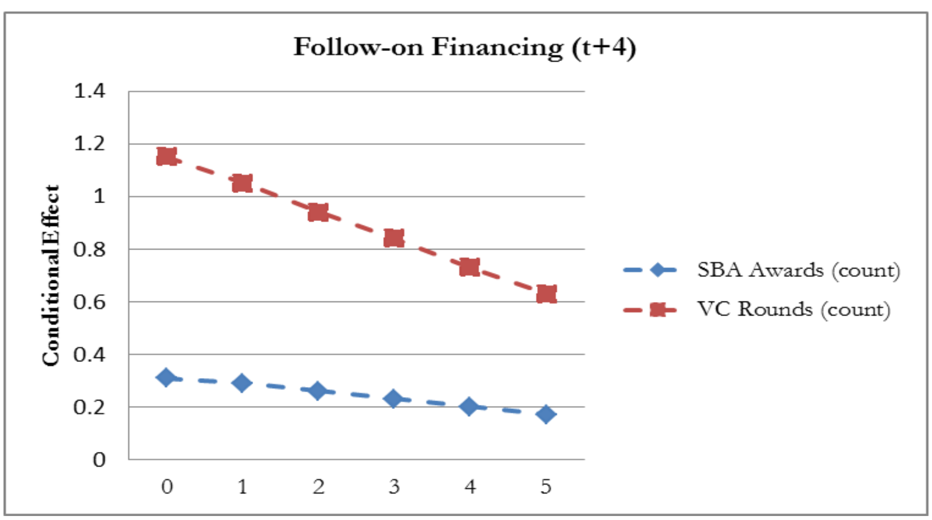
2.5a Startup has (vs does not have) Prior VC$ or SBA Award



2.5b Startup Distance from VC Hub within the State (in miles)



2.5c Startup Age in Years (Application Year minus Founding Year)



[14] Dashed lines indicate that the conditional effect is statistically insignificant.

Table 2.1 Summary Statistics

Variable	Obs	Mean	S.D.	Min	Max
Basic Information					
Normalized score (1st Round)	297	-4.46	19.04	-58.5	32
Normalized score (2nd Round)	152	-0.68	17.43	-79.5	31
Funded	297	0.21	0.41	0	1
Age in application year	297	4.29	4.03	0	15
Sector = advanced auto	297	0.29	0.46	0	1
Sector = alternative energy	297	0.08	0.28	0	1
Sector = homeland security	297	0.13	0.34	0	1
Sector = life science	297	0.49	0.50	0	1
Application category = applied research project	297	0.23	0.42	0	1
Application category = commercialization project	297	0.77	0.42	0	1
Survival Status					
Survival in the following year 1-2	297	0.89	0.31	0	1
Survival in the following year 1-4	297	0.79	0.41	0	1
SBA Awards					
SBA awards (counts) in year 1-2 prior to application	297	0.43	1.20	0	10
SBA awards (counts) in year 1- 4 prior to application	297	0.76	2.33	0	21
SBA awards (counts) in the following year 1-2	297	0.57	1.43	0	10
SBA awards (counts) in the following year 1-4	297	1.10	2.67	0	17
VC Investment					
No. of VC investments (count) in year 1-2 prior to application	297	0.43	1.79	0	15
No. of VC investments (count) in year 1-4 prior to application	297	0.73	2.55	0	19
No. of VC investments (count) in the following year 1-2	297	0.37	1.28	0	11
No. of VC investments (count) in the following year 1-4	297	0.66	2.21	0	19
VC or SBA Investment					
Has VC Fund or SBA award in the year 1-2 prior to application	297	0.30	0.46	0	1
Has VC Fund or SBA award in the year 1-4 prior to application	297	0.34	0.47	0	1
Patent					
Patent filed (count) in year 1-2 prior to application	297	0.47	1.42	0	9
Patent filed (count) in year 1-4 prior to application	297	0.79	2.41	0	20
Patent filed (count) in the following year 1-2	297	0.48	1.58	0	10
Patent filed (count) in the following year 1-4	297	0.80	2.63	0	17
Geography					
Driving distance from VC hub (unit=100 miles)	297	0.46	0.66	0	5.69

Table 2.2 Summary Statistics – just above and below cutoff

	Panel A			Panel B		
	Just Below cutoff (-20)	**Just above cutoff (+20)**	**Two Tailed t-test for equality of means**	**Just Below cutoff (-15)**	**Just above cutoff (+15)**	**Two Tailed t-test for equality of means**
	Mean	Mean	P-value	Mean	Mean	P-value
Basic Information						
Normalized score (2nd Round)	-8.27	9.55		-6.36	7.93	
Funded	0.00	0.71		0.00	0.72	
Age in application year	4.16	3.50	0.33	4.35	3.23	0.12
Driving distance to VC hub (100s miles)	0.44	0.40	0.79	0.41	0.42	0.98
Pre-treatment Performance						
SBA Awards (count) in year 1-2 prior to application	0.65	0.73	0.80	0.78	0.53	0.42
SBA Awards (count) in year 1-4 prior to application	1.31	1.15	0.80	1.55	0.86	0.27
No. of VC investments (count) in year 1-2 prior to application	0.31	0.99	0.10	0.38	0.97	0.14
No. of VC investments (count) in year 1-4 prior to application	0.94	1.38	0.46	1.10	1.34	0.72
Patent filed (count) in year 1-2 prior to application	0.43	0.73	0.27	0.38	0.61	0.34
Patent filed (count) in year 1-4 prior to application	0.76	1.09	0.43	0.75	0.80	0.89
Pre-treatment Dummy (mean = percentage)						
Has SBA Award in year 1-2 prior to application?	0.20	0.33	0.12	0.23	0.30	0.43
Has SBA Award in year 1-4 prior to application?	0.24	0.33	0.29	0.28	0.30	0.81
Has VC Fund in year 1-2 prior to application?	0.18	0.23	0.53	0.23	0.27	0.65
Has VC Fund in year 1-4 prior to application?	0.22	0.28	0.48	0.25	0.30	0.61
Has VC Fund or SBA Award in year 1-2 prior to application?	0.35	0.51	0.07	0.40	0.50	0.32
Has VC Fund or SBA Award in year 1-4 prior to application?	0.43	0.54	0.23	0.48	0.52	0.69
Has patent filed in year 1-2 prior to application?	0.16	0.28	0.13	0.18	0.27	0.29
Has patent filed in year 1-4 prior to application?	0.22	0.31	0.31	0.22	0.28	0.53
Observations	49	78		40	64	

Table 2.3 Linear Probability Regressions on Survival

	Panel A: Survival 2 years after competition		
	(1)	(2)	(3)
Sample	Full Sample	20 Bandwidth	15 Bandwidth
Funded	0.121***	0.117**	0.129**
	(0.027)	(0.050)	(0.056)
Age in application year	0.002	0.007	0.005
	(0.005)	(0.006)	(0.008)
Constant	0.920***	0.869***	0.861***
	(0.042)	(0.068)	(0.078)
Observations	297	127	104
R2	0.067	0.077	0.109
	Panel B: Survival 4 years after competition		
	(4)	(5)	(6)
Sample	Full Sample	20 Bandwidth	15 Bandwidth
Funded	0.225***	0.230***	0.213***
	(0.038)	(0.059)	(0.063)
Age in application year	0.008	0.012	0.015
	(0.006)	(0.008)	(0.009)
Constant	0.771***	0.727***	0.748***
	(0.058)	(0.085)	(0.095)
Observations	297	127	104
R2	0.084	0.159	0.181

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Year, industry and application category dummies are included in all regressions

Table 2.4 Poisson Regressions on Follow-on Financing

	Panel A: SBA Awards (count)					
	In years 1-2 following the application			**In years 1-4 following the application**		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full Sample	20 Bandwidth	15 Bandwidth	Full Sample	20 Bandwidth	15 Bandwidth
Funded	0.829***	0.119	0.154	0.844***	0.065	0.302
	(0.270)	(0.383)	(0.448)	(0.284)	(0.403)	(0.398)
Age in application year	0.087***	0.075**	0.099***	0.053*	0.037	0.067**
	(0.026)	(0.032)	(0.031)	(0.030)	(0.037)	(0.029)
Constant	-1.657***	-1.119**	-1.265**	-0.864**	-0.284	-0.743
	(0.385)	(0.500)	(0.623)	(0.435)	(0.538)	(0.596)
Observations	264	118	95	235	109	88
Pseudo R2	0.177	0.194	0.247	0.143	0.182	0.256
Log-likelihood	-296.6	-161.4	-125.7	-497.2	-263.2	-195.6
	Panel B: VC Investments (count)					
	In years 1-2 following the application			**In years 1-4 following the application**		
	(7)	(8)	(9)	(10)	(11)	(12)
Sample	Full Sample	20 Bandwidth	15 Bandwidth	Full Sample	20 Bandwidth	15 Bandwidth
Funded	1.029***	0.767*	0.854*	0.963**	0.649	0.625
	(0.365)	(0.419)	(0.478)	(0.415)	(0.497)	(0.557)
Age in application year	0.012	-0.028	-0.010	-0.026	-0.072	-0.061
	(0.036)	(0.047)	(0.059)	(0.042)	(0.055)	(0.064)
Constant	-0.337	-0.060	-0.169	0.251	0.634	0.698*
	(0.403)	(0.363)	(0.375)	(0.354)	(0.393)	(0.411)
Observations	264	118	95	235	109	88
Pseudo R2	0.220	0.186	0.182	0.235	0.223	0.233
Log-likelihood	-225.6	-138.3	-119.5	-339.4	-224.5	-194.2

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: 1. Year, industry and application category dummies are included in all regressions
2. All results are conditional on firm survival

Table 2.5 Poisson Regressions on Follow-on SBA Awards with Interaction Effects (t+2)

Sample	**Panel A: Full Sample**				**Panel B: 15 Bandwidth**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Funded	0.829***	1.990***	0.080	0.844*	0.154	1.444	-0.506	0.314
	(0.270)	(0.412)	(0.308)	(0.450)	(0.448)	(0.922)	(0.458)	(0.679)
Funded * Has prior VC or SBA award (prior 1_4)		-2.045***				-1.647*		
		(0.497)				(1.001)		
Has prior VC or SBA award (prior 1_4)		1.879***				1.837**		
		(0.399)				(0.794)		
Funded * Driving distance to VC hub (100s miles)			3.139***				3.806**	
			(0.981)				(1.519)	
Driving distance to VC hub (100s miles)			-3.070***				-3.604**	
			(0.839)				(1.399)	
Funded*Age in application year				-0.003				-0.028
				(0.058)				(0.072)
Age in application year	0.087***	0.046**	0.083***	0.088**	0.099***	0.072**	0.105***	0.112**
	(0.026)	(0.023)	(0.025)	(0.037)	(0.031)	(0.036)	(0.036)	(0.047)
Constant	-1.657***	-2.802***	-0.958***	-1.665***	-1.265**	-2.694***	-0.636	-1.328**
	(0.385)	(0.525)	(0.330)	(0.470)	(0.623)	(0.882)	(0.545)	(0.663)
Observations	264	264	264	264	95	95	95	95
Pseudo R2	0.177	0.267	0.263	0.177	0.247	0.295	0.309	0.248
Log-likelihood	-296.6	-264.0	-265.7	-296.6	-125.7	-117.7	-115.3	-125.6

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: 1. Year, industry and application category dummies are included in all regressions
2. All results are conditional on firm survival

Table 2.6 Poisson Regressions on Follow-on VC Investment with Interaction Effects (t+2)

Sample	Panel A: Full Sample				Panel B: 15 bandwidth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Funded	1.029***	1.813***	0.343	1.284**	0.854*	1.560**	0.310	1.154**
	(0.365)	(0.593)	(0.492)	(0.499)	(0.478)	(0.704)	(0.669)	(0.540)
Funded * Has prior VC or SBA award (prior 1_4)		-1.526**				-1.258		
		(0.736)				(0.949)		
Has prior VC or SBA award (prior 1_4)		1.609***				0.931		
		(0.531)				(0.652)		
Funded * Driving distance to VC hub (100s miles)			2.011**				1.476	
			(0.886)				(0.991)	
Driving distance to VC hub (100s miles)			-1.333**				-0.611	
			(0.589)				(0.678)	
Funded*Age in application year				-0.072				-0.105
				(0.073)				(0.115)
Age in application year	0.012	-0.039	0.035	0.035	-0.010	-0.001	0.038	0.055
	(0.036)	(0.049)	(0.043)	(0.040)	(0.059)	(0.087)	(0.083)	(0.095)
Constant	-0.337	-1.134**	-0.010	-0.438	-0.169	-0.755	-0.109	-0.330
	(0.403)	(0.527)	(0.458)	(0.448)	(0.375)	(0.561)	(0.493)	(0.394)
Observations	264	264	264	264	95	95	95	95
Pseudo R2	0.220	0.267	0.252	0.223	0.182	0.200	0.209	0.187
Log-likelihood	-225.6	-212.0	-216.3	-224.8	-119.5	-117.0	-115.7	-118.8

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: 1. Year, industry and application category dummies are included in all regressions
2. All results are conditional on firm survival

Table 2.7 Poisson Regressions on Follow-on SBA Awards with Interaction Effects (t+4)

Sample	Panel A: Full Sample				Panel B: 15 Bandwidth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Funded	0.844***	1.823***	0.246	0.746	0.302	1.328*	-0.233	0.325
	(0.284)	(0.449)	(0.299)	(0.488)	(0.398)	(0.717)	(0.421)	(0.603)
Funded * Has prior VC or SBA award (prior 1_4)		-1.925***				-1.386*		
		(0.511)				(0.823)		
Has prior VC or SBA award (prior 1_4)		1.576***				1.428**		
		(0.418)				(0.632)		
Funded * Driving distance to VC hub (100s miles)			2.389**				3.379**	
			(1.109)				(1.372)	
Driving distance to VC hub (100s miles)			-2.710***				-3.649***	
			(0.994)				(1.278)	
Funded*Age in application year				0.018				-0.004
				(0.062)				(0.068)
Age in application year	0.053*	0.015	0.051*	0.046	0.067**	0.043	0.059*	0.069
	(0.030)	(0.027)	(0.029)	(0.045)	(0.029)	(0.034)	(0.031)	(0.046)
Constant	-0.864**	-1.707***	-0.183	-0.818	-0.743	-1.781**	-0.049	-0.753
	(0.435)	(0.580)	(0.342)	(0.516)	(0.596)	(0.725)	(0.523)	(0.632)
Observations	235	235	235	235	88	88	88	88
Pseudo R2	0.143	0.224	0.233	0.144	0.256	0.294	0.336	0.256
Log-likelihood	-497.2	-450.2	-445.1	-497.0	-195.6	-185.4	-174.4	-195.6

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: 1. Year, industry and application category dummies are included in all regressions
2. All results are conditional on firm survival

Table 2.8 Poisson Regressions on Follow-on VC Investment with Interaction Effects (t+4)

Sample	Panel A: Full Sample				Panel B: 15 Bandwidth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Funded	0.963**	1.648**	0.260	1.240**	0.625	1.091	0.127	0.909
	(0.415)	(0.729)	(0.579)	(0.569)	(0.557)	(0.825)	(0.747)	(0.667)
Funded * Has prior VC or SBA award (prior 1_4)		-1.395*				-0.897		
		(0.742)				(0.842)		
Has prior VC or SBA award (prior 1_4)		1.421**				0.586		
		(0.667)				(0.736)		
Funded * Driving distance to VC hub (100s miles)			2.007**				1.325	
			(0.903)				(1.134)	
Driving distance to VC hub (100s miles)			-1.251*				-0.547	
			(0.706)				(0.890)	
Funded*Age in application year				-0.084				-0.107
				(0.085)				(0.117)
Age in application year	-0.026	-0.067	0.006	0.004	-0.061	-0.053	-0.005	0.002
	(0.042)	(0.047)	(0.047)	(0.046)	(0.064)	(0.077)	(0.089)	(0.091)
Constant	0.251	-0.440	0.524	0.128	0.698*	0.354	0.701	0.544
	(0.354)	(0.614)	(0.392)	(0.416)	(0.411)	(0.679)	(0.482)	(0.477)
Observations	235	235	235	235	88	88	88	88
Pseudo R2	0.235	0.274	0.269	0.239	0.233	0.243	0.256	0.238
Log-likelihood	-339.4	-322.3	-324.3	-337.8	-194.2	-191.8	-188.4	-192.9

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: 1. Year, industry and application category dummies are included in all regressions
2. All results are conditional on firm survival

Table 2.9 Conditional Effects of State R&D Awards on Follow-on Financing

	# SBA Awards		# VC Rounds	
	T+2	T+4	T+2	T+4
Panel A: Had prior VC or SBA?				
Yes	-0.2	-0.06	0.3	0.19
No	1.44	1.33*	1.56**	1.09
Panel B: Distance to VC Hub				
Distance = 0	-0.51	-0.23	0.31	0.13
Distance = 50 miles	1.40**	1.46**	1.05**	0.79
Distance = 100 miles	3.30**	3.15**	1.79***	1.45
Distance = 150 miles	5.20**	4.84**	2.52**	2.12
Distance = 200 miles	7.11**	6.53**	3.26**	2.78
Panel C: Firm Age in Application Year				
Age = 0	0.31	0.33	1.15**	0.91
Age = 1	0.29	0.32	1.05**	0.80
Age = 2	0.26	0.32	0.94**	0.70
Age = 3	0.23	0.31	0.84*	0.59
Age = 4	0.20	0.31	0.73	0.48
Age = 5	0.17	0.30	0.63	0.37

Notes: 1. Estimations are based on sample within 15-point of the awards cutoff score
2. Conditional effects in the four columns(from left to right above) are based on regression results reported in Panel B of Tables 2.5, 2.7, 2.6, 2.8, correspondingly.

Table 2.10 Poisson Regressions on Patent Productivity

	Panel A: # of Patents filed in years 1-2 following the application		
	(1)	(2)	(3)
Sample	Full Sample	20 Bandwidth	15 Bandwidth
Funded	0.529	0.140	0.026
	(0.413)	(0.536)	(0.771)
Age in application year	0.072*	0.052	-0.056
	(0.039)	(0.059)	(0.067)
Constant	-1.787***	-2.025***	-1.654**
	(0.586)	(0.636)	(0.719)
Observations	264	118	95
Pseudo R2	0.139	0.180	0.168
Log-likelihood	-312.2	-156.2	-119.4
	Panel B: # of Patents filed in years 1-4 following the application		
	(4)	(5)	(6)
Sample	Full Sample	20 Bandwidth	15 Bandwidth
Funded	0.538	0.226	0.191
	(0.403)	(0.582)	(0.760)
Age in application year	0.058	0.032	-0.082
	(0.038)	(0.058)	(0.062)
Constant	-1.452**	-1.698***	-1.172*
	(0.587)	(0.617)	(0.692)
Observations	235	109	88
Pseudo R2	0.179	0.211	0.180
Log-likelihood	-428.4	-218.2	-167.0

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: 1. Year, industry and application category dummies are included in all regressions
2. All results are conditional on firm survival

CHAPTER 3

FOUNDING ENVIRONMENT AND NEW VENTURE SURVIVAL: THE ROLE OF STATE INNOVATION PROGRAMS[1]

3.1 Introduction

The phase between idea discovery and commercialization can be treacherous for new science and technology companies (Kerr & Nanda, 2009a; Shane & Stuart, 2002). In order to survive, new ventures must be able to steer their product ideas across the "valley of death" — a difficult transition period when a developing technology is too new to validate its commercial potential and therefore may be unable to attract the capital and other resources necessary to bring it to the market (Audretsch *et al.*, 2002a; Wessner, 2005). Aimed at stimulating entrepreneurial activity within their borders, US state governments, joint with other organizations, have launched large-scale initiatives since the mid-1980s to alleviate imperfections in markets for entrepreneurial resources and aid new ventures during this critical stage of their development

Despite the popularity of these programs with policymakers, systematic evidence regarding the effects of state innovation programs on entrepreneurial firms remains lacking

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(Brander, Du, & Hellmann, 2011; Lerner, 2009). Unlike federal initiatives such as the Small Business Investment Research (SBIR) program (Audretsch, Link, & Scott, 2002b; Lerner, 1999; Wallsten, 2000), information on programs at the state level is fragmented and thus cumbersome to assemble. In addition, teasing apart the causal effect of these programs is complicated by the absence of viable control group for comparison. Given the increased prominence of state governments in creating and administering entrepreneurship programs, understanding the effect of state innovation programs on entrepreneurial firms is critical from both a practical (policy/managerial) and scholarly perspective.

In this study, I investigate the extent to which these state initiatives improve the founding environment of entrepreneurial firms and, in turn, enhance the post-entry survival of startups. To explore this research question, I compile program information from Great Lakes states and investigate the impact of major innovation programs on life sciences startups. To identify the causal effect of these initiatives on entrepreneurial firms, I first divide the sample into two cohorts: entrants founded when an innovation program is present and entrants founded without the presence of a program. After controlling for observable differences between these two cohorts, the founding environment should then be the main reason for any differences in survival patterns between the two cohorts. I further divide both cohorts into two subsamples: startup companies and new subsidiaries. Since state innovation programs mainly target at technology-based startup companies, new subsidiaries founded during the same time period provide a natural baseline for measuring program effects on startups.

The results indicate that, after controlling for observable firm-level, industry-level, and macroeconomic-level factors, startup companies founded when an active state innovation program is underway are more likely to survive than startups established in the absence of an active state program within my observation period. This evidence suggests that the founding environment altered by these programs affects startup companies' survival prospects. In addition, I find that the effect of programs on new venture survival is more pronounced for biopharmaceutical companies, which have higher resource requirements in moving to commercialization, than for medical device companies. Indeed, for medical device companies, the impact of state innovation programs decays significantly over time. This result suggests that innovation programs may lower barriers to entry and thus encourage more marginal startups in the medical device industry that are not able to survive in the long run.

This study contributes to two strands of literature. First, it contributes to a growing literature in strategy and economics on how institutional and policy changes affect entrepreneurial firms and how public sector intervention impacts market failure (Aghion, Fally, & Scarpetta, 2007; Kerr & Nanda, 2009b). Prior studies on entrepreneurship have explored the effects of institutional changes on entrepreneurial firms. Specifically, empirical research based on institutional theory shows that entrepreneurial behavior and performance hinge on the institutional environment within which firms were founded (Eesley, 2009; Tolbert, David, & Sine, 2011). Most of the evidence from this stream of research is based on institutional or policy reforms, such as non-competition law changes (Marx, Strumsky, & Fleming, 2009; Samila & Sorenson, 2011a), banking deregulations (Kerr & Nanda, 2009a, 2010), changes of trade secrets laws (Png, 2011) or intellectual property reforms (Cockburn & MacGarvie, 2009; Hall & Ziedonis, 2001). However, these studies do not provide systematic evidence on the effect of institutional changes resulting from public efforts to create a more hospitable environment for entrepreneurial firms.

Second, the study is salient to the literature on the association between founding environment and post-entry performance (Agarwal, Sarkar, & Echambadi, 2002; Audretsch & Mata, 1995; Geroski, Mata, & Portugal, 2010; Mata, Portugal, & Guimarães, 1995; Sarkar, Echambadi, Agarwal, & Sen, 2006; Swaminathan, 1996). This study provides the first systematic, cross-state evidence about whether a regime shift in the institutional environment engendered by public efforts can causally affect entrepreneurial firms' subsequent survival prospects.

In addition to its contributions to current entrepreneurship research, this study provides insights for managers of entrepreneurial firms and policymakers. From a managerial perspective, it is important to know the performance implications of startup companies when major state programs are active, so appropriate decisions can be made about whether, where, and when to start a company. From a policy perspective, it is beneficial for policymakers to know whether these entrepreneurship programs encourage "marginal" entrants (i.e., less promising entrants that exit quickly) or if they have long-term positive effects for entrepreneurial firms.

The rest of the paper is organized as follows. Section 2 explains the theoretical framework and develops hypotheses for this study. Section 3 describes the empirical context, data and methodology. I present results in Section 4 and Section 5 concludes.

3.2 Theory and Hypotheses

3.2.1 *Founding environment and post-entry performance*

New ventures in high-tech industries often face a resource gap between technology development and commercialization. This resources gap occurs due to market imperfections caused by an information gap between the firm and private sector resource providers (Moore & Garnsey, 1993; Stuart, Hoang, & Hybels, 1999).

The information gap may systematically deter private investment in early stage technology development (Arrow, 1962; Nelson & Romer, 1996; Zeckhauser, 1996). Entrepreneurial firms that are characterized by significant intangible assets, expect years of negative earnings, and have uncertain prospects are unlikely to receive bank loans or other debt financing (Audretsch *et al.*, 2002a; Lerner, 2009). Therefore, the asymmetric information problem between entrepreneurial firms and investors renders resource providers in private sector unable to make appropriate decisions regarding when and where to invest and hence reluctant to make investments. Moreover, many startup companies based on advanced technologies are founded by technical specialists, who have different objectives and reward structures than people focused on commercialization (Markham, 2002). When the founders are technically-focused and the investors are commercially-focused, this creates a difference in objectives that makes it challenging to translate research findings into successful products.

This issue is compounded by the spatial difference of entrepreneurial resources (Almeida & Kogut, 1997; Chen, Gompers, Kovner, & Lerner, 2010; Fleming, King, & Juda, 2007). In some regions, such as the Great Lakes states, the human capital and technology "at risk" of commercializing are geographically distributed, where numerous top-ranked universities and research institutions are housed (Austin and Affolter-Caine 2006). Yet the resources required for commercialization remains lacking in these regions. From 1995 to 2009, for example, Great Lakes states received 11.5 percent of the total NIH funding while only 3.9 percent of venture capital (VC) investment in life sciences sector was invested there. In the same time period, California and Massachusetts received 25.8 percent of the total NIH funding while 56.2 percent of venture capital investment was agglomerated in those two states.[2] Other resources such as law, accounting and service firms also tend to collocate with each other, which increase the resource gap in these regions (Stuart & Sorenson, 2003a).

For these reasons, technology-based startups face a major challenge in identifying and accumulating the resources necessary to help them bridge the valley of death and survive. Previous literature has linked environmental conditions at founding directly to new ventures' post-entry performance and commercial viability (i.e., survival). For example, Romanelli (1989) concludes that the greater availability of environmental resources at founding significantly influences the likelihood of an organization's survival. In particular, Brito and Mello (1995) find evidence that availability of external capital links directly to firm post-entry performance. In another study, Sarkar, Echambadi, Agarwal & Sen (2006) show that the aligned state of the innovative environment, where product innovation exists in tandem with abundant innovation opportunities, increases chances of survival. Moreover, Lerner (2009) finds that founders and entrepreneurial investors (e.g., venture capitalists) benefit from the sharing of experience and knowledge across peers. For instance, if entrepreneurs are already active in a given region, then investors, employees, and intermediaries such as lawyers, regulatory experts, and data providers are likely to be knowledgeable about the venture process and what strategies, financing, support, and exit mechanisms a new venture requires. As a consequence, new ventures founded in this environment can accumulate more resources to cross the difficult valley of death period.

3.2.2 *State innovation programs, founding environment and new venture survival*

In order to mitigate market imperfections faced by entrepreneurial firms and to help them bridge the valley of death, state innovation programs seek to address two perceived

[2] Calculated by the author using NIH RePORT and VentureXpert data.

sources of market imperfections: capital constraints and other entrepreneurial factor input constraints.

State innovation programs shape the entrepreneurial founding environment through various mechanisms including direct funding to startup companies, funding to research institutions, funding to intermediary organizations, funding to VCs and other private parties, and tax credits for startups or investors. State innovation programs often employ several of these mechanisms, which can be categorized as either mechanisms aimed at addressing imperfections in the entrepreneurial capital market or mechanisms aimed at addressing weaknesses in the broader factor input market for entrepreneurial firms.

In mitigating the imperfections of entrepreneurial capital market and reduce initial capital constraints of new ventures, state programs provide indirect certification of the quality of a new technology through their provision of funding to a firm (Feldman & Kelley, 2003; Lerner, 1999; Zhao & Ziedonis, 2012). To further mitigate information gap and reconcile asymmetric interests between startups and potential private investors, various intermediary organizations established by state innovation programs play the role of linking entrepreneurial firms with potential investors and other resources necessary for commercialization. Public-private interaction at the founding stage of new ventures is especially helpful for mitigating market imperfections.

In mitigating other entrepreneurial factor input constraints, state programs provide entrepreneurial services, incubator support, and increase the availability of human capital (e.g., managers, lawyers, and regulatory experts) to help accelerate a firm's shift from a technology focus to a market focus. Bridging the valley of death not only requires "bridge capital," it also requires shifting quickly to a market focus and getting a better understanding of private sector risk perspectives.

Therefore, state innovation programs use multiple mechanisms to provide capital, credibility, talent, services, and facilities and seek to create a more favorable founding environment to entrepreneurial firms. If these innovation programs can mitigate imperfections in the entrepreneurial resource market, after controlling for changes of market competition and intensive margin of entry (e.g., entrant size) at founding, the effect of these mechanisms on firm survival would be predicted to be positive. Hence, I arrive at the following hypotheses.

- ***Hypothesis 1: Companies founded when an active program exists will have a higher survival rate than startups established in the absence of such a program***

Keeping this baseline hypothesis in mind, a second related question is whether the effect of state innovation programs on startup firms is relatively fleeting or more long-lasting. To answer this question, I take a close look at the types of new ventures founded and the resources provided by these innovation programs, and theoretically predict their consequent effects on average firm survival rates in both the short and long run.

The effect of state innovation programs on firm survival depends on how the availability of a favorable founding environment helps firms. For potentially less promising firms, a favorable founding environment may solve immediate liquidity constraints but will not help them bridge the valley of death. Consequently, these firms will show a higher short-term survival rate but a lower survival rate in the long run.

By contrast, for more promising firms, a favorable founding environment will not only help with immediate financial constraints but will provide additional resources that will help them bridge the resource gap and thus increase their long-term survival rate. In other words, if resources accumulated at their founding stages help new ventures successfully transit from a technology focus to a market focus, cross the valley of death, and attract follow-up commercialization resources from the private sector, then these startup companies are very likely to survive in the long run.

Public resources provided by state innovation programs may lower the entry barriers and increase the proportion of less promising startups established after the program launch. These startups are expected to show much higher exit rate in the long run, which will partially offset program positive effect on average survival rate. Therefore, the overall effect of such programs on the average survival rate would be expected to decrease over the long term. This leads to my next hypothesis.

- ***Hypothesis 2: The difference in survival rates between startup companies founded when an active state innovation program exists and startups established in the absence of such a program will diminish over time.***

3.2.3 *Heterogeneous effects within the life sciences industry*

Startup companies in different industries face different resource gaps. Within the life sciences industry, although medical device and biopharmaceutical startup companies may face the same valley of death problem, there is a meaningful difference between these two sectors. In general, innovations in the medical device sector are much less risky than their counterparts in the biopharmaceutical sector, since medical devices enjoy lower development costs, shorter product development times and less regulatory approval risk. (Ackerly, Valverde, Diener, Dossary, & Schulman, 2009). For example, medical device product development time averages only about 33 to 50 percent of the time required for drug development (Rosen, 2008). Research shows that it takes medical device companies an average of 113 days to go through the FDA 510(k) application process, compared to an average of 322 days to go through the FDA new drug approval process (Downing *et al.*, 2012; MassDevice, 2009). Furthermore, the survey, conducted on twenty experienced fund managers whose funds have been invested in more than 1100 companies in health care sectors, shows that they view the medical device sector as a sector with lower risk, compared to the biopharmaceutical sector (Ackerly *et al.*, 2009).

Therefore, the medical device sector has lower resource requirements for commercialization, less uncertainty, and a lower entry barrier. On the other hand, entrepreneurs in the biopharmaceutical sector face a higher entry barrier, higher product development costs, and a wider gap between the development and commercialization stages.

Since medical device companies have fewer resource requirements and regulatory restrictions in bringing their technology ideas from the lab to the market, the presence of a state innovation program may encourage more marginal startups to be founded in this industry. By contrast, given the higher barriers to entry and commercialization challenges in the biopharmaceutical industry, a state innovation program would not be expected to encourage as many risky biopharmaceutical startups relative to the medical device industry. These differences between medical device and biopharmaceutical startups lead to my third hypothesis on the effect of state innovation programs on firm survival.

- ***Hypothesis 3: The program effects will be more pronounced in sub-sectors with greater resource requirements for commercialization.***

3.3 Method

3.3.1 *Empirical context*

My study focuses on the effect of state innovation programs in the Great Lakes region[3] on startups in the life sciences industry for the following reasons. First, life sciences startup companies, which face a long and costly product development process, provide an ideal sample to investigate the effect of state innovation programs intended to help new ventures bridge the resource gap.

Second, the Great Lakes states face common economic challenges owing to the prolonged decline of their manufacturing industries. In addition, these states are each endowed with major assets such as a strong research, innovation, and talent cultivation infrastructure. Entrepreneurial ideas and human capital in the life sciences sector—universities, major hospitals and medical institutions, and incumbent firms—are widely distributed throughout the Great Lakes region. However, entrepreneurial resources remain lacking in this area.

Finally, state governments in the Great Lakes region have been very active in launching innovation programs since the mid-1980s. As described in the data section, all the focal states in the region launched at least one program with a budget of more than $1 billion during the sample period. These types of programs, which embrace the concept of "economic gardening," focus on new firms and technology development and build up "startup communities" and "entrepreneurial systems" (Plosila, 2004).

[3] The Great Lakes region is one of the eight distinct regions defined by the Bureau of Economic Analysis (BEA), and includes five states: Illinois, Indiana, Michigan, Ohio, and Wisconsin. The BEA groups 50 states and the District of Columbia into regions for the purpose of data collection and analysis.

3.3.2 *Data*

Using the life sciences industry in the Great Lakes region as my empirical context, I employ multiple data sources to construct a unique dataset to address my research questions. To obtain a "big picture" overview of innovation programs in the Great Lakes states and to define major programs based on size, I compile historical information about these programs from a combination of archives and websites. I then supplement this program information with a dynamic establishment-level panel dataset that includes all medical devices and biopharmaceutical establishments located in the Great Lakes region during the period 1990-2009.

To collect state program information, I first use Berglund and Cohurn (1995)[4], the State Science and Technology Institute (SSTI) archives[5], and government economic development websites to identify innovation programs during this period in the Great Lakes region. I next cross-check this information by searching Battelle/Bio State Bioscience Initiatives reports, Google archives, and Factiva to eliminate programs that were announced but never implemented. I then use key information about these programs obtained from program descriptions, program reports, and press releases to identify relevant program characteristics. This information includes program starting year, ending year (if any), and total budget commitment. I collect information on all program types to provide a broad vantage point from which to view the evolution and range of these programs, and then narrow my focus to programs with a major component related to the life sciences industry.

[4] Berglund and Cohurn(1995)'s compendium of state and federal cooperative technology programs provides an early attempt to describe and classify state programs and is the most comprehensive source for historical information about state innovation programs launched before 1995. Building upon that seminal effort, SSTI provides a wealth of information accessible through the SSTI archives, a central digital repository classified by state (Feldman, Lanahan & Lendel, 2012).

[5] Source: http://www.ssti.org/Digest/Indices/indexstate.php?page=indextext2 (accessed August 17, 2012)

Table 3.1 lists state innovation programs with an initial total budget larger than 20 million dollars launched between 1990 and 2009 in four focal Great Lakes states: Illinois, Indiana, Michigan, and Ohio. Wisconsin does not have a pivotal program; instead, it has many programs housed in various units of the Department of Economic Developments.[6] Based on the distribution of program size as measured by their budgets, I define programs with a budget of more than 500 million dollars as "major" programs[7]. As shown in Table 3.1, compared to major programs, other programs are much smaller. The average size of these major state innovation programs is $1.6 billion, and total budget of all rest programs is only $985 million. During the observation period, Illinois, Indiana, and Ohio each launched one major program while Michigan launched two. However, since the second program in Michigan was launched in 2006, the time window is not yet long enough to effectively assess post-entry performance for the cohort of entrants established after the program launch. Thus, I limit my focus for Michigan to the program launched in 1999.

Figure 3.1 plots the timing of major state innovation programs relative to real gross domestic product (GDP) growth by state. In Illinois, the VentureTECH program was launched in 2000 when GDP growth had declined from around 5.9 percent in 1997 to 3.5 percent in 2000, and continued to decrease in 2001. Indiana launched its major program in 2002 when the state GDP was climbing from -1.7 percent in 2001 to 2.7 percent in 2002, and continued to growth in 2003. Michigan and Ohio launched their major programs at a turning point when the state GDP growth rates are lower both before and after that year. From Figure 3.1, it is clear that the timing of major program launch in the focal states does

[6] For example, Wisconsin had 152 State Economic Development Programs from 2001 to 2004. In 2011 it has more than 25 separate business development programs administered by the Division of Business Development.
[7] The threshold and list of major programs do not change after I convert all budgets into constant-dollars. In terms of 2009 constant dollars, the average size of major programs is 1.9 billion and the total budget of all rest programs is $1.1 billion.

not have a strong correlation with the trend of state economy. In some cases, the program was launched when the state economy was growing stronger, while in other cases, the program was established in a period of decline. Large state initiatives launched at different times help to identify the program effects from common industrial or macro-economic trends that may affect the performance of entrepreneurial firms.

To obtain information on the new ventures in this study, I use the National Establishment Time-Series (NETS) database to track the new ventures' entry, exit, and post-entry performance in the Great Lakes region. The NETS database is compiled by Walls Associates using Dun and Bradstreet's (D&B's) Market Identifier (DMI) file and includes annual snapshots beginning with January 1990. The NETS database covers nearly every business unit that has operated in the United States over the past two decades and provides rich information such as business name, address, headquarter, year active, industry classification, type of establishment, employment, sales, and other indicators. Compared to government data based on ES-202 unemployment insurance filings, NETS provides better coverage of young and/or small firms (Kunkle, 2011).

To identify those ventures in the life sciences industry, I use the 2006 Biosciences Industry Report. This report provides a definition of the life sciences industry that has been widely accepted and used by various industry and government reports. It also lists detailed 6-digit North American Industry Classification System (NAICS) codes for each sub-sector in the life sciences industry. I use these NAICS codes to select and construct comprehensive panel data that includes all entrants in the (1) biopharmaceutical and (2) medical device sectors that were founded in the focal Great Lakes region between 1990 and 2009.

Figure 3.2 plots the number of life sciences entrants in the Great Lakes region– Illinois, Indiana, Michigan, Ohio, and Wisconsin – from 1990 to 2009. The average number of entrants per year is 347, with a minimum of 259 entrants and a maximum of 534. As shown in Table 3.2, in addition to Sector I biopharmaceuticals (NAICS 325411-325414), I further divide the medical devices industry into two subsectors (Sectors II and III) based on their four-digit NAICS codes. These two subsectors belong to NAICS 3345 "navigational, measuring, electromedical, and control instruments manufacturing" and NAICS 3391 "medical equipment and supplies manufacturing", respectively.

Although all belong to the life sciences industry, firms in these three industry subsectors have different R&D intensities. Based on the average R&D intensity figures by 4-digit NACIS codes for 1999-2003 from the "Survey of Industrial Research and Development," published by the National Science Foundation (NSF), the R&D intensities for Sectors I, II and III are 7.8, 12.3, and 6.3 percent, respectively, compared to the average R&D intensity for all industries of 3.7 percent.

There are several advantages to using a combination of historical program information and NETS data to investigate the effects of state innovation programs on new venture creation and post-entry performance. First, NETS data cover almost all new establishments, including new ventures and subsidiaries, in the sectors of interest, and are representative of the whole population of establishments. It follows their post-entry performance for a decade and allows me to construct the industry-level control variables that are important to this study. Second, the dynamic nature of this dataset enables me to better investigate time-related effects such as the short-term and long-term effects of state programs, while controlling for other time-variant factors. Finally, the use of objective and archival state innovation program data from various sources ensures that this study does not suffer from the potential self-reporting bias of survey-based data.

3.3.3 *Sample construction*

Since the NETS database is constructed by taking a series of "snapshots" of Dun and Bradstreet (D&B) data every January, my sample is based on snapshots taken from January 1991 to January 2010. If the first year an establishment appears in the D&B databases is January 1991, the starting year of this establishment is assumed to be 1990. All establishments founded in the four focal Great Lakes states after 1990 are followed until they exit from the database or until the end of the observation period[8].

The sample used in this study includes two types of entrants: new ventures (startup companies) and new subsidiaries. I distinguish startup companies and new subsidiaries by comparing the unique IDs (i.e., DUNS numbers from D&B database) of the entrants to their headquarters' unique IDs. For startup companies, their DUNS number is equal to the DUNS number of their headquarters, since the startup company is its headquarter. By contrast, for new subsidiaries, D&B assigns new DUNS numbers that differ from those of their headquarters. Entrants that moved out of their home states during the observation period are excluded from the estimation sample.

In order to identify the effects of state innovation programs on entrepreneurial firms, I create two cohorts. Pre-launch Cohort is defined as entrants founded when a major state program is active; this cohort consists of establishments founded within three years after the launch of a major innovation program. Post-launch Cohort is defined as entrants founded when there is no active major state program. This cohort includes all establishments founded three years before the launch of a major state program.

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[8] The unique identification number at establishment level allows me to follow every active entrant even if it was merged or acquired.

3.3.3.1 *Variable definitions*

The final dataset consists of all Pre-launch and Post-launch Cohort entrants from Illinois, Indiana, Michigan, and Ohio. The total number of new ventures in the sample is 1555, including 1226 startup companies and 329 new subsidiaries. Table 3.3 shows the number of entrants and startups in each cohort in my sample. As expected, Post-launch Cohort contains more startups than Pre-launch Cohort in all four states, which means that there are more startup companies established after the major program launch. Overall, 53 percent of startups are established within three years after the program launch, compared to 47 percent established within three years before the program.

3.3.3.2 *Dependent variable: survival or hazard rate*

Based on previous literature, in order to investigate whether founding environment shaped by state innovation programs can be effective in helping startups to bridge the valley of death, the most direct outcome measure is survival. Since well-performing companies survive while poor performers exit, survival is a good proxy for performance (Penrose, 1952; Williamson, 1991). Additionally, studies in the fields of industrial organization, strategy, and sociology have considered survival as a valid outcome in examining the effects of founding environment (Audretsch & Mata, 1995; Geroski *et al.*, 2010; Romanelli, 1989; Sarkar *et al.*, 2006). Finally, startup company survival is of importance to both managers and policy makers, especially those considering state innovation programs as a major regime shift of the entrepreneurial environment within the state.

To measure new venture survival, the dependent variable is coded in two different ways based on the estimation method. In a probit model that tests the effect of a program on survival, the dependent variable is coded as 1 if a new venture has survived at least three (five) years after entry and is coded as 0 otherwise. For the survival analysis, the dependent variable, entrant exit, is coded as 1 if an entrant has exited in a given year and 0 otherwise. As noted in Table 3.4, about 19 percent of the establishments in this study exit after three years and approximately 32 percent after five years.

3.3.3.3 Explanatory variables

Program Indicator

The key explanatory variable in this study is the cohort indicator: *program*. The variable *program* is coded as 1 if an entrant was founded within three years after the launch of a major program (i.e., these entrants belong to Post-launch Cohort), and is coded as 0 if an entrant was established within three years before a major program launch (i.e., these entrants belong to Pre-launch Cohort).

To account for founding and time-varying effects, I also control for other entrant-level, industry-level and macroeconomic-level variables that may affect post-entry performance

Entrant-level variables

Previous literature shows that the initial size and current size of new ventures are both responsible for the observed variation in post-entry performance for such ventures (Geroski *et al.*, 2010). Consequently, the entrant-level controls in this study include both the *initial size* of the entrant at founding and the *current size* observed at the end of the observation period, or in the year that the entrant exited. Both of these variables are measured by the number of employees in the firm.

Industry-level variables

To capture market competition and industry dynamics, following prior literature (Eisenhardt & Schoonhoven, 1990; Geroski *et al.*, 2010; Sarkar *et al.*, 2006; Swaminathan, 1996), I construct several time-variant controls at the industry subsector level by state. First, I calculate *industry concentration*, as measured by the Herfindahl-Hirschman Index (HHI) for each industry subsector by state. In addition, I aggregate the establishment-level data to the industry subsector level and calculate the *entry rate*, *exit rate*, and *relative density* to measure the intensity of competition faced by the new venture. The entry (exit) rate is computed as the number of entrants (exits) in a year divided by the total number of firms that existed in the industry subsector in the preceding year for each state. I use 1-year lagged values rather than contemporaneous values for entry and exit rates to reduce the concerns of endogeneity of these two variables with the dependent variable. For each state, the relative density is computed by dividing the number of establishments in an industry subsector in a given year by the maximum number of establishments in this industry subsector from 1990 to 2009. The *industry growth* rate, as measured by the percentage change of total sales by industry subsector for each state over time, is constructed to control for sector fluctuation over time.

Macroeconomic-level variables

Although the industry growth rate can be used to capture the change of macroeconomic situation faced by a focal industry over time, as a robustness check, I also compute the state real GDP growth rate as a macroeconomic-level control variable.

3.3.4 *Model specification and estimation*

My identification strategy includes two important components. I first divide the sample into two cohorts A and B, as described in the previous section. These cohorts mainly differ in their "founding environment" – whether or not entrants were founded during the existence of a major innovation program. After controlling for observable differences between these two cohorts, the founding environment should then be the main reason for any differences in survival patterns between the two cohorts.

I further divide both cohorts into two subsamples: startup companies and new subsidiaries. I do so because startup companies and new subsidiaries in the same cohort may face similar unobservable factors over time that could affect survival but may be insufficiently captured by the controls. Since state innovation programs target startup companies rather than new subsidiaries, if I use the subsample of new subsidiaries as a benchmark and discern a significant effect of the state programs on startup companies rather than new subsidiaries in the same cohort, it would relieve my concern that the results are due to unobserved factors not attributable to these entrepreneurship-focused innovation programs.

After narrowing the sample to those companies established before and after the major innovation program launch in each state, I use several different estimation methods to identify the program's effect on new firm survival.

First, I use traditional probit regressions to test whether a program has a significant effect on the new ventures' probabilities of survival in the following three (five) years.

Equation (1) represents my baseline model:

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

where $Y_{it+1} = P(\lambda_{it+1} = 1|Z_{it})$ and t represents analysis time. Thus, the entrant is founded at t=0, and t+1 indicates a certain time period after the entrant was founded. Furthermore, λ is the binary indicator that equals 1 if the entrant survives at least three (five) years, and equals 0 otherwise. I use probit estimation with a robust standard error and report the marginal effects for ease of interpretation. In this estimation, $Program_i$ is the cohort indicator that equals 1 if the entrant is founded during the existence of an active innovation and 0 otherwise. X_{it} represents a vector of the entrant and industry-level control variables described in the previous section. I use the three- (five-) year growth rates of the specific industry subsector to control for different time trends faced by the two cohorts. I also include industry subsector and state fixed effects to control for any time-invariant differences across industry subsectors or states.

Second, to examine the conditional exit probability of a new venture, I use the Cox proportional hazards model with right censoring. A similar procedure has been used in previous studies on firm survival (e.g., Audretsch & Mahmood, 1995; Disney, Haskel, & Heden, 2003; Huyghebaert & Van de Gucht, 2004; Wagner, 1994). In this model, the hazard rate represents the probability that a new venture will exit the industry within a particular time interval, conditional upon survival until that period. The effects of the explanatory variables are measured using the following model:

$$h(t) = h_0 \exp(\alpha Program_i + X_{it}\delta) \tag{2}$$

where h_0 is the baseline hazard rate. $Program_i$ and X_{it} are defined similarly as in the probit regression.

There are several advantages to use this semi-parametric estimation model. The first is that the baseline hazard is given no particular parameterization and, in fact, can be left unestimated; the model makes no assumptions about the shape of the hazard over time. Second, compared to the probit model, it can include time-varying covariates and takes into account that the entrants may exit after the observation period. Therefore, the Cox model with right censoring can accommodate incomplete survival durations for entrants that cease to exist by the end of the sample period. Furthermore, this estimation model enables me to study how the exit rates of new ventures change over time, and to study how such rates are affected by the presence of a state innovation program, while controlling for other industry- and entrant-level characteristics. Finally, the Cox proportional hazards model includes time-variant covariates that the program effect can differ linearly or non-linearly over time.

To investigate whether the program effect changes over the observation period, I extend the Cox model and include an interaction term between "*Program"* and time trend "*Time*", as indicated in Equation (3). If α_2 is significantly different from 0, then the program effect may decay or increase over time.

$$h(t) = h_0 \exp[\alpha_1 Program_i + \alpha_2 Time \times Program_i + X_{it}\delta] \quad (3)$$

Since my data are annual snapshots, the durations are grouped into yearly intervals. I use two versions of the Cox model based on the data structure. The first is the baseline setup in which each subject (i.e., new venture) has one observation. The second is a panel version in which I split the duration of each subject by year so that each subject has multiple observations over time. In the panel setup, I add time-variant industry-level characteristics to control for the overall industry variations. I also include an additional macroeconomic-level control to test the robustness of the results. Robust standard errors are used to account for intra-firm nonindependence of observations.

3.4 Results

The key question in this study is whether state innovation programs alter the entrepreneurial founding environment, and in turn, affect the post-entry survival of startup companies. In addition, I am interested in understanding whether the existence of major state innovation programs during the startup stage of new ventures brings short-term or long-term effects and whether the effects differ by industry. To shed empirical light on these questions, I first conduct a non-parametric analysis without controls and plot the overall patterns of survival using Kaplan-Meier estimates. I then use the probit and Cox proportional hazard models to investigate the program effect while controlling for other entrant- and industry-level characteristics.

Table 3.4 presents the summary statistics for the full sample. Panel A shows the summary statistics for all variables used in the baseline regressions. Panel B presents the summary statistics for variables after splitting the full sample into yearly time-intervals in which each entrant has multiple observations over time. Table 3.5 displays correlation of each of the variables described in the prior section. The key independent variable (Program) has very low correlation with other control variables (all lower than 0.14). Although there is high correlation between initial and current size of entrants (0.86 and 0.84 in two samples respectively), I run additional estimations (available upon request) without one of the size controls, and all main results do not change.

3.4.1 *Patterns of survival*

Figure 3.3 plots the non-parametric Kaplan-Meier survival estimates, which suggest the probability of survival past time t without controls. Figure 3.3a indicates that the cohort of new ventures established before the launch of a major innovation program (Pre-launch Cohort) experience similar survival patterns over time as the cohort of new ventures established after the major program launch (Post-launch Cohort). However, for each time interval, Post-launch Cohort exhibits a slightly higher probability of survival than Pre-launch Cohort, with this difference decreasing over time. Figures 3.3b and 3.3c provide the estimates when I divide the sample into two subsamples: startups and new subsidiaries. Figure 3.3b shows that, in the short-term, startup companies founded when there is an active state program have a higher probability of survival than startups founded when there is no active program. This difference is less pronounced in the long-run. For new subsidiaries, Figure 3.3c shows that there is no clear pattern regarding whether Pre-launch Cohort or Post-launch Cohort is more likely to survive. Instead, survival probability depends on the analysis time and time interval.

3.4.2 *Long-term vs. short-term effects*

Figure 3.3 provides an overview of how the respective survival probabilities of the two focal cohorts evolve over time. However, since other founding and current conditions may also affect subsequent survival probability, I use parametric and semi-parametric regression models to isolate the program effect, while controlling for other factors that may affect survival. Using these models, I examine both long-term and short-term effects.

Table 3.6 presents the results from the probit regression model. The dependent variable is a binary indicator of whether the entrant is still in business after three (five) years. Columns (1) and (4) present the baseline results without controls. These results are robust after entrant-level and industry-level controls are added to the baseline regression. Overall, entrants established when there is an active program are more likely to survive than those established before the program was initiated.

Table 3.7 presents the results by startups versus new subsidiaries. These results show that program effect is still quite robust with or without entrant-level and industry-level controls. Specifically, columns (1)-(6) show that startups founded after the launch of a major state program are 7.0 percent more likely to survive in the next three years and 6.9 percent more likely to survive in the next five years. The program effect on survival does not hold for new subsidiaries and I do not find any significant program effect in any of the cases presented in Columns (7)-(12). If some unobservable factors other than the state programs make the entrants in Post-launch Cohort more likely to survive than those in Pre-launch Cohort, we would expect new subsidiaries in Post-launch Cohort to also be affected by these factors. The significant difference of survival probability between startup companies in Pre-launch and Post-launch Cohorts and the insignificant difference between new subsidiaries in Pre-launch and Post-launch Cohorts suggest that the entrepreneurial founding environment potentially altered by state innovation programs may be the main explanation for the different survival patterns of new ventures. Thus, both the non-parametric estimates (Figure 3.3) and baseline regression results (Table 3.7) support Hypothesis 1.

The results in Table 3.7 also show that, although startups in Post-launch Cohort are more likely to survive than startups in Pre-launch Cohort, both the magnitude and significance of the difference decreases in the long-run. To get a clearer idea of whether innovation programs have a time-variant effect, I use the Cox proportional hazard model to better address right censoring and to test the program effect over a longer time period.

Table 3.8 presents the results from the Cox proportional hazards model. Columns (1) and (2) show the baseline results for startups, based on Equation (2). Note that, although built on different model assumptions, the estimation results are quite consistent with those from the baseline probit regressions. Overall, the findings indicate that the cohort of new ventures established during an active state program faces a lower hazard rate of 9.8 percent (=1-exp(-0.103)), compared to those established without an active state program. These results suggest that entrepreneurial resources provided by state programs improve founding environment for startup companies, and in turn, make those companies less likely to exit. By contract, the results for new subsidiaries indicate no differences based on the presence of an innovation program.

One potential disadvantage of the basic Cox model with one observation per subject is that it assumes that all control variables are time-invariant. To address this issue, I use the panel version of the Cox model and split the time interval by year, providing annual observations for each entrant from entry through exit. This panel version includes time-variant covariates that may affect post-entry survival. The regression results, presented in Table 3.9 yield findings consistent with those from the basic Cox model.

Overall, the results in Table 3.9 indicate that startup companies in Post-launch Cohort have lower hazard rates (hazard=exit) than those in Pre-launch Cohort, and the magnitude of this program effect increases when industry-level controls are made time-variant. Specifically, the estimation suggests that startup companies in Post-launch Cohort face a lower hazard rate of 25 percent (1-exp(-0.288)) after I include state-level macroeconomic trends, as measured by state real GDP growth, to alleviate the concern that macroeconomic fluctuation (e.g., the economic recession) may affect the two cohorts differently.

To test whether the program effect is time variant in the long-run, I estimate Equation (3) including an interaction term between analysis time T and the key variable *Program*. The results in Column (3) in Table 3.9 show that the program effect decays significantly over time. For example, one year after being founded, startup companies in Post-launch Cohort have a 45 percent lower hazard rate than startups in Pre-launch Cohort, while after five years, the difference in hazard rates becomes 15 percent. In other words, although the presence of an innovation program when startup companies are founded is associated with greater firm survival rates, this overall effect decays over time. Hence, Hypothesis 2 is supported.

This decay of program effect over time may have two reasons. First, at least for some startup companies in Post-launch Cohort, state innovation programs only alleviate their liquidity constraint at their founding stages rather than helping them bridge the valley of death. These companies have lower hazard rates in their initial years, but are actually more likely to exit after a certain period of time, decreasing the long-term program effect on firm survival. Second, an indirect effect of these state programs is to entice marginal entrants that are less promising. As a consequence, Post-launch Cohort may include higher proportion of less promising entrepreneurial-firms. These companies may rely on less mature technology or target a market with greater uncertainty. The exit of these less promising companies after certain period of time may thus increase the average hazard rates of Post-launch Cohort compared to Pre-launch Cohort.

3.4.3 *Heterogeneous effects on biopharmaceutical vs. medical device startups*

Biopharmaceutical companies and medical device companies differ in terms of the resources required for commercialization. In particular, biopharmaceutical startup companies require more capital and other commercialization resources and may face a deeper "valley of death" at their founding stage. The results in Column (4) of Table 3.9 show that the difference in hazard rates between Post-launch and Pre-launch Cohorts is more pronounced for biopharmaceutical companies than for medical device companies.

By contract, I find no significant program effect on new subsidiaries. This finding reinforces the argument that a causal relationship between program existence and post-entry survival can be inferred from these results with robust program effects on startups.

To further investigate program effects on biopharmaceutical versus medical device startup companies, I conduct sub-sample analysis. The results in Table 3.10 reconfirm my observation based on Table 3.9 and indicate that the program effect on biopharmaceutical companies is bigger than that on medical device companies. Interestingly, I also find that the program effect only decays significantly over time on the subsample of medical device companies. These findings support my Hypothesis 3 and suggest heterogeneous program effects on different industry subsectors with different levels of resource requirement for commercialization.

3.4.4 *Other findings and robustness checks*

The control variables also offer some interesting findings. As shown in Table 3.7 and Table 3.8, I consistently find that the lagged exit rates at founding in the entrants' industry sector increase the new ventures' probability of survival. The results in Table 3.9 show that the time-variant exit rate has even larger effects. In other words, when more firms exit from the market, the startup has a higher probability of survival. As presented in Table 3.9, the time-variant relative density of the focal industry subsector has a significantly positive effect on startups' hazard rates, so startups located in a state and industry subsector with higher density have a lower survival probability. As expected, positive industry growth in a focal state reduces the hazard rates for startup companies.

To further examine the sensitivity of my results, I conducted several robustness checks. The results are presented in Table 3.11. For example, one concern that might arise in interpreting the results is that firms with good technologies may postpone founding if a program is anticipated, in the hopes of receiving program benefits. To test whether this potential self-selection problem affects my results, I limit the sample by excluding new ventures established in the program launch year or in the prior year. Re-estimating the main results with this refined sample does not change my main findings, as shown in Panel A.

Second, as a falsification test, I assume the program launch year in each state to be the year three years before the actual launch year. In this case, both Pre-launch and Post-launch Cohort companies are founded before the actual program launch year. The results in panel B show that these cohorts do not show any difference in their survival rates in either the short or long term. These results provide additional evidence for the robustness of my previous results.

3.5 Discussion and Conclusion

This study investigates the extent to which major state innovation programs designed to shape the entrepreneurial founding environment for startup companies affect new ventures' post-entry survival patterns. To address this question, I compile historical innovation program information for a group of states in the Great Lakes region and focus my analysis on the effects of state programs on two important sectors – biopharmaceutical and medical device –within the life sciences industry. To identify the causal effect of state programs on new venture survival, I create two cohorts for each state. Pre-launch Cohort includes entrants that were founded within three years before a major program launch and Post-launch Cohort includes entrants founded within three years after a major program launch. The main difference between these two cohorts is their founding environment. I also divide all entrants into startup companies and new subsidiaries, as state innovation programs are expected to have a more pronounced effect on startups than on new subsidiaries established by existing companies. I use multiple methods to examine the overall, long-term, and short-term program effects and also to investigate potential heterogeneous program effects on biopharmaceutical versus medical device startups.

The results provide compelling and robust evidence that startups founded when a major state program exists are more likely to survive than those established without a program in place at their founding stage. This finding holds after I control for observable entrant-level and industry-level covariates identified in prior studies (Disney *et al.*, 2003; Geroski, 1995; Geroski *et al.*, 2010; Mata *et al.*, 1995; Sarkar *et al.*, 2006; Swaminathan, 1996).

In addition, my results based on a semi-parametric survival analysis show that the effect of major innovation programs on firm survival diminishes over time. Although Post-launch Cohort companies founded in the presence of an active innovation program face lower hazard rates in their initial years compared to those founded without an innovation program in place, the difference in survival probability between the two cohorts is less pronounced in the long-run.

As expected, my results also show that the program effect is more pronounced for pharmaceutical startup companies, which have higher resource requirements for commercialization, than for medical device companies. For medical device startup companies, the evidence suggests that higher proportion of less promising companies are established after the program launch, and these startups show higher exit rates in the long run.

Finally, my results show no effect of state innovation programs on either the short- or long-term survival rate for new subsidiaries. This lack of effect for subsidiaries suggests that the results are not impacted by some common industry or macroeconomic trends that may make Post-launch Cohort startups more likely to survive than those in prior-launch Pre-launch Cohort.

The evidence from this study suggests that at least for some startup companies, the state innovation programs only solve their immediate liquidity constraint rather than helping them bridge the valley of death at their founding stage. At the same time, the innovation program may also entice some less promising startups that reveal higher hazard rates after certain period of time, especially in industries with lower resource requirement for commercialization

Overall, this study represents an important first step in providing empirical evidence for the effects of state innovation programs on new ventures. It also builds a natural stage for further research. Specifically, this study treats a major program launch as a regime shift in the entrepreneurial founding environment. Future research could explore the effects of different program components by probing more deeply into how the specific design of entrepreneurial programs impacts their effects on entrepreneurial firms. Understanding the pros and cons of various program mechanisms and their performance implications for entrepreneurial firms remains a fruitful avenue for further investigation.

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Figure 3.1 Timing of Major Program Launches

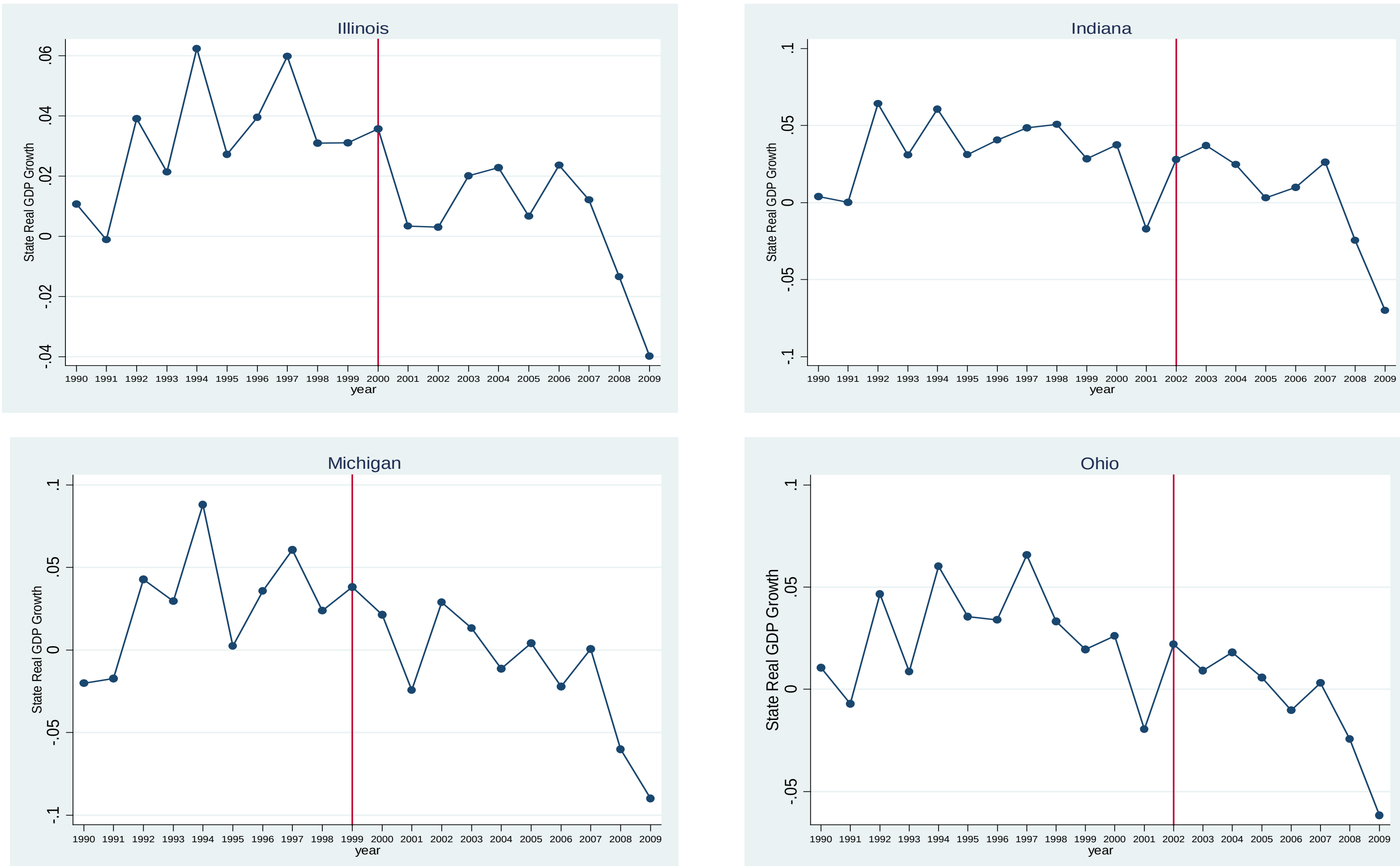


Figure 3.2 New Life Sciences Establishments Founded in the Great Lakes Region, 1990-2009

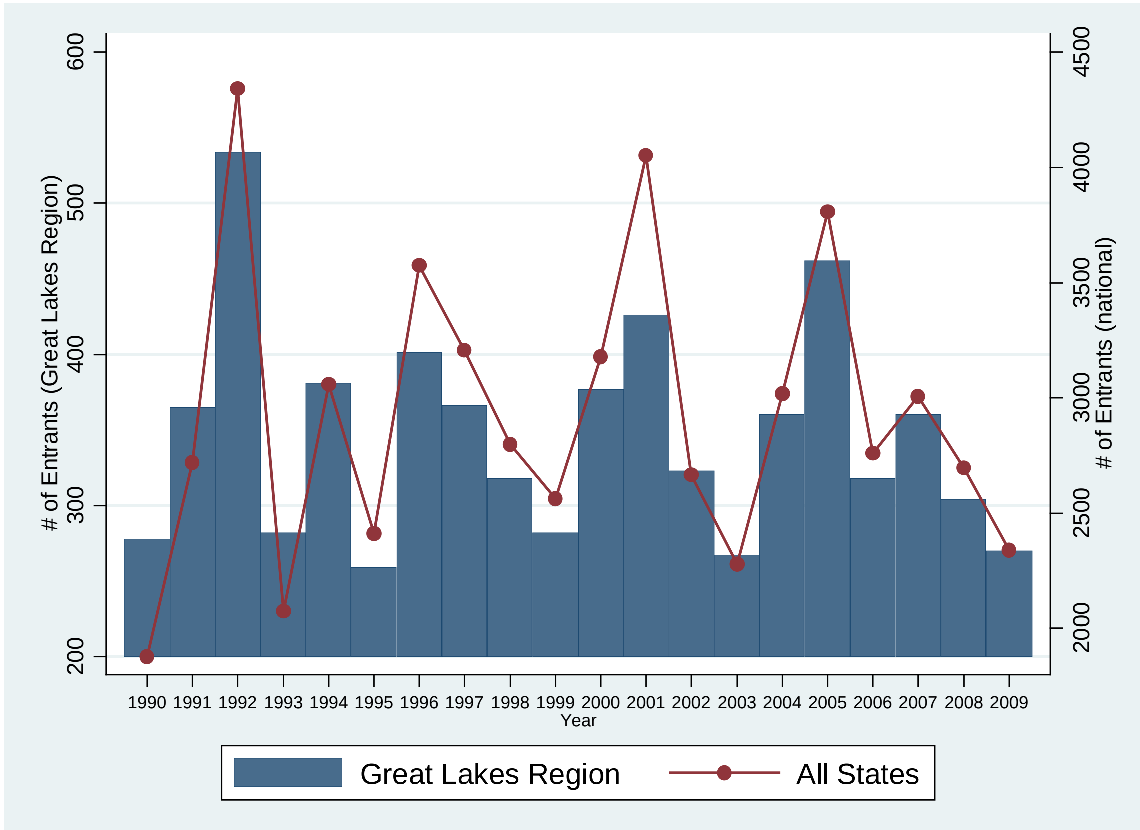
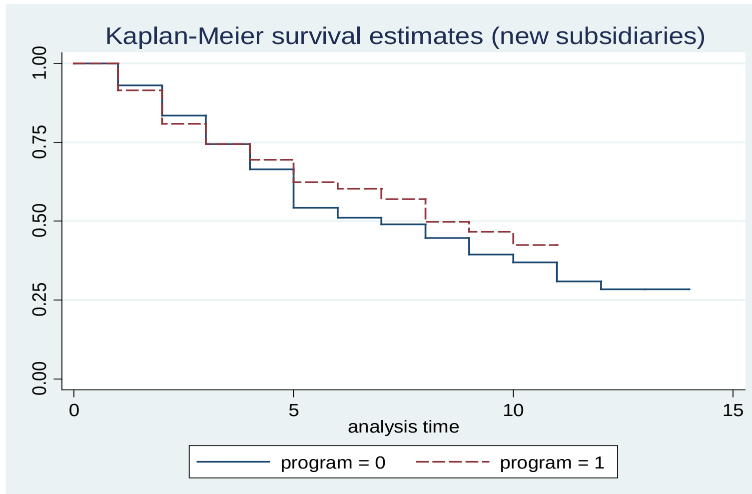
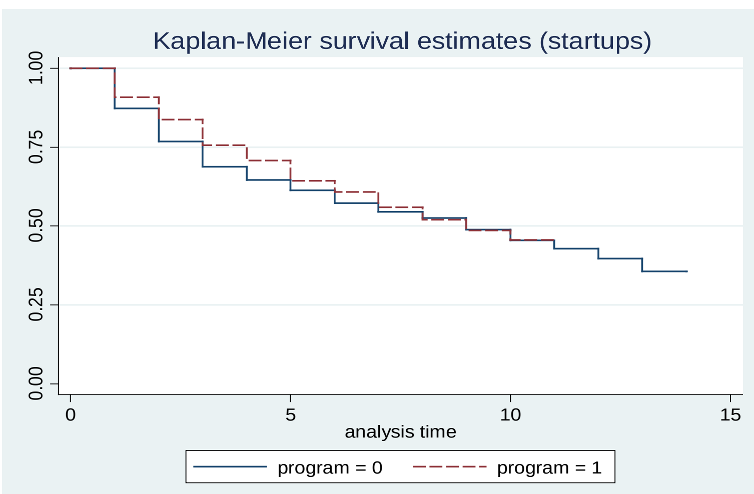


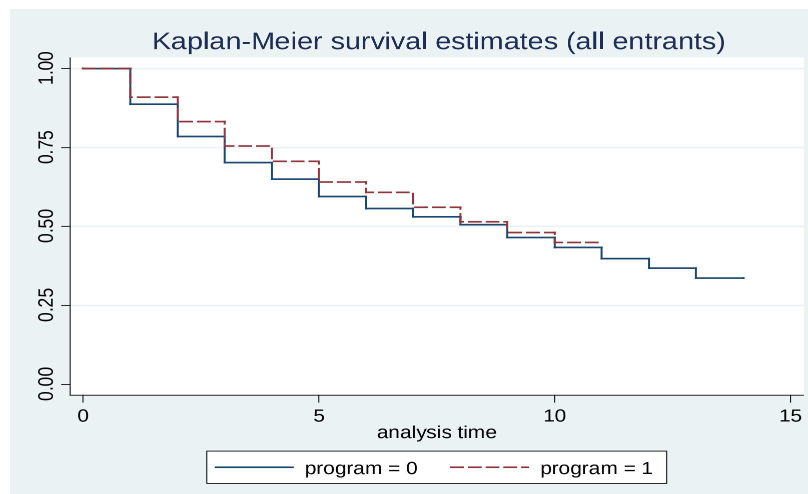
Figure 3.3 Kaplan-Meier Survival Estimates



3.3a



3.3b



3.3c

Table 3.1 State Innovation Programs in Four Great Lakes States, 1990-2009

State		Program	Year started	Year ended/inactive	Initial Budget Announced ($M)
IL	*	**IL VentureTECH**	**2000**	**2005**	**1900**
		Technology Development Account (fund of funds)	2004	ongoing	50
		State Supported Stem Cell Research	2007	2012	100
IN		21st Century Research & Technology Fund	1999	ongoing	50
		Indiana Genomics Initiative (INGEN)	2000	ongoing	105
	*	**BioCrossRoads (Central Indiana Life Sciences Initiative)**	**2002**	**ongoing**	**1500**
		Life Sciences R&D Growth Fund	2008	2009	20
		Indiana Innovation Alliance	2009	ongoing	20
MI	*	**Michigan Life Science Corridor (Michigan Technology Tri-corridor after 2004)**	**1999**	**2005**	**1000**
		Smart Zones	2001	ongoing	50
	*	**The 21st Century Job Fund**	**2006**	**ongoing**	**2000**
		Venture Michigan Fund I	2006	ongoing	95
		Invest Michigan! Fund	2008	ongoing	300
OH		Ohio Technology Investment Tax Credit	1996	ongoing	45
	*	**Ohio Third Frontier**	**2002**	**ongoing**	**1600**
		Ohio Capital Fund/Ohio Venture Capital Authority	2003	ongoing	150

Notes:
1. This table lists state innovation programs identified with initial budgets of $20 million or more.
2. “Major programs” with "*" are defined as those with initial budgets exceeding $1 billion.

Table 3.2 Industry Sector Classification

Industry Sectors	NAICS Codes (2002)
I. BIOPHARMACEUTICALS	
Medicinal and botanical manufacturing	325411
Biopharmaceutical preparation manufacturing	325412
In-vitro diagnostic substance manufacturing	325413
Other biological product manufacturing	325414
II. MEDICAL DEVICES (Navigational, Measuring, Electromedical, and Control Instruments)	
Electromedical apparatus manufacturing	334510
Analytical laboratory instrument manufacturing	334516
Irradiation apparatus manufacturing	334517
III. MEDICAL DEVICES (Medical Equipment and Suppliers)	
Laboratory apparatus and furniture manufacturing	339111
Surgical and medical instrument manufacturing	339112
Surgical appliance and supplies manufacturing	339113
Dental equipment and supplies manufacturing	339114
Ophthalmic goods manufacturing	339115
Dental laboratories	339116

Table 3.3 Number of Life Sciences Entrants by Cohort

	# of Entrants	%	# of Startups	%
Full Sample				
Pre-launch Cohort	761	48.91	573	46.74
Post-launch Cohort	794	51.06	653	53.26
IL	# of Entrants	%	# of Startups	%
Pre-launch Cohort	235	45.9	171	43.62
Post-launch Cohort	277	54.1	221	56.38
IN	# of Entrants	%	# of Startups	%
Pre-launch Cohort	91	51.12	66	49.62
Post-launch Cohort	87	48.88	67	50.38
MI	# of Entrants	%	# of Startups	%
Pre-launch Cohort	183	46.92	153	46.79
Post-launch Cohort	206	52.96	174	53.21
OH	# of Entrants	%	# of Startups	%
Pre-launch Cohort	252	52.94	183	48.93
Post-launch Cohort	224	47.06	191	51.07

Notes: Pre-launch Cohort = entrants founded within 3 years before a major program launch
Post-launch Cohort = entrants founded within 3 years after a major program launch

Table 3.4 Summary Statistics

Panel A: Variables in Probit and Cox regressions (one observation per entrant) (N=1555)	Mean	Std. Dev.	Min	Max
Entrant-level				
Survival after 3 years	0.81	0.39	0	1
Survival after 5 years	0.68	0.47	0	1
Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	0.51	0.50	0	1
Initial number of employees (10s)	2.26	18.29	0.10	600.00
Current number of employees (10s)	2.62	21.11	0.10	600.00
Industry-level				
Herfindahl–Hirschman Index (HHI) at founding	0.10	0.09	0.01	0.58
Entry rate at founding (1-year lagged)	0.07	0.03	0.01	0.20
Exit rate at founding (1-year lagged)	0.06	0.02	0.00	0.15
Relative density at founding	0.83	0.11	0.43	0.93
Industry growth at founding	0.03	0.14	-0.40	0.49

Panel B: Variables in Cox regressions panel version (multiple observations per entrant) (N=10356)	Mean	Std. Dev.	Min	Max
Entrant-level				
Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	0.47	0.50	0	1
Initial number of employees (10s)	2.51	20.41	0.10	600.00
Current number of employees (10s)	3.22	24.86	0.10	600.00
Industry-level				
Herfindahl–Hirschman Index (HHI)	0.10	0.09	0.01	0.58
Entry rate (1-year lagged)	0.07	0.03	0.01	0.20
Exit rate (1-year lagged)	0.06	0.03	0.00	0.20
Relative density	0.88	0.10	0.43	1.00
Industry Growth	0.00	0.13	-0.69	0.73
Macroeconomic-level				
Gross State Product (GSP) growth	0.00	0.03	-0.09	0.06

Table 3.5 Correlations of Variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Variables in Probit and Cox regressions (one observation per entrant) (N=1555)											
(1)	Survival after 3 years	1									
(2)	survival after 5 years	0.706	1								
(3)	Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	0.061	0.059	1							
(4)	Initial number of employees (10s)	0.012	0.030	0.025	1						
(5)	Current number of employees (10s)	0.025	0.043	-0.005	0.859	1					
(6)	Herfindahl–Hirschman Index (HHI) at founding	0.037	0.061	0.011	0.064	0.077	1				
(7)	Entry rate at founding (1-year lagged)	0.005	0.010	-0.024	0.047	0.031	0.530	1			
(8)	Exit rate at founding (1-year lagged)	0.029	0.053	0.002	0.066	0.038	0.259	0.278	1		
(9)	Relative density at founding	-0.026	-0.072	0.064	-0.086	-0.105	-0.616	-0.527	-0.175	1	
(10)	Industry growth at founding	0.001	0.029	-0.199	0.099	0.083	-0.129	-0.280	-0.142	0.059	1
Panel B: Variables in Cox regressions panel version (multiple observations per entrant) (N=10356)											
		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	
(11)	Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	1									
(12)	Initial number of employees (10s)	0.022	1								
(13)	Current number of employees (10s)	-0.015	0.840	1							
(14)	Herfindahl–Hirschman Index (HHI)	0.047	0.076	0.091	1						
(15)	Entry rate (1-year lagged)	0.012	0.063	0.073	0.511	1					
(16)	Exit rate (1-year lagged)	-0.016	0.012	0.015	0.235	0.103	1				
(17)	Relative density	0.103	-0.052	-0.072	-0.357	-0.336	-0.216	1			
(18)	Industry growth	-0.045	0.013	0.015	-0.064	-0.151	-0.019	-0.105	1		
(19)	Gross state product (GSP) growth	-0.153	0.002	-0.005	-0.068	0.045	-0.361	-0.304	0.076	1	

Table 3.6 Probit Regressions on Survival (Sample = All Entrants)

	Survival after 3 years			Survival after 5 years		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	0.048**	0.050**	0.053**	0.055**	0.055**	0.070***
	(0.020)	(0.020)	(0.021)	(0.024)	(0.024)	(0.025)
Entrant-level Controls						
Initial size (initial # of employees)		0.000	-0.002		0.001	-0.003
		(0.001)	(0.002)		(0.001)	(0.002)
Current size (current # of employees)			0.003*			0.005**
			(0.002)			(0.003)
Industry-level Controls						
Industry concentration (HHI) at founding			-0.035			0.006
			(0.211)			(0.251)
Entry rate at founding (1-year lagged)			-0.447			-0.857
			(0.512)			(0.615)
Exit rate at founding (1-year lagged)			0.669			1.389**
			(0.562)			(0.696)
Relative density at founding			-0.076			-0.396
			(0.219)			(0.268)
Industry growth (measured by sales growth)			0.016			0.137
			(0.075)			(0.094)
Subsector dummies	No	Yes	Yes	No	Yes	Yes
State dummies	No	Yes	Yes	No	Yes	Yes
Log likelihood	-755.4	-749.6	-746.6	-973.9	-961.8	-953.3
Observations	1,555	1,555	1,555	1,555	1,555	1,555

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: 1. The unit of employment is 10s
2. Marginal effects are reported

Table 3.7 Probit Regressions on Survival (Startup Companies vs. New Subsidiaries)

	Startup Companies						**New Subsidiaries**					
VARIABLES	Survival after 3 years			Survival after 5 years			Survival after 3 years			Survival after 5 years		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Program (0=Pre-launch Cohort;	0.070***	0.068***	0.070***	0.062**	0.056**	0.069**	-0.027	-0.028	-0.060	0.030	0.021	0.006
1=Post-launch Cohort)	(0.023)	(0.023)	(0.023)	(0.027)	(0.027)	(0.027)	(0.043)	(0.044)	(0.049)	(0.052)	(0.053)	(0.058)
Entrant-level Controls												
Initial size (initial # of employees)		0.017	-0.007		0.046**	-0.002		0.000	-0.001		0.001	-0.001
		(0.010)	(0.013)		(0.019)	(0.020)		(0.000)	(0.001)		(0.001)	(0.002)
Current size (current # of employees)			0.025**			0.050***			0.002			0.003*
			(0.013)			(0.019)			(0.001)			(0.001)
Industry-level Controls												
Industry concentration (HHI) at Founding			-0.106			0.022			0.137			-0.500
			(0.247)			(0.307)			(0.478)			(0.614)
Entry rate at founding (1-year lagged)			-0.559			-1.458*			0.134			1.127
			(0.608)			(0.747)			(0.855)			(1.168)
Exit rate at founding (1-year lagged)			1.224*			2.153**			-0.399			-0.291
			(0.710)			(0.891)			(0.918)			(1.184)
Relative density at founding			-0.314			-0.722**			0.743*			0.530
			(0.258)			(0.324)			(0.406)			(0.518)
Industrial growth (measured by sales)			-0.005			0.119			0.053			0.133
			(0.082)			(0.102)			(0.157)			(0.202)
Subsector dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Log likelihood	-600.1	-591.2	-586.7	-767.1	-744.1	-730.9	-153.0	-149.8	-147.4	-206.6	-200.9	-198.1
Observations	1,226	1,226	1,226	1,226	1,226	1,226	329	329	329	329	329	329

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: 1. The unit of employment is 10s

2. Marginal effects are reported in the table

Table 3.8 Cox Proportional Hazard Regressions (Baseline Results)

	Startup Companies		New Subsidiaries	
VARIABLES	(1)	(2)	(3)	(4)
Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	-0.055**	-0.103*	-0.184	-0.079
	(0.023)	(0.057)	(0.165)	(0.128)
Establishment-level Controls				
Initial size (initial # of employees)		0.056		0.004
		(0.038)		(0.003)
Current size (current # of employees)		-0.146		-0.004
		(0.109)		(0.003)
Industry-level Controls				
Industry concentration (HHI) at founding		0.202		-1.346
		(1.463)		(0.848)
Entry rate at founding (1-year lagged)		2.495		0.796
		(4.129)		(4.027)
Exit rate at founding (1-year lagged)		-5.158**		-0.576
		(2.169)		(3.967)
Relative density at founding		1.380		-2.360***
		(1.009)		(0.866)
Industry growth at founding		-0.370**		0.141
		(0.164)		(0.199)
Subsector dummies	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
log-likelihood	-4349	-4333	-1061	-1059
Observations	1,226	1,226	329	329

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: Unit of employment = 10s

Table 3.9 Cox Proportional Hazard Regressions (with Time-variant Covariates)

	Startup Companies			New Subsidiaries		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	-0.288***	-0.597***	-0.207**	-0.243	-0.215	-0.184
	(0.090)	(0.142)	(0.093)	(0.177)	(0.320)	(0.211)
Program* Analysis Time (_t)		0.086***			-0.007	
		(0.030)			(0.066)	
Program * Pharmaceutical (Y/N)			-0.774***			-0.152
			(0.235)			(0.292)
Entrant-level Controls						
Initial size (initial # of employees)	0.058	0.058	0.056	0.005	0.005	0.005
	(0.056)	(0.056)	(0.056)	(0.004)	(0.004)	(0.004)
Current size (current # of employees)	-0.150**	-0.150**	-0.151**	-0.005	-0.005	-0.005
	(0.063)	(0.063)	(0.061)	(0.004)	(0.004)	(0.004)
Industry-level Controls						
Industry concentration (HHI)	1.409	1.223	1.818**	0.165	0.166	0.265
	(0.865)	(0.864)	(0.856)	(1.373)	(1.375)	(1.383)
Entry rate (1-year lagged)	-4.219**	-4.107**	-4.405**	-0.595	-0.600	-0.606
	(1.879)	(1.888)	(1.887)	(2.160)	(2.161)	(2.168)
Exit rate (1-year lagged)	-11.534***	-12.155***	-11.688***	-10.426***	-10.395***	-10.451***
	(1.595)	(1.596)	(1.609)	(2.388)	(2.443)	(2.391)
Relative density	3.595***	3.103***	3.991***	-0.058	-0.047	-0.015
	(0.780)	(0.769)	(0.786)	(1.078)	(1.082)	(1.090)
Industry growth	-0.710**	-0.770***	-0.685**	-0.774	-0.768	-0.763
	(0.290)	(0.289)	(0.290)	(0.533)	(0.541)	(0.534)
Macroeconomic-level Control						
GSP growth	-2.919	-2.358	-2.951	-0.272	-0.323	-0.278
	(2.001)	(1.989)	(2.003)	(3.666)	(3.647)	(3.669)
Subsector dummies	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes
log-likelihood	-4300	-4296	-4295	-1052	-1052	-1052
Observations	8,189	8,189	8,189	2,167	2,167	2,167

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

Notes: 1. Unit of employment = 10s; 2. All industry-level and macroeconomic-level controls are time-variant

Table 3.10 Subsample Analysis – Cox Proportional Hazard Regressions (with Time-variant Covariates)

	Biopharmaceuticals		Medical Devices	
VARIABLES	(1)	(2)	(3)	(4)
Program (0=Pre-launch Cohort; 1=Post-launch Cohort)	-0.629*	-0.623	-0.233**	-0.567***
	(0.378)	(0.522)	(0.095)	(0.152)
Program* Analysis Time (_t)		-0.002		0.093***
		(0.084)		(0.032)
Entrant-level Controls				
Initial size (initial # of employees)	0.710	0.710	0.001	0.000
	(0.550)	(0.550)	(0.062)	(0.062)
Current size (current # of employees)	-0.738	-0.738	-0.168**	-0.170**
	(0.550)	(0.550)	(0.068)	(0.068)
Industry-level Controls				
Industry concentration (HHI)	-4.678	-4.691	2.570**	2.062*
	(3.213)	(3.328)	(1.135)	(1.139)
Entry rate (1-year lagged)	-6.105*	-6.111*	-1.603	-1.614
	(3.266)	(3.267)	(2.680)	(2.629)
Exit rate (1-year lagged)	-5.471	-5.463	-15.115***	-15.836***
	(3.717)	(3.759)	(2.006)	(1.973)
Relative density	0.995	0.998	4.444***	3.788***
	(2.738)	(2.717)	(1.036)	(0.979)
Industry growth	-1.222*	-1.223*	-0.551	-0.628*
	(0.675)	(0.675)	(0.337)	(0.338)
Macroeconomic-level Control				
GSP growth	1.006	0.996	-3.856*	-3.276
	(5.544)	(5.564)	(2.118)	(2.107)
State dummies	Yes	Yes	Yes	Yes
log-likelihood	-388.8	-388.8	-3646	-3643
Observations	1,262	1,262	6,927	6,927

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: 1. Unit of employment = 10s
2. All industry-level and macroeconomic-level controls are time-variant

Table 3.11 Robustness Checks - Cox Proportional Hazard Model (Sample = Startup Companies)

	Panel A Refined Sample			Panel B Falsification Test		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Program (0=Pre-launch Cohort ; 1=Post-launch Cohort)	-0.557***	-0.992***	-0.464***	-0.106	-0.169	-0.075
	(0.121)	(0.185)	(0.126)	(0.078)	(0.127)	(0.082)
Program* Analysis Time (_t)		0.130***			0.014	
		(0.041)			(0.023)	
Program * Biopharmaceutical (Y/N)			-1.143***			-0.233
			(0.284)			(0.202)
Entrant-level Controls						
Initial size (initial # of employees)	-0.071	-0.068	-0.074	0.047	0.047	0.049
	(0.074)	(0.074)	(0.072)	(0.050)	(0.051)	(0.051)
Current size (current # of employees)	-0.213**	-0.215**	-0.208**	-0.101*	-0.101*	-0.102*
	(0.094)	(0.093)	(0.091)	(0.061)	(0.061)	(0.061)
Industry-level Controls						
Industry concentration (HHI)	0.675	0.316	1.509	-0.069	-0.050	-0.030
	(1.066)	(1.062)	(1.026)	(0.780)	(0.779)	(0.785)
Entry rate (1-year lagged)	-4.314*	-3.947	-4.635*	-1.967	-2.019	-2.030
	(2.407)	(2.423)	(2.443)	(1.474)	(1.466)	(1.464)
Exit rate (1-year lagged)	-14.475***	-15.352***	-14.662***	-7.135***	-7.194***	-6.972***
	(2.097)	(2.053)	(2.132)	(1.394)	(1.407)	(1.387)
Relative density	3.850***	2.850***	4.698***	3.268***	3.222***	3.384***
	(1.006)	(0.998)	(1.023)	(0.545)	(0.544)	(0.553)
Industry growth	-1.172***	-1.263***	-1.144***	-0.637**	-0.643**	-0.633**
	(0.398)	(0.394)	(0.400)	(0.288)	(0.289)	(0.289)
Macroeconomic-level Control						
GSP growth	-7.421***	-6.996***	-7.494***	-2.168	-2.116	-2.173
	(2.436)	(2.444)	(2.423)	(1.677)	(1.672)	(1.680)
Subsector dummies	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes
log-likelihood	-2719	-2714	-2712	-5146	-5146	-5146
Observations	5,413	5,413	5,413	9,993	9,993	9,993

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Notes: 1. Unit of employment = 10s; 2. All industry-level and macroeconomic-level controls are time-variant

CHAPTER 4
STAYING LOCAL OR MOVING AWAY?
RELOCATION DECISIONS OF ENTREPRENEURIAL FIRMS AND THE IMPACT OF STATE INNOVATION PROGRAMS

4.1 Introduction

Research has shown that the geographic location of a firm can impact its performance. Motivated by Marshall's seminal work (1920), scholars have investigated numerous environmental, industrial and organizational factors that affect the geographic location decisions of firms (e.g., Alcacer, 2006; Alcacer & Chung, 2010; Audretsch, Lehmann, & Warning, 2005; Shaver, 1998). Despite compelling evidence of a "home sweet home" bias (Dahl & Sorenson, 2012), anecdotes of business relocations are plentiful. Consider, for example, BlueWare, an information technology company from northern Michigan. When CEO Rose Harr decided to expand and hire an additional 190 workers, she moved the company to Florida, leaving behind close family and business contacts (Lovy, 2012)

The decision to "stay local" can pose difficult trade-offs for entrepreneurial firms, particularly in sectors that require external financing and support during the commercialization process. Prior research suggests that staying local allows entrepreneurs to leverage interpersonal networks and existing organizational ties (e.g., with universities or other research institutions) while avoiding the disruptions and costs of relocation (Dahl & Sorenson, 2012; Feldman, 2004).Yet, failure to move could make it more difficult or costly to secure expansion capital, management talent or business services, thus limiting the upside potential of these ventures (Chen, Gompers, Kovner, & Lerner, 2010; Hochberg, Ljungqvist, & Lu, 2007; Porter & Stern, 2001). Perhaps due to the difficulty of tracking cross-state movement by entrepreneurial firms with Census data, empirical evidence on the relocations of new science and technology companies is sparse.

Little also is known about the effects, if any, of state innovation programs aimed at stimulating entrepreneurship in science and technology industries and, in turn, building more robust clusters of innovative activity within the state. Since the mid-1980s, numerous states have pursued "economic gardening strategies" to support local entrepreneurial activity. As discussed in the earlier chapters, the Michigan Life Sciences Corridor (MLSC), for example, emerged from the state's $1 billion legal settlement with the tobacco industry in 1999. Prominent among technology-based economic development programs, the MLSC initiative is credited with making Michigan one of the fastest-growing U.S. states in the life sciences sector (MEDC, 2010). In 2002, the state of Ohio launched a similar Ohio Third Frontier (OTF) Program, which has grown to a $2.3 billion endeavor. According to OTF reports, the program has supported the creation and financing of over 571 Ohio-based companies since 2005 (SRI, 2009).

If these public initiatives help develop a stronger infrastructure of entrepreneurial resources, the relative disadvantage of staying local should decline over time and reduce the likelihood that promising companies will relocate to more resource-rich locations. As Lerner (2009) and others report, however, there is valid skepticism of public efforts to support entrepreneurial activity: such programs are notoriously difficult to design and run. The null hypothesis—that state programs will *fail* to alter entrepreneurial-firm relocation decisions—is therefore worthy of investigation in itself.

To contribute to our understanding of the relation between state innovation programs and firm relocation decisions, this study examines the relocation decisions of more than forty thousand life sciences and information technology companies initially located in five Great Lakes states: Indiana, Illinois, Michigan, Ohio, and Wisconsin, from the period of 1990 to 2010. In this study, relocation decisions are identified as events indicated in the Dun and Bradstreet database that signal departures due to standalone firm decisions as well as relocations driven by corporate takeover (M&A) activity by firms in other states. Since this database includes information compiled from multiple sources, I am able to follow each startup and its location before and after the creation of state incentive programs.

To conduct my analysis, I use a competing risks model to identify the cumulative incidence function of relocation and then examine the impact of state innovation programs on the subhazard of relocation (after treating firm closure as a competing risk). Overall, my results show that high technology companies in the life sciences sector in the Great Lakes region are more likely to move away from their home states than are companies in the information technology industry. In addition, I find that growing companies are more likely to depart than are non-growing companies. These results suggest that firms with higher requirements for external resources face higher hazard rates of outmigration.[1]

To examine the impact of state innovation programs on firm relocation decision, I also exploit time-varying differences across Great Lakes states in the launch of major entrepreneurial programs. Major programs are defined as those with either an initial budget or committed funding of more than $1 billion. To compare the hazard of relocation before and after a major program launch, I construct two program event windows – a short 6-year event window and a longer 10-year event window. Doing so, I find a consistent and

[1] In this study, I use "relocation", "outmigration", "departure" and "moving away" interchangeably.

significant decrease in the relocation hazard for young firms. This evidence suggests that state initiatives may bolster the retention of entrepreneurial firms, with more pronounced effects occurring in the longer event window.

In a final set of analyses, I restrict attention to the subset of programs that target firms in the life sciences, and apply a difference-in-differences framework. This approach allows me to compare the extent to which relocations in targeted versus non-targeted sectors are affected by the existence of a state innovation program. The results provide consistent evidence that such programs reduce the likelihood of entrepreneurial firm relocations more dramatically within the sector targeted by an innovation program.

Overall, my results contribute to the nascent literature on entrepreneurial location decisions and the public policies that affect such decisions. Specifically, this study extends work on economic geography and industry agglomeration by introducing a dynamic view of firm location decisions. Although previous studies have identified institutional, industrial and firm-level factors that may affect firm location decisions (Alcacer & Chung, 2007; Head, Ries, & Swenson, 1995; Stuart & Sorenson, 2003b), little is known about the proclivity of new science and technology companies in particular to relocate to another state once they have been established.

Furthermore, this study extends previous literature by focusing on state innovation programs in a region outside traditional national hubs of entrepreneurial activity. By focusing on the Great Lakes region, I am able to provide a more complete picture of how firms develop and migrate across a broader portion of the United States. Finally, this study contributes to the literature on institutional changes and their impact on entrepreneurial development. While prior studies have shown how institutional and policy reforms affect the decisions of entrepreneurs to start companies (Aldrich & Fiol, 1994; Eesley, 2009;

Eisenhardt & Schoonhoven, 1990), little is known about the effect of such reforms on the geographic location choices of new ventures. In sum, this study provides new evidence of interest not only to scholars, but also to managers, investors, and policymakers involved in the creation and implementation of technology-based economic development programs (Lerner, 2009, 2010; Porter, 2000).

The reminder of this paper is organized as follows. In Section 2, I review the literature and prior empirical evidence related to the geographic location decisions of companies. In Section 3, I describe the empirical approach and describe the context, data, sample and empirical methods. In Section 4, I report my findings, including descriptive statistics and regression results. Finally, in Section 5, I summarize the results and discuss opportunities for future research.

4.2 Related Literature and Prior Empirical Work

In analyzing the effects of state innovation programs on entrepreneurial location decisions, this study builds on prior research on the more general determinants of location choices of firms, an issue that is examined extensively in the international business and industry agglomeration literature (e.g., Alcacer & Chung, 2007; Wheeler & Mody, 1992). In a classic framework, Marshall (1920) identifies three mechanisms that entice firms to locate within close geographic proximity to one another: labor market pooling, the presence of specialized suppliers, and knowledge spillover. Prior studies provide evidence for all three agglomeration forces (Ellison & Glaeser, 1999; Jofre-Monseny, Marín-López, & Viladecans-Marsal, 2011). More recently, Shaver (2000) extends Marshall's framework by arguing that the positive externalities (e.g., uncompensated knowledge flows) associated with industrial clusters may actually motivate some firms to locate elsewhere. More specifically, while some firms benefit from co-locating, those with superior technologies, capabilities, or know-how may locate away from other firms to better safeguard their competitive advantages. This framework suggests that, while positive externalities may compel some firms to locate in clusters (Chung & Kalnins, 2001), the risk of losing proprietary information and human talent to rivals may lead others to remain distant (Shaver & Flyer, 2000).

Recent studies regarding entrepreneurial location decisions build on the work of Marshall, extending it to the field of entrepreneurship to examine patterns in the initial location choices of startup companies. These studies also draw on the work of other researchers who have identified a number of mechanisms affecting the location decisions of new ventures, such as the presence of small suppliers, an abundant pool of workers (e.g., Glaeser and Kerr, 2009), funding opportunities (e.g., Chen *et al.*, 2010), or social and professional networks (e.g, Stuart and Sorenson, 2003).

Studies of science and technology startups further document that such firms benefit from close proximity to relevant research institutes and universities that can provide knowledge spillover (Audretsch *et al.*, 2005; Buenstorf & Geissler, 2011). Indeed, biotechnology startups have been shown to benefit from access to star faculty at nearby academic institutions (Zucker, Darby and Brewer, (1998).

Finally, previous studies find that the regional benefits of proximity occur at the state border level. That is, state borders have independent effects on knowledge diffusion (Belenzon & Schankerman, 2012; Singh, Marx, & Fleming, 2010). This evidence implies that firms located in the same state as related universities, research labs, hospitals and other knowledge sources are more likely to benefit from the knowledge spillover from these institutions.

This strand of research yields insight into how entrepreneurs select the initial location of their companies. However, it leaves two issues unaddressed in how such decisions are made. First, R&D resources are just one factor in determining where to locate. Depending on a startup's stage of development, the firm may find it difficult to secure capital and talent to bring their innovative products and services to the market, and may consider moving to a new location. A second unresolved question in understanding entrepreneur location decisions is whether a firm chooses to remain in its initial location over time. Since most location determination studies rely on cross-sectional data, assessing location choices at a specific time point, they are unable to inform the extent to which firms may change their primary locations over time.

4.2.1 *Relocation decisions: the trade-offs between staying local and moving away*

As discussed above, entrepreneurship has a surprisingly local flavor in that entrepreneurs tend to disproportionately found firms in the cities and states in which they currently reside (Chatterji, Glaeser, & Kerr, 2013). Existing studies tend to argue that entrepreneurs are more likely to stay local due to "regional embeddedness." University spinoffs usually locate near their research facilities, and spin-out firms tend to take root near their parent companies (Klepper & Sleeper, 2005; Saxenian, 1996).

This home bias stems from multiple factors, including family ties, access to established social capital, and the avoidance of relocation costs. In their study, Figueiredo, Guimaraes and Woodward (2002) quantify the home bias, finding that entrepreneurs are more willing to accept over three times higher labor costs to compete in their resident areas of business. Michelacci and Silva (2007) document the benefits of staying local; firms created by locals are bigger, operate with more capital-intensive technologies, and obtain greater financing per unit of capital invested. Dahl and Sorenson (2012) provide corroborating evidence that entrepreneurs tend to locate in regions in which they have deep roots. Overall, this strand of research shows that individuals start companies in the location where they have formed business networks and have access to resources (Feldman & Francis, 2004).

While entrepreneurs may find initial benefits in locating in their home states, these entrepreneurs may subsequently face strong pressure to relocate as they seek to build their companies and commercialize their products. A recent study by Berchicci, King, and Tucci (2011), for example, documents that many spinoffs end up moving to more remote geographic areas as they develop. Two main reasons are documented for such departures. First, as discussed, some firms move to better safeguard their technologies and assets from rivals (Shaver & Flyer, 2000). Romo and Schwartz (1995) argue, however, that such departures arise only when the viability of the firm is threatened. Second, firms may move in hopes of garnering access to the resources required for growth and expansion, such as the financial capital and services provided by VCs and incumbent firms. Indeed, Stuart and Sorenson (2003a) argue that the local conditions that promote the initial establishment of new companies can differ substantially from those needed for the successful expansion and development of those companies. The findings of this study suggest that although founders may be able to leverage relationships and social networks to mobilize resources to create a new firm by staying local, these firms may not perform well in the long run.

Moreover, Kenney and Patton (2005) show evidence that biotechnology and its support network do not exhibit as great a clustering as do semiconductors and telecommunications equipment and their support networks. Although scholars agree that high technology industries are based on particular knowledge bases, but few studies investigate how the knowledge bases and entrepreneurial resources may impact spatial distribution of entrepreneurial firms.

In sum, staying local may enable entrepreneurs to better leverage existing organizational ties and social contacts while avoiding the disruption and cost of relocation (Dahl & Sorenson, 2012; Feldman, 2004). However, as a firm grows, staying local may impede that same firm from obtaining the resources needed to commercialize its products (Chen *et al.*, 2010; Porter & Stern, 2001), and the trade-offs of staying local and moving away may differ by industries.

4.2.2 *Effects of institutional changes on entrepreneurial firms*

In addition to the research on firm location determinants, a separate strand of research in strategy and economics investigates the effects of institutional and policy changes on sources of friction in entrepreneurial resource markets (Aghion, Fally, & Scarpetta, 2007; Kerr & Nanda, 2009b). Within this stream of research, numerous institutional reforms and policy initiatives have been examined, including the effects of non-compete contract enforcement (Marx, Strumsky, & Fleming, 2009; Samila & Sorenson, 2011), banking deregulation (Kerr & Nanda, 2009a, 2010), and intellectual property reforms (Cockburn & MacGarvie, 2009; Hall & Ziedonis, 2001; Png, 2011). Systematic evidence on state innovation programs aimed at facilitating the development of entrepreneurial resource markets remains lacking (Chatterji *et al*, 2013; Lerner, 2009).

As discussed in earlier chapters, the past few decades have witnessed increased activism among state governments aiming to transform entrepreneurial talent and resources into high-growth companies that "stay local", therefore diversifying the employment and tax base within the state. Although these public interventions are often justified by the theoretical arguments of mitigating market frictions, their more direct aim is to create jobs within state borders. To achieve this goal and to stimulate the longer-term development of innovative clusters, state governments strive to retain local companies with high growth potential. A related concern is one of "brain drain," the loss of valuable human capital to other states and regions. To achieve these objectives, state initiatives use public funding in various ways. For example, they may provide funding directly to for-profit companies to help them overcome liquidity constraint and bridge the "valley of death" (Chapter 2 provides a detailed example of such mechanism in the state of Michigan) or to research institutions to support research in leading technology areas and facilitate the technology transfer process. They may also allocate funding to establish intermediary organizations (i.e., catalytic enterprises, incubators), or establish a "fund of funds" program or tax credit program to encourage venture capital investment in the private sector.

If state governments realize these policy objectives and improve the local infrastructure of resources required to form and build new science and technology companies (e.g., managerial training; subsidized or easier access to incubators, plants, investors, or other startups), they may create an environment more hospitable toward new science and technology companies. In turn, the relative disadvantage of these locales relative to more established hubs of entrepreneurial activity could be reduced. If true, state innovation initiatives should increase the baseline propensities of startup companies to "stay local", thus accomplishing the stated policy objectives. If, however, such programs stimulate entry by firms that compete in similar markets, competition over local resources and/or increased concerns of leakage could entice firms to move elsewhere.

Despite the economic salience of retaining home-grown companies and related job positions, prior evidence on the effects of state innovation programs is largely based on news articles,[2] case studies (Lerner, 2009), and program-specific reports (MEDC, 2010; SRI,

[2] For example, see: Covel, Simona "High-Tech Startups Put Down Roots in New Soil", *Wall Street Journal*, May 26, 2009.

2009). Lerner (2009) suggests that the governments can provide to create a stronger business environment and improve the entrepreneurial ecosystem by "setting the table" and make entrepreneurial resources more accessible to startup companies. However, systematic evidence on the effects of such programs is still lacking and a number of important questions remain unanswered. How likely are new science and technology companies to leave their home states once they have been established? Does this likelihood differ by different types of companies? To what extent, if at all, do state innovation programs impact outmigration decisions? The answers to these questions are important from both a practical (policy/managerial) and scholarly perspective. This study represents a first step in providing more systematic evidence to answer these questions.

4.3 Empirical Approach

4.3.1 *Context and background*

To study the impact of state innovation programs on entrepreneur relocation decisions, three contextual characteristics must be considered. First, such a study requires an industry in which startups typically rely on external resources for product commercialization and company growth. It is reasonable to assume that these firms in particular are "at risk" of relocation during the commercialization process, in part due to the need to secure better access to such resources. Second, this study requires a geographic setting with less well-developed entrepreneurial resource markets (whether for capital, management talent, or business services) relative to startups in other states or regions. Firms in such an environment would be more likely to consider the benefits of relocating vs. staying put. Third, this study requires a context with data available on the location decisions of firms to both prior to and following the intervention program.

For these reasons, this study examines the relocation of life sciences and information technology (IT) startups initially incorporated in a Great Lakes state between 1990 and 2009. As Hall and Lerner (2010) discuss, biomedical and IT startups typically require significant external resources from financiers and corporate partners to commercialize their products. However, beyond this similarity, the sectors differ in ways that are particularly useful in the context of this study. First, the external resources required to commercialize a new drug or complex medical device tend to be an order of magnitude larger than those typically required for the commercialization of IT products. Unlike most IT companies, biomedical firms must obtain regulatory approval prior to the first sale of their products. The cost and complexity of that process, which averages $800 million to $1.2 billion for a new drug and $24 million to $94 million for complex medical devices (Adams & Brantner, 2010; DiMasi, Hansen, & Grabowski, 2003; Rosen, 2008), leads many biomedical startups to seek expertise and capital from industry incumbents during the product approval process (Hess & Rothaermel, 2011; Pisano, 1990).

Another difference between the two sectors relates to the existence of sector-specific state initiatives. Within the Great Lakes region, several state initiatives explicitly target the life sciences sector. From a research design perspective, this allows me to construct target groups and use non-target groups as a baseline for comparison. With two industries and life sciences innovation programs, the information technology industry can be used as a comparison group. Thus, the hypothesis is that the institutional shifts caused by these large public initiatives would be expected to have more pronounced effects on innovation-oriented life sciences companies than on IT companies.

In addition, the Great Lakes region[3] represents an appropriate context for my sample as states in the region possess a strong research, innovation, and talent cultivation infrastructure but economically challenging conditions. Specifically, entrepreneurial ideas and human capital in the life sciences and information technology areas — universities, research institutions and incumbent firms — are widely distributed throughout the Great Lakes region (Austin & Affolter-Caine, 2006). Nonetheless, Samuel (2010) provides evidence from both statistical analysis and interviews that venture investment funds in this region are presently not large enough to meet later-stage financing requirements for such firms. Austin and Affolter-Caine (2006) similarly assert that a lagging entrepreneurial ecosystem is a factor contributing to regional talent outmigration.

The Great Lakes region also represents a useful source for study due to the active development of innovation programs in the region. As described in the data section, four out of five states in the region launched at least one program with a budget of more than $1 billion during the sample period. In contrast with policies aimed at attracting large firms to relocate to the state (i.e., "smoke-stack chasing"), these programs focus more on "economic gardening," or the development of services and resources to fund and develop new companies, particularly those in science and technology-related sectors (Plosila, 2004). Overall, the region and time period for the sample provide an appropriate context in which to study how state initiatives impact entrepreneur relocation decisions.

4.3.2 *Data and sample*

Although research on the conditions impacting startup choices is growing rapidly, few datasets provide reliable time-varying information on the geographic location choices of

[3] The Great Lakes region is one of the eight distinct regions defined by the Bureau of Economic Analysis (BEA). The BEA groups 50 states and the District of Columbia into regions for the purpose of data collection and analysis.

these startups. In this study, I rely on the National Establishment Time Series (NETS) [4] dataset, which is based on Dun and Bradstreet (D&B) data that tracks firm locations as well as location changes. The data are constructed by taking annual snapshots of Dun and Bradstreet records every January since 1990. For every establishment identified, D&B assigns a unique "Duns" number as a means of tracking the establishment. The original data is recorded at the establishment level. However, it also provides detailed annual information regarding the hierarchy between the focal establishment and its headquarters.

To determine the geographic location of each firm, I use the annual six-digit zip code provided for each startup. Changes in zip codes across years for a firm allow me to identify cross-state relocations. The NETS data can indicate firm relocation in a number of ways. Most of the time, there is a forwarding address or continuing telephone number or email address that allows D&B to identify the new location and movement. Moreover, any establishment that cannot be contacted at the previous year's address or telephone number will go to the "out of business or inactive" file and before any potential new establishment can be given a new Duns Number, it will be checked against the file to see if there is any indication of a movement. When D&B finds evidence that establishment has existed elsewhere, it retains the original Duns number but reports the new address and the year it changed (Neumark, Zhang, & Wall, 2007).

I next restrict my sample to only innovation-oriented, or "high technology," startups, since such firms are more likely to require significant external resources for commercialization and expansion relative to their less innovation-intensive counterparts. High technology companies are defined as those "engaged in the design, development, and introduction of new products and/or innovative manufacturing processes through the

[4] I thank the Institute for Exceptional Growth Companies and the Edward Lowe Foundation for providing access to the data.

systematic application of scientific and technology knowledge" (Office of Technology Assessment, 1982). The Census Bureau classifies exports and imports that embody new or leading-edge technologies, and the Bureau of Labor Statistics assigns products in technology categories to four-digit NAICS industries that produce them (Heckler, 2005). Based on these NAICS codes, I compile a sample of high-tech life sciences and information technology companies that can be categorized into five industry subsectors: Biopharmaceutical, Medical Devices, Computers, Software, and Computer System Design.[5]

To identify state innovation programs, I use the Berglund and Coburn (1995)[6], the State Science and Technology Institute (SSTI) archives[7], and the respective state government economic development websites to obtain innovation programs during the study period in the Great Lakes region. I next verify the existence of each program by searching Battelle/Bio State Bioscience Initiatives reports, Google archives, and Factiva. This step is designed to eliminate any programs that may have been announced but not implemented. I then examine descriptions, program reports, and press releases to identify the relevant characteristics of each program. This information includes program starting year, ending year (if any), and total budget commitment. Note that I collect information on all program types to provide a broad vantage point from which to view the evolution and range of these programs before narrowing my focus to those initiatives with a minimum one billion dollar budget. The average size of these major state innovation programs is $1.6 billion, while the

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[5] The specific NAICS codes are as follows: (1) Biopharmaceuticals (NAICS 325411-325414); (2) Medical devices (NAICS 334510, 334516, 334517) (3) Computer and related products (NAICS 3341-3342, 3344-3345 excluding 334516 and 333517); (4) Software (NAICS 5112) and (5) Computer system design (NAICS 5415).

[6] Berglund and Coburn (1995)'s compendium of state and federal cooperative technology programs describes and classifies state programs and provides comprehensive information about state innovation programs launched before 1995. Building on that seminal effort, SSTI provides a wealth of information accessible through the SSTI archives, a central digital repository of press releases and news reports about state programs (Feldman, Lanahan & Lendel, 2012).

[7] Source: http://www.ssti.org/Digest/Indices/indexstate.php?page=indextext2 (last accessed August 17, 2012)

combined budget for the remaining within-state programs focusing on innovation or entrepreneurial activity is only $985 million.

Table 4.1 lists the major state innovation programs with an initial total budget larger than one billion dollars launched between 1990 and 2009 in four of the focal Great Lakes states: Illinois, Indiana, Michigan, and Ohio. Wisconsin does not have a pivotal program; instead, it has many programs housed in various units of the Department of Economic Developments.[8] Any targeted sectors of the programs are also list in Table 4.1.

During the observation period, Illinois, Indiana, and Ohio each launched one major innovation program; Michigan launched two. Of these initiatives, The BioCrossRoads initiative in Indiana and Life Science Corridor program in Michigan each targeted the life sciences sector. In contrast, the other initiatives were non-sector-specific, emphasizing a broader array of sectors ranging from IT and advanced materials to alternative energy and the life sciences. Of the two initiatives launched in Michigan, I restrict my attention to the first Life Science Corridor program. Since Michigan's second program, the 21st Century Jobs Fund, was formed in the immediate aftermath of the first large-scale program, I am unable to observe a clean pre-program trend for the 21st Century Jobs Fund.

4.3.3 *Variable definitions*

4.3.3.1 Dependent variable

The dependent variable, *Relocation*, is set as equal to one when a focal firm initially incorporated in one of the five Great Lakes States relocates to another state and zero otherwise. The unit of analysis is thus a firm-state-year. A firm is at risk of relocation after it

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8 More specifically, Wisconsin had 152 State Economic Development Programs from 2001 to 2004. As of 2011, it had more than 25 separate business development programs administered by the Division of Business Development.

is founded in a focal state. Once a startup relocates out of its home state, it is dropped from the analyses.

Relocation is defined broadly to include not only the firm's departure from the state as a standalone company, but also business relocation driven by mergers and acquisitions (M&A). More specifically, relocation is set to 1 if either (1) a startup moves out of its home state or (2) a startup changes its headquarters (typically due to M&A) to another state and its employment count declines after the change. The latter restriction (of an employment decrease post-headquarter move) helps me distinguish between corporate takeovers where the startup and its employees are left "in tact" within the state and ones where business operations are redirected to the headquarter state, a more worrisome outcome for state policy-makers.

Furthermore, I identify the observation period for my sample firms from 1990 to 2010. All of the firms in my sample are founded after 1990 (inclusive) and right censored at year 2010. Firm closure before 2010 is treated as a competing-risk event that prevents the focal firm from experiencing a relocation event. Details regarding my empirical treatment of the competing-risk event are discussed in the next section. Overall, my sample includes 44,513 firms and five states over a 20-year time period (1990-2010). Of these firms, I observe 1,080 relocation events. Among the 1080 relocation events, 96.8 percent are classified as moves by standalone companies, while 3.2 percent are classified as relocations driven by M&A. Within the subsample of firms in the life sciences sector, 91.7 percent of the relocations are classified as moves by standalone companies; within the subsample of firms in the information technology sector, 97 percent of the relocations are classified as moves by standalone companies. The average relocation ages for life sciences and information technology companies are 5.8 and 5.6 years old, respectively

4.3.3.2 Key Independent variables

When predicting the hazard that a given startup will leave the state, I am interested in the effects of the following independent variables on the startup's relocation decision:

Life Sciences Firm: This variable represents a time-invariant industry sector indicator. This indicator takes a value of one if the focal company is from the life sciences sector and zero if the company is from the information technology sector. This sector-level variable captures any heterogeneity between life sciences and IT firms in the average resource needs for commercialization, and thus enables me to identify startups in sectors targeted by state innovation programs.

Growing Firm: Growing firms are expected to have greater needs for external resources than non-growing firms. To test whether growing companies are more likely to relocate, I define the variable *Growing Firm* as a time-invariant indicator that equals one if the number of the focal firm's current (or most recent) employees is more than its initial employment number and zero if it is the same or lower.

Young Firm: State innovation programs are designed to aid entrepreneurs in their early stage of development by providing resources to conduct applied R&D, transform innovations to the commercialization stage, and grow their companies. To test whether state innovation programs have more pronounced effects on young companies, I define *Young Firm* as a time-invariant indicator equal to one if the focal firm is founded within three years before the major program launch or when the program is active in its home state, and zero otherwise. For example, if a program is launched in 1999, any firm incorporated after 1996 would be considered a *Young Firm*.

Program Window Indicator and Post-program Indicator. To test the impact of state innovation programs on the likelihood of entrepreneurial-firm relocation, I construct two program indicators. First, *Program Window Indicator* is a state-year program indicator set as equal to one for the three (five) years following a major program launch and equal to zero for the three (five) years preceding the program launch. *Program Window Indicator* therefore provides a 6 (10) -year program event window within which to compare the hazard rates of relocation before and after a program launch. As an alternative measure, *Post-program Indicator*, measured at the state-year level, is set as equal to one for the time period after the program launch and equal to zero for the time period before the program launch. *Post-program* Indicator therefore provides a longer pre- and post-program estimation period for firms at the state level.

4.3.3.3 Control variables

A number of additional factors at the firm, industry, or macroeconomic level could influence the hazard rate of an entrepreneur firm moving to another state.

At the firm level, I control for the *size* of the focal company. *Size* is measured as the number of employees in a specific year, and thus is a time-variant variable.

At the industry and macroeconomic level, I construct the Herfindahk-Hirschman Index (HHI), industry growth rate and state real GDP growth rate for each state. Specifically, I measure the *Local market concentration* using the Herfindahl-Hirschman Index (HHI). To do so, I first aggregate the establishment-level data from the NETS dataset to the industry subsector level for each state and then calculate the time-variant HHI. I compute the *local industry subsector growth rate* for each state as the percentage change of total sales by industry subsector for each state over time. At the macroeconomic level, I also compute the *state real GDP growth* as a control variable. The state GDP growth rate is calculated as the percentage of real state GDP, using data from the Bureau of Economic Analysis (BEA). Note that all industry and macroeconomic-level variables are lagged one year to allow time for relocation.

Table 4.2 reports the summary statistics for the firms in my sample. All covariates pass the variance inflation factor (VIF) test for multicollinearity. The mean value of the *Growing Firm* indicator shows that only 23 percent of the firms have more employees than their initial number when founded. The average number of employees of sample companies is 6.5. These statistics suggest that the firms constitute an appropriate sample range of entrepreneurial firms.

4.3.4 *Estimation approach*

To obtain baseline statistics on the extent of relocation for the firms in my sample, I first track the relocation patterns of a cohort of companies established at the beginning of the observation period (1990-1994) and investigate whether the relocation likelihood differs by the type of company within the sample. I then use a competing-risks regression model to examine the relocation hazard across different types of companies.

The selection of a hazard model to estimate the effects of covariates on the hazard rates of specific events has been utilized in previous studies (e.g., Shane, 2002). In these studies, a Cox proportional hazard model is often used since it does not require a parametric function form for the baseline hazard (Allison, 1984; Cleves, Gould, & Gutierrez, 2008). In the context of this study, however, a firm may experience a competing event (closure) before it experiences relocation. If these events are not independent, treating the firm that experienced the competing event as censored can bias the estimation. Thus, my hazard model must count firms that experience the competing risk as having no chance to experience the alternative event. To fulfill this requirement, I use the competing risks model proposed by Fine and Gray (1999). This model enables me to assess the effect of covariates on the subhazard for both the event of interest and the competing event of failure (Cleves *et al*., 2008).

The competing risks model uses semiparametric methods to model the covariate effects on the cumulative incidence function (CIF). The cumulative incidence function (CIF) measures the probability that the event of interest occurs before a given time. In order to define the CIF, I first define the subhazard function for the event of interest as follows:

$$\bar{h}(t) = lim_{\Delta t \to 0} \frac{P\{t \leq T < t + \Delta t, event\ of\ interest \mid T > t\ or\ (T \leq t\ and\ other\ events)\}}{\Delta t} \quad (1)$$

Note that CIF(t) is a function of the subhazard only for the event of interest, so if a regression model is defined for $\bar{h}(t)$, it can be used to interpret the covariate effects on CIF(t). This leads to the following representation:

$$CIF(t) = 1 - exp\left\{- \int_0^t \bar{h}(u)du\right\} \quad (2)$$

The Fine and Gray (1999) model is a direct analog to a Cox regression where the subhazard function takes a traditional semiparametric function form. In the context of this study, the subhazard function estimates the hazard of firm *i* relocating out of state *j* in year *t* using the following functional form[9]:

$$\bar{h}_{ij}(t) = \bar{h}_0(\mathrm{t})\exp[\beta X_{it} + \gamma Y_{jt}] \quad (3)$$

where $\bar{h}_{ij}(t)$ is the hazard rate that firm *i* relocates out of state j in year *t* conditional on having not done so by year *t*, while treating firm closure as a competing-risk event. Furthermore, $\bar{h}_{ij}(t)$ represents an arbitrary baseline hazard function. X_{it} is a vector of firm characteristics and Y_{jt} is a vector of state characteristics including industry-level and macroeconomic-level controls. Robust standard errors, clustered by startup, allow for intra-firm nonindependence of observations.

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[9] For simplicity, I use the term "hazard of relocation" instead of "subhazard of relocation" to refer to the marginal occurrence probability for the event of relocation. Both terms have the same meaning in the text.

As shown in model (4), I add a time-invariant *life science* industry indicator to estimate the difference of relocation patterns between life sciences companies and information technology companies. I also include the *Growing Firm* indicator to the baseline model (1) to estimate difference in relocation hazard rates between growing companies and non-growing companies.

$$\bar{h}_{ij}(t) = \bar{h}_0(\mathrm{t})\exp[\alpha LifeScience_i + \beta X_{it} + \gamma Y_{jt}] \qquad (4)$$

To estimate the major innovation program effect on relocation, I use two different approaches. First, I use the *Program Window Indicator* to construct a 6-year (10-year) program event window for Illinois, Indiana, Michigan, and Ohio with billion dollar programs and compare the relocation hazard rates three (five) years before and three (five) years after the program launch. For Indiana and Michigan, since their focal programs target the life sciences industry, the sample includes only life sciences companies for these two states. For Illinois and Ohio, since their programs target both life sciences and information technology sectors, the sample includes both industries for these two states. Equation (5) presents the estimation model.

$$\bar{h}_{ij}(t) = \bar{h}_0(\mathrm{t})\exp[\alpha Program\_1_{jt} + \beta X_{it} + \gamma Y_{jt}] \qquad (5)$$

Second, for the two states that launched life sciences-oriented programs (Indiana BroCrossRoads and Michigan Life Science Corridor), I apply a difference-in-differences analytical framework. As shown in model (6), the main coefficient of interest is α, which indicates the program impact on life science companies compared to information technology companies.

$$\bar{h}_{ij}(t) = \bar{h}_0(\mathrm{t})\exp[\alpha Program\_2_{jt} * Life\ Science_i + \beta Program\_2_{jt} + Life\ Science_i + \rho X_{it} + \tau Y_{jt}] \qquad (6)$$

4.4 Empirical Evidence

Given the current lack of research on the location choices of entrepreneurs, a number of intriguing questions arise. First, it would be useful to know how likely new science and technology companies are to leave their home states. A related question is whether this likelihood is different depending on the sector. Finally, the main question of interest in this study is how the presence of a state innovation program affects the relocation likelihood. To shed empirical light on these questions, I first conduct a non-parametric analysis without controls by examining the proportion of companies founded in an early cohort that relocated out of their home states by 2010. Note that the statistics are conditional on firm survival until the end of our observation period. After establishing the base likelihood of relocation, I use a more rigorous competing-risks regression model to investigate whether life sciences and information technology firms have different likelihoods of relocation and whether state innovation programs impact a firm's relocation likelihood.

4.4.1 *Relocation patterns: different types of companies*

Figure 4.1 presents the proportion of firms established between 1990 and 1994 that chose to relocate by 2010. Conditional on survival until 2010, I find that 4.6 percent of companies in the sample moved out of their home states. Not surprisingly, this percentage is higher for growing firms, which may have greater incentives to search for additional external resources in a new location. Indeed, the results show that 5.9 percent of high-growth firms in the sample relocated by 2010. Furthermore, since life sciences companies have higher requirements for external resources for commercialization and company growth than do IT companies, a higher proportion of life science companies should relocate. After dividing the sample into life sciences and IT industries, I find that 11.8 percent of growing life sciences companies relocated, while only 5.6 percent of growing IT firms departed (see Figure 4.2).

In the above analysis, closure and relocation are treated as independent events. However, to estimate the probability of relocation before a certain time, it is more precise to take into account that firm closure may also occur and to treat this possibility as a competing risk. When competing risks exist, the cumulative incidence function is used instead of the normal survival function.

To empirically tests the covariate effects on the hazard rates of entrepreneurial-firm relocation, I use the semiparametric method of modeling covariate effects on the cumulative incidence function as described in the previous section. Using the full sample of companies, Figure 4.3 plots the overall cumulative incidence for the event of relocation while treating closure as a competing risk. The overall hazard rate for relocation accumulates to around 3.2 percent by the end of the analysis time period.

Table 4.3 presents the results from the competing risks analysis. Column (1) shows the baseline results for the difference in relocation probability between the life sciences and information technology samples. Column (2) presents the results adding founding year fixed effects to allow for firms founded in different calendar years to face different hazards. The results in Columns (1) and (2) show that, after controlling for time-variant firm-level, industry-level and macroeconomic-level covariates, life sciences companies have a significantly higher rate of relocation than IT companies. More specifically, over the analysis time period, life science companies face a 135 percent (=exp(0.854)-1) to 160 percent (=exp(0.957)-1) higher hazard rate of relocation. This result is depicted graphically in Figure 4.4, which plots the predicated cumulative incidence of relocation for life sciences and information technology companies.

Similarly, the results in Columns (3) and (4) in Table 4.3 show the comparative relocation hazards for growing vs. non-growing companies. Growing companies are expected to have higher incentives to move due to their greater need for external resources. The result provided in Column (3) is consistent with this prediction. More specifically, the estimates suggest that growing companies face a 98.2 percent (=(exp(0.638)-1) to 99.1 percent (=exp(0.689)-1) higher hazard rate of relocation than do non-growing companies. Figure 4.5 graphically depicts the predicted cumulative incidence of relocation for growing versus non-growing firms. These results suggest that companies with more employees in the current year than their initial year have significantly higher relocation rates than companies with the same or fewer current employees.

Examining the results for the control variables, I find that the coefficients for firm size are consistently significant at the 1% level, indicating that larger firms are more likely to move out of their home state. In addition, I find that higher local market concentration is significantly associated with a lower likelihood of departure. That is, firms prefer to stay when their local market shows relatively higher concentration. Moreover, the results show that both higher local industry subsector growth and higher economic growth may lower the likelihood of firm relocation. This result is not surprising; favorable industry and economic conditions provide incentives for a firm to remain.

Overall, the evidence suggests that life sciences startups are more likely to relocate than are new information technology companies, and that growing companies are more likely to relocate than are non-growing companies. I interpret this evidence as consistent with the view that firms that require more external resources (financial/human capital, services) during the commercialization process are disproportionately more likely to leave the state than firms that do not face such challenges.

4.4.2 *Impact of state innovation programs*

In this section, I outline the two empirical approaches I use to test whether state innovation programs in the focal Great Lakes states reduce relocation likelihood. In the first approach (as shown in Equation (5)), I create two event windows — a 6-year short event window and a 10-year long event window — around the major program launch time. After controlling for other time-variant firm-level, industry-level and macroeconomic-level covariates, I can then investigate whether the relocation hazard rate changes after program launch.

The results based on this first approach are presented in Table 4.4. Column (1) of Table 4.4 shows that after the program launch, firms have a lower hazard rate of relocation. The effect is not, however, statistically significant at the conventional statistical level. Column (2) suggests that evidence that the program has a significant impact on firms established within three years before the program launch or when the program is active. On average, the point estimate shows a 2.4 percent (=1-exp(0.444-0.468)) lower hazard rate of relocation for young firms after the program launch. Interestingly, after I add an interaction term between program indicator and growing firm indicator, the results in Column (2) shows that the program effects do not differ by growing vs. non-growing firms.

Panel B of Table 4.4 presents the results using a10-year event window. The overall results are consistent with those in Panel A. However, both the magnitude and significance of the program effects on firm relocation are larger. These results suggest that the program effects are more pronounced over a longer time period.

In the second approach, shown in Equation (6), I restrict my attention to those programs targeting firms in the life science industry. Specifically, I analyze the effects of the Indiana and Michigan state innovation programs on life sciences firm location decisions within the respective states. The difference-in-differences framework tests the extent to which the rate of relocation hazard for life sciences companies changes more dramatically than that of information technology companies. The intuition behind this analysis is that if life sciences-oriented programs are effective in retaining high technology firms, then the relocation hazard rate should decrease more dramatically in the life sciences versus information technology sector. Table 4.5 presents the results from this second approach. In all three model specifications, the coefficients of the interaction terms are negative and consistently significant. Including industry and macroeconomic control variables yields similar results.

Overall, my findings suggest that the probability that new science and technology companies from the Great Lakes states will relocate decreases following the launch of a major state innovation program. Furthermore, I find that this effect is more pronounced for young firms and for firms targeted by such a program.

4.5 Discussion and Conclusion

This study has explored the question of whether entrepreneurship is a local phenomenon, or whether commercialization and expansion requirements require firms to relocate as they grow. In an effort to "set a better table" for new innovation-oriented companies, many state governments, joint with other organizations, have poured billions of public monies toward infrastructure development and support to encourage entrepreneurs (Lerner, 2009). Given the magnitude of this financial commitment, there are valid reasons to be skeptical about the extent to which such policy initiatives shape firm decisions and thus a state's economic development.

One key firm decision with a direct impact on the goals of building a vibrant entrepreneurial hub is the decision whether to remain in the state when reaching the commercialization stage. Despite the implications of this decision for both policymakers and innovation scholars, empirical evidence on the baseline proclivity of such firms to "stay home" or move away remains limited. Likewise, the question of whether state innovation programs can impact this decision has been untested, perhaps due to the difficulty of tracking the geographic movement of entrepreneurial firms over time or a lack of centralized information about innovation programs administered at the state level.

To address this gap in the research, this study contributes new evidence based on a sample of life sciences and IT startups established in the Great Lakes region between 1990 and 2010. Based on both nonparametric and semiparametric analyses, I find compelling evidence that high technology companies in the life sciences sector are more likely to relocate out their home states compared to those in the information technology sector during the same observation period. Among startups, growing firms are disproportionately more likely to leave their originating state. These findings are consistent with the view that "leaving home" is in part driven by the need to secure access to external resources required for commercialization and expansion.

I also find that this proclivity of science and technology startups to relocate to other states declines significantly in the wake of major program launches by state governments in the Great Lakes region, particularly for young firms and for those firms in sectors directly targeted by the program.

In combination, these findings suggest that high technology companies initially located in a region with a good i*nnovation infrastructure* but a relatively weak *entrepreneurial ecosystem* may decide to relocate. A good entrepreneurial ecosystem is important as it corresponds to a well-developed entrepreneurial resource market. If the entrepreneurial resource market is perfect, capital, talent and other related services can be allocated effectively to startup companies at the right place and right time (Arrow, 1962; Nelson & Romer, 1996; Stuart, Hoang, & Hybels, 1999). Consequently, the findings in this study imply the existence of market frictions for entrepreneurial resources. They also suggest that one reason entrepreneurial firms may strategically decide to relocate is to overcome the market frictions. Indeed, even after controlling for local market and industry sector conditions, the empirical evidence shows that firms with higher requirements for external resources for commercialization and expansion are still more likely to relocate.

Interestingly, state innovation programs are often justified by market friction arguments. If such programs can improve the local entrepreneurial ecosystem, then there should be a lower hazard of relocation. The empirical results support this prediction. The results also show that these programs do not have a strong impact in retaining growing firms, which suggests that the firms that remain are those with less promising growth expectations. From a public policy perspective, this selection process may have a long-term consequence that contradicts the main objective of these public initiatives.

While a first step towards understanding the impact of state innovation programs on firm relocation decisions, this study has several limitations that build a natural stage for further research. First, this study focuses on the home state without considering the state of relocation destination. By investigating where these firms move, we can get a more complete picture of the reasons for firm outmigration. Second, this study does not fully explore the performance of companies that are more likely to relocate. Due to potential self-selection problems, a more refined study design needs to be conducted in order to investigate whether companies with high growth potential are more likely to move away and to what extent, if at all, state innovation initiatives affect their relocation propensity (Acs, 2011; Acs & Mueller, 2008; Stangler, 2010). Third, this study treats a major program launch as a regime shift and implicitly assumes that programs are randomly distributed across states. Future research could explore the effects of different program components by probing more deeply into the specific design of each program to explore any potential bias caused by the non-randomness of a program launch.

In conclusion, this study provides the first systematic evidence that policy interventions at the state level can significantly alter geographic movement among entrepreneurial firms. It thus sheds light on our understanding of the dynamics of location choices of innovation-oriented technology companies and opens a fruitful avenue for further research.

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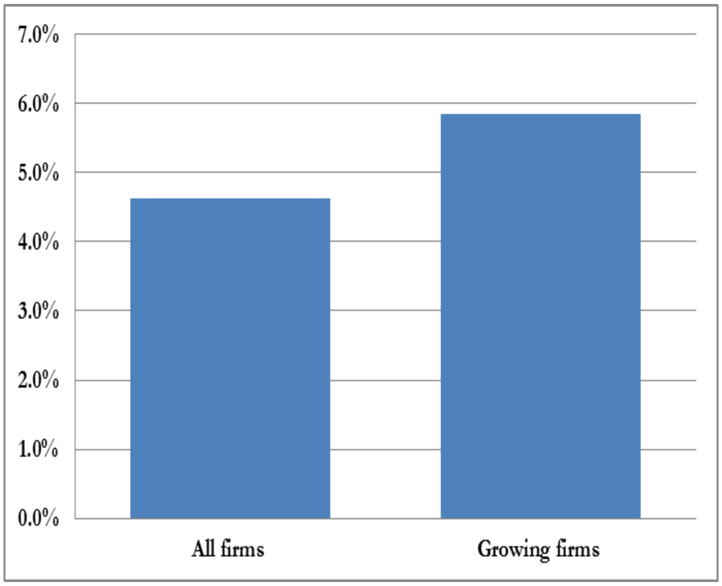
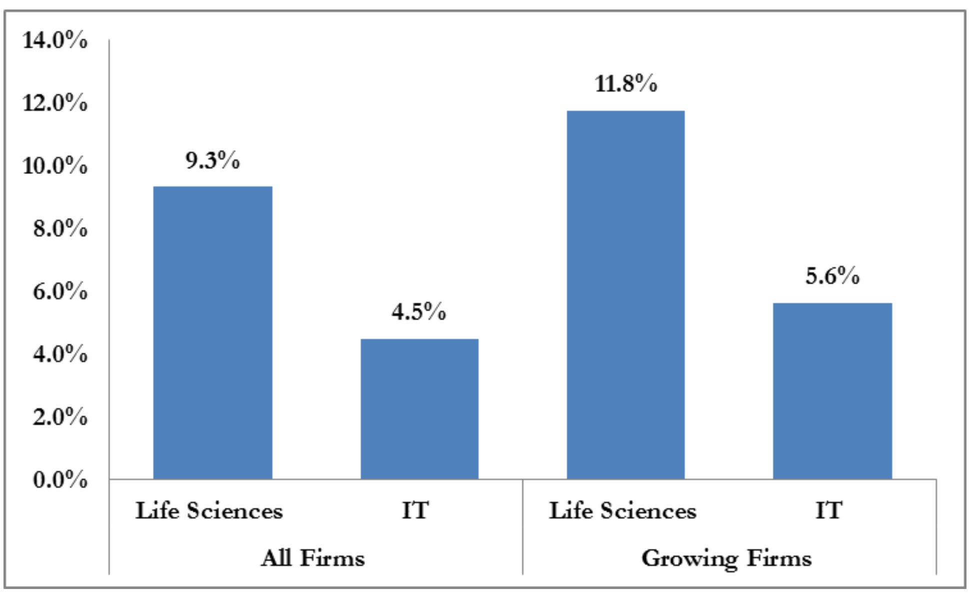
Figure 4.1 Proportion of Firms Formed in 1990-94 and Relocated Out of the Home State by 2010



Note: Based on 2555 life sciences and IT startups initially incorporated in IL, IN, MI, OH, and WI still active as if 2010

Figure 4.2 Proportion of Firms Formed in 1990-94 and Relocated Out of the Home State by 2010 (Life Sciences vs. Information Technology)



Note: Based on 2555 life sciences and IT startups initially incorporated in IL, IN, MI, OH, and WI still active as if 2010

Figure 4.3 Cumulative Incidence of Relocation (Full Sample)

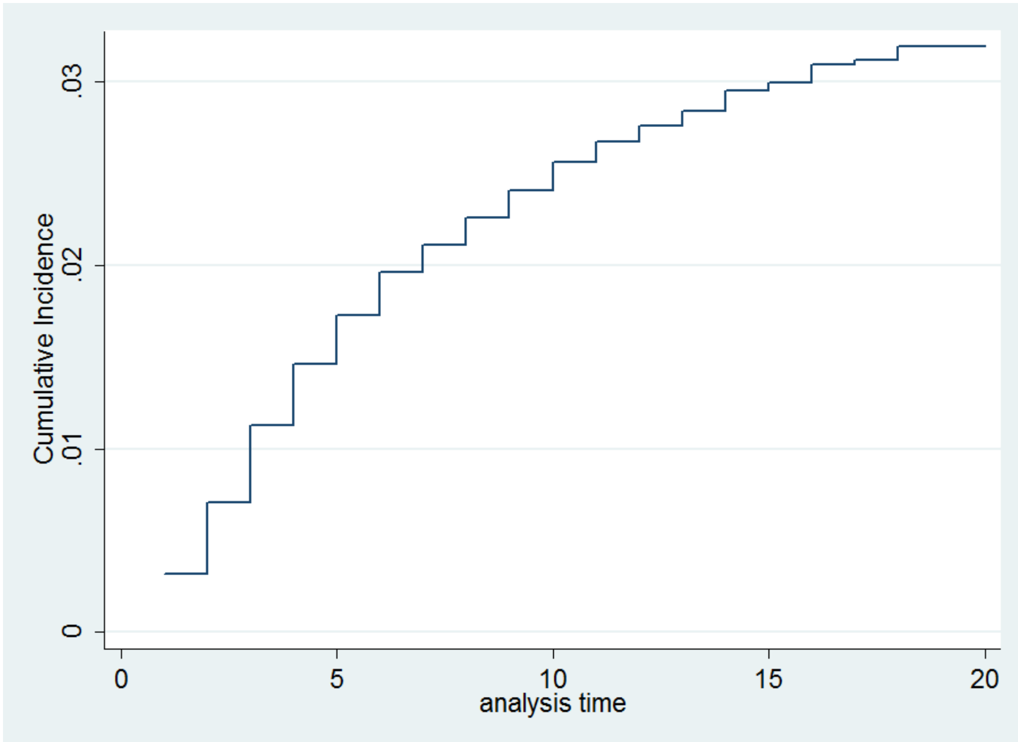


Figure 4.4 Cumulative Incidence of Relocation
(Life Sciences versus Information Technology Companies)

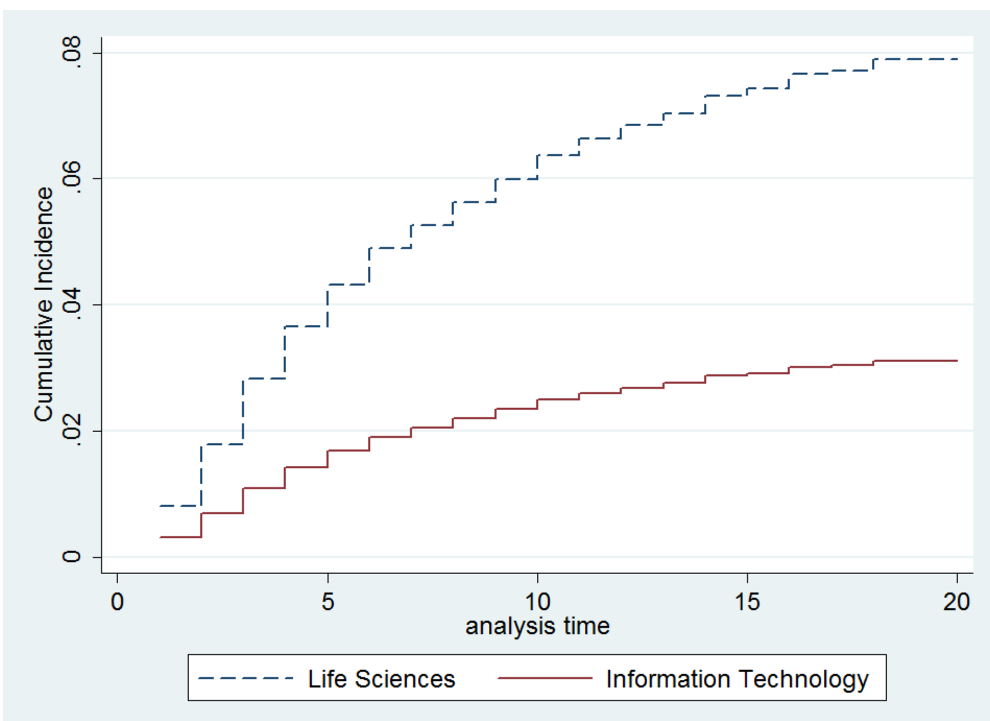


Figure 4.5 Cumulative Incidence of Relocation (Growing versus Non-growing Firms)

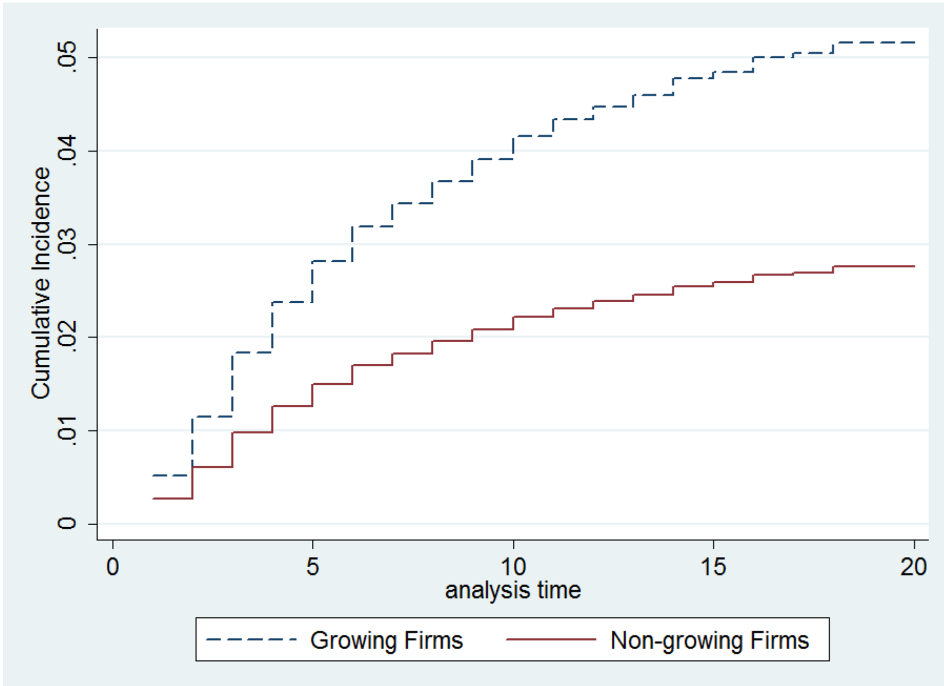


Table 4.1 Major State Innovation Programs, 1990-2009

State	Program	Year started	Year ended/inactive	Initial Budget Announced/Committed ($M)	Major Target Technology Areas
Illinois	IL VentureTECH	2000	2005	1900	**Life Sciences, Information Technology**, Advanced Physics
Indiana	BioCrossRoads (Central Indiana Life Sciences Initiative)	2002	ongoing	1500	**Life Sciences**
Michigan	Michigan Life Science Corridor (Michigan Technology Tri-corridor after 2004)	1999	2005	1000	**Life Sciences** (extended to Advanced Manufacturing, Homeland Security after 2004)
	The 21st Century Job Fund	2006	ongoing	2000	**Life Sciences**, Advanced Manufacturing, Homeland Security, Defense, Alternative Energy
Ohio	Ohio Third Frontier	2002	ongoing	1600	**Life Sciences, Information Technology** and others

Table 4.2 Summary Statistics

	Variables	Obs.	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Growing firm	292936	0.23	0.42	1								
(2)	Life Sciences firm	292936	0.03	0.16	0.017	1							
(3)	Young firm indicator	292936	0.45	0.50	-0.118	0.007	1						
(4)	Employment (10s)	292936	0.65	4.14	0.078	0.044	-0.026	1					
(5)	Local market concentration (%)	292936	2.33	3.89	0.006	0.720	-0.037	0.038	1				
(6)	Local industry subsector growth (%)	292936	4.81	11.01	0.003	-0.028	-0.241	-0.004	0.038	1			
(7)	State real GDP growth (%)	292936	1.78	2.43	0.017	-0.026	-0.297	0.000	0.017	0.316	1		
(8)	Program window indicator (10-year)	168631	0.55	0.50	-0.021	0.046	0.457	-0.003	-0.113	-0.509	-0.519	1	
(9)	Program window indicator (6-year)	66243	0.53	0.50	-0.010	0.016	0.181	-0.010	-0.101	-0.696	-0.288	0.870	1
(10)	Post-program indicator	95896	0.63	0.48	-0.020	0.029	0.466	-0.002	0.074	-0.583	-0.483	1.000	1.000

Table 4.3 Competing Risks Regressions: Comparison of Different Types of Firms (Event of Interest = Relocation)

VARIABLES	(1)	(2)	(3)	(4)
Key Independent Variables				
Life Sciences firm	0.854***	0.957***		
	(0.227)	(0.232)		
Growing firm			0.689***	0.638***
			(0.067)	(0.069)
Control Variables				
Firm size (# of employees in 10s)	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Local market concentration (%)	-0.048***	-0.053***	-0.029**	-0.033**
	(0.013)	(0.013)	(0.013)	(0.014)
Local industry subsector growth (%)	-0.025***	-0.031***	-0.025***	-0.031***
	(0.003)	(0.003)	(0.003)	(0.003)
State real GDP growth (%)	-0.092***	-0.136***	-0.093***	-0.131***
	(0.014)	(0.015)	(0.014)	(0.015)
State dummies	Yes	Yes	Yes	Yes
Industry subsector dummies	No	No	Yes	Yes
Founding year dummies	No	Yes	No	Yes
# of Observations	292,936	292,936	292,936	292,936
# of Firms	44513	44513	44513	44513
Log-Likelihood	-11186	-11154	-11133	-11109

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

Note: All regressions are estimated using competing-risks model with time-variant covariates. The event of interest is relocation and the competing-risk event is firm closure

Table 4.4 The Impact of State Innovation Programs on Relocation

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: 6-Year Program Event Window			**Panel B: 10-year Program Event Window**		
Key Independent Variables						
Program window indicator	-0.044	0.444*	-0.140	-0.132	0.649***	-0.186
	(0.182)	(0.250)	(0.194)	(0.161)	(0.225)	(0.176)
Program window indicator * Young firm		-0.468*			-0.828***	
		(0.251)			(0.223)	
Program window indicator * Growing firm			0.403			0.252
			(0.250)			(0.211)
Young firm		-0.623***			-0.295*	
		(0.185)			(0.158)	
Growing firm			0.295			0.590***
			(0.199)			(0.169)
Control Variables						
Firm size (# of employees in 10s)	0.009***	0.009***	0.009***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Local market concentration (%)	-0.060	-0.058	-0.062	-0.063	-0.070	-0.064
	(0.046)	(0.045)	(0.046)	(0.040)	(0.043)	(0.040)
Local industry subsector growth (%)	-0.016**	-0.016**	-0.015**	-0.021***	-0.019***	-0.020***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
State real GDP growth (%)	-0.100***	-0.131***	-0.102***	-0.119***	-0.149***	-0.123***
	(0.033)	(0.033)	(0.033)	(0.030)	(0.031)	(0.030)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry subsector dummies	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	66,243	66,243	66,243	107,344	107,344	107,344
# of Firms	16849	16849	16849	20515	20515	20515
Log-likelihood	-3031	-3017	-3020	-4301	-4279	-4276

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Notes:

1. Program window indicator is a time-variant variable equal to one for the three (five) years after the program launch and equal to zero for the three (five) years before the program launch

2. All regressions are estimated using a competing-risks model with time-variant covariates. The event of interest is relocation and the competing-risk event is firm closure

Table 4.5 Difference-in-differences Estimates of State Innovation Program Effects on Relocation (Life Sciences Programs only)

VARIABLES	(1)	(2)	(3)
Key Independent Variables			
Post-program indicator * Life Sciences firm	-1.296**	-1.093*	-1.076*
	(0.605)	(0.621)	(0.619)
Post-program indicator	0.979***	0.984***	0.778***
	(0.122)	(0.122)	(0.172)
Life Sciences firm	1.054**	0.848*	1.450**
	(0.464)	(0.484)	(0.648)
Control Variables			
Firm size (# of employees in 10s)		0.006***	0.007***
		(0.001)	(0.001)
Local market concentration (%)			-0.027
			(0.017)
Local industry subsector growth (%)			-0.011
			(0.007)
State real GDP growth (%)			-0.037
			(0.023)
State dummies	Yes	Yes	Yes
# of Observations	95,896	95,896	95,896
# of Firms	14928	14928	14928
Log-Likelihood	-3293	-3289	-3284

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

Notes:

1. Post-program indicator is a time-variant variable equal to one for the years after the program launch and equal to zero for the years before the program launch.
2. All regressions are estimated using a competing-risks model with time-variant covariates. The event of interest is relocation and the competing-risk event is firm closure

CHAPTER 5
CONCLUSION

My dissertation provides new evidence regarding the effects of state innovation programs on the performance and behavior of entrepreneurial science and technology companies in the Great Lakes region. Specifically, I assemble novel databases and use multiple research methods to address the effects in three essays.

The first essay examines the extent to which, if at all, competitive R&D awards from Michigan innovation programs enhance the performance of participating ventures relative to startups that seek but fail to receive an award. The results show strong and compelling evidence that state R&D awards enhance the commercial viability (i.e., survival) of recipient firms, suggesting a relaxation of financial constraints. I also find that receipt of state R&D funding enhances the follow-on financing for these new ventures, but only for those with more onerous information challenges in entrepreneurial capital markets.

My second essay broadens the scope to other states in the Great Lakes region and investigates whether state innovation programs alter the entrepreneurial founding environment and, in turn, shape the post-entry survival of new ventures. Based on state initiatives launched in the Great Lakes region from 1990 to 2009 and evidence from the life sciences industry, I find that new ventures formed when an innovation program is present have significantly higher survival rates than new ventures formed without the presence of such a program. I also find that program effects on firm survival diminish over time and that they are more pronounced in sub-sectors with greater resource requirements for commercialization. This study provides new evidence on the heterogeneous effects of state policy initiatives on entrepreneurial activity.

In the third essay, I examine the baseline proclivity of science and technology startups to leave their state of initial incorporation and the effects, if any, of state innovation programs on such outmigration in the life sciences and information technology industries. Based on evidence from the Great Lakes states during 1990 to 2010, I find that firms with greater resource requirements for commercialization are more likely to leave their home states. The evidence in this essay also shows that, for young firms, the relocation hazard is significantly lower following the launch of a large innovation program by the home state. Moreover, in states that have launched innovation programs with specific industry targets, firms within the targeted sector are less likely to leave the state as they grow. Overall, this study provides the first systematic evidence that policy interventions at the state level can significantly alter the geographic movement among entrepreneurial firms.

My dissertation opens rich venues for future research and points to several directions for this research. First, future research could probe more deeply into the mechanisms of these public initiatives. For example, it would be interesting to investigate the different performance implications of the use of public funding to directly subsidize new ventures or to indirectly fund entrepreneurial firms through private sectors. In both my second and third essays, I treat major programs across states as homogeneous. Disentangling and comparing the effects of different program components would be interesting and could provide a more precise understanding of what drives the state innovation program effect on entrepreneurial firms.

A second area of interest for future research is the extent to which the results from my dissertation can be generalized to other contexts. Although my dissertation focuses on the Great Lakes region in the United States, future research could expand the scope to include other states or countries, ideally using insights from my dissertation research to inform comparative assessments of public efforts aimed at stimulating entrepreneurial activity. In particular, Asian countries such as China and Singapore could be interesting contexts to explore, as these countries have central and local governments that have launched large-scale initiatives with the aim to mitigate imperfections in resource markets for entrepreneurial firms.

In sum, my dissertation provides new insight into the role of state innovation programs on entrepreneur firms; it also provides intriguing possibilities for future research. Such future research could have important implications for academics as well as entrepreneurs, investors, and policymakers in understanding the relation between public innovation initiatives and the performance and behavior of firms they are designed to support.