FUNDING EMERGING ECOSYSTEMS

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Funding Emerging Ecosystems

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Abstract: Although prior research argues that location is important for firm performance, we lack an understanding of how resources accumulate in regions and how innovative ecosystems emerge and evolve over time. This paper focuses on the temporal development of an industry in a region and provides a framework for characterizing phase changes in a geographically defined entrepreneurial ecosystem. We add to the literature on entrepreneurial ecosystems by considering emergence as a temporal process and explicating finance as a mechanism that transitions between phases. Emergence is captured by the accumulation of individual entry by entrepreneurs, and punctuated by phase changes as the region accumulates resources and evolves. We use threshold regression to identify inflection points in stages of industry emergence. We then focus on the role of finance, from both public and private sources. Using a dynamic random effects probit model with regime analysis, we demonstrate interrelationships between public and private funding sources that differ over time. Finally, we estimate the relationship between the funding from various sources and firm survival within different phases using a discrete event history analysis. Our results demonstrate that public and private funding sources are complementary but with different impacts on firm survival during different phases. The results have implications for startup firms seeking funding and for policy making trying to encourage industry emergence.

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INTRODUCTION

Our understanding of the emergence of Silicon Valley, the archetype of a geographically defined entrepreneurial ecosystem, has evolved from attributing primacy to venture capital to recognizing the importance of early seeding from federal grants (Baker 2017; Lécuyer 2006; Kenney & Von Berg 2000). Understanding how industries take hold and transform regional economies is critical for both public and private investment and also for entrepreneurs who find they are attracted to agglomerations. Our understanding of the spatial-temporal geographic emergence of new industries coincides with other exploration of the dynamics of industry emergence (Moeen & Agarwal 2017). Current economic development theory and policy advice ignores the intricate historical processes inherent in the creation of an industry in a regional economic context. Until scholars provide more evidence on how funding affects regional dynamics, investors and policymakers will continue to make decisions with little evidence to guide them.

In considering emergence within a local entrepreneurial ecosystem, the focus has been on the entry and survival of start-up firms, and the availability of resources (Spigel & Harrison 2017). We heed Stam's (2015) call for more theory development on entrepreneurial ecosystems. Through an empirical assessment of historical context, we gain numerous insights from a careful study of industrial development within its regional ecosystem. While social networks and support organizations certainly play a role in industrial ecosystem development, the literature on new industry financing is generally underdeveloped (Goldfarb et al. 2012). Influencing financial investment can be useful to the myriad places trying to create innovative local economies.

In order to explain geographic ecosystem emergence, we analyze the long term development of an industry in one region. Specifically, we examine the development of the life sciences industry in the Research Triangle Region from 1980 to 2016. We focus on entrepreneurial entry and trace the interacting roles of state and federal public funding and private funding of new firms. Specifically, we ask how the interplay of these three sources of funding influenced the emergence of the Research Triangle region's life science industry. Emergence is straightforward to track in this example because there was very little life science activity that existed previously, either in the region or nationally. Of paramount importance to entrepreneurial ecosystem emergence is the need for new ventures to survive long enough to contribute as a part of the whole. We find that the steady hand of government provides financing to allow entrepreneurs to realize opportunity. Over time, the private sector, attracted by these opportunities, becomes active as an investment vehicle. Thus, an industry emerges through public-private interaction. Key to the idea of emergence, though, is that these interactions are nonlinear with phase changes moving the system along.

This paper makes the following contributions. First, we add more theoretical and analytic rigor to the study of regional entrepreneurial ecosystems. We introduce that is the culmination of a long term project that aims to take a long term perspective on ecosystem development. Our second contribution is methodological: to address phase changes in the ecosystem, we provide a method for detecting ecosystem life-cycle transition points. Finally, we contribute to our understanding of how finance from blended sources affects ecosystem development.

THEORETICAL BACKGROUND

In examining the industrial evolution of a regional economy, the product life cycle model, a biological metaphor, is often used. It is modeled by the canonical S-curve, where growth is some function of time against a metric of industry dynamics, such as entry, with three or four defined stages. The application of the life cycle model to geographic clusters has been criticized as atheoretical and lacking a mechanism for an evolutionary framing (Bathelt & Boggs 2003; Essletzbichler & Rigby 2007). Moving to an ecosystem framework, and away from a consideration of clusters, permits a more dynamic focus on the context in which entrepreneurs, as the prime actors in industry evolution, operate and an opportunity for appreciative theorizing.

In reviewing industry life cycle models, Agarwal et al. (2002) find theoretical explanations from evolutionary economics, technology management, and organizational ecology. Each stream offers differing arguments for the movement between phases, emphasizing the process of shakeout as the industry moves from growth to maturity: evolutionary economics attributing maturity to routinization; technology studies to the appearance of dominant designs; and organizational ecology to population density. These theories are still dominant (Wang et al. 2014). These theories may be applicable to understanding why certain regions become dominant in an industry but do not address the question of how an industry initially begins in a specific location.

Recently, attention has turned to industry emergence (Agarwal et al. 2017; Moeen & Agarwal 2017; Stine et al. 2015). Prior frameworks did not explain the initial birth phase of an industry and the conditions that precede growth and industry shakeouts. The concept of emergence is especially important for the development of a geographically defined ecosystem. While the importance of geography to novel ideas and innovation is well established, we lack an understanding of the dynamics of this advantage. As regions emerge, there is consensus that a variety of endogenous forces are at work but these are not well specified (Martin & Sunley 2011). Our understanding of the process of geographic emergence can only be understood within the context of temporal dynamics. Organizational ecology offers one potential avenue yet our view of emergence is based on the actions of agents which encompass more than population dynamics.

Finance and Ecosystem Emergence

Of course, building ecosystems requires financial resources. Publicly funded R&D is associated with increased local firm births (Chen & Marchioni 2008; Kolympirisa et al. 2014; Zucker et al. 1998). Kolympirisa et al. (2014) empirically demonstrate that public funds to firms are associated more strongly with local firm births when compared with funds directed toward universities, research institutes and hospitals, establishing the importance of examining firm level R&D awards in order to understand geographic dynamics.

Private sources of new firm funding, once entrepreneurs move beyond friends and family, include venture capital (VC) and angel investors (see Drover et al. 2017 for a review). A common question in policy discourse is the effectiveness of government R&D subsidies relative to private funds. Skeptics and opponents argue that public funds may crowd-out private funds while proponents argue that public funding alleviates the market failures associated with the private sector investment below a socially optimal level (David & Hall 2000). Montmartin & Massard (2015) further argue that public funding creates knowledge externalities that are important to locations with young firms. Samila & Sorenson (2010) find that public research funding and VC are complementary and result in more innovative activity, as measured by patents and startups, when a region has a greater amount of VC. Yet, public R&D financing programs, especially for high-risk, new technologies are provided by a multitude of federal, state and local agencies, involving questions of multi-level governance and coordination between different funding sources (Charbit 2011; Duruflé et al. 2018). Scholars have looked at public and private funding, or multi-level public funding, but are rarely able to obtain data to examine all of these sources together.

Related work uses university research as the unit of analysis. Blume-Kohout et al. (2015) are able to distinguish federal funding from non-federal sources, which include philanthropic organizations, industry, and state government. Using the National Institute of Health (NIH) budget doubling in late 1990s and early 2000s as an exogenous shock, they find that federal research funding at universities crowded-in funding from these non-federal sources for biomedical research. Using more recent data, Lanahan et al. (2015) find an increase of 1% increase in federal funding, "is associated with a 0.411% increase in nonprofit research funding, a 0.217% increase in state and local research funding, and a 0.468% increase in industry research funding," arguing these results indicate that federal government induces complementary investments by other sources. With regard to federal versus local funding, Wu & Merriman (2017) find a substitution effect between federal and state funding of university research, with effect depending on federal R&D spending trends. A stronger effect is found during times of slow growth in federal R&D spending. Wu & Merriman suggest that local funds may be used to stabilize the amount of financial resources available.

Research has considered the interrelation between private and federal R&D funding for firms (Zúniga-Vicente et al. 2014). For example, Lerner (1996) finds that federal SBIR funding serves as a certification effect to entice private funding for entrepreneurial firms. David et al. (2000) find disagreement about the degree to which public funding is a complement or substitute for private funding, noting that the literature is mostly based on cross-sectional or limited time series data, with limited nuance about the firm's context. In a 10-year panel study of 316 MSAs, Lee (2018) found no significant regional employment or income growth effects from SBA guaranteed small business loans. In contrast, Minniti & Venturini (2017) find R&D tax credits have a significant and economically important effect on the rate of long-term productivity growth. Duruflé et al. (2018) analyze emerging ecosystems around universities and suggest that further research consider the appropriate combination of different types of policies for emergence.

EMPIRICAL CONTEXT

North Carolina's Research Triangle region's life science cluster ranks 5th in the US for life science clusters, following Boston-Cambridge, the Bay Area, San Diego, and New Jersey (CBRE Research 2019). What makes the Research Triangle unique is that it has been able to establish preeminence without any industrial strength in related sectors before the 1980s. Unlike Cambridge and the San Francisco Bay area—the country's leading life science regions—the Research Triangle region was not an obvious candidate to develop a life science industry (Markusen 1996; Luger & Goldstein 1991). The origins of the Research Triangle region's life science cluster can be traced back to the establishment of Research Triangle Park in 1958. The Park was the result of a collaborative effort involving politicians, academics, and financiers to make the region more competitive (Leyden & Link 2011). Over time, in the region adjacent to and surrounding the Park, an ecosystem developed.

Insert Figure 1 about here

Figure 1 displays an increasing number of active life science entrepreneurial firms founded in the Triangle over the time period analyzed. The ecosystem is defined as dedicated biotechnology firms, human therapeutics, diagnostics, medical devices, biomaterials, health IT, and service providers (including contract research organizations). The Research Triangle region's development, in terms of the number of start-ups established per year, largely mirrors the general national trend, taken from Bioscan in 2013. While the region lags a few years behind the national trend, there was significant divergence beginning in the mid 1990s, when the region begins to take-off. After 2010, while Bioscan indicates a decrease in number of firms founded, the Research Triangle region's number continues to increase.[1]

DATA & DESCRIPTIVES

For this analysis, we use data on the universe of 933 firms that were founded between 1980 and 2016 in the Research Triangle Region. The year 1980 is when the Cohen-Boyer patent (which allowed patenting of recombinant DNA) was issued, the Bayh-Dole Act was passed, and Genentech was founded as the first dedicated biotechnology firm. This is an appropriate time to begin an analysis of industry and ecosystem emergence.[2] The data used in the analysis is obtained from the PLACE: Research Triangle Database, which contains information on the universe of life science firms founded in the Research Triangle region.[3] PLACE: Research Triangle includes information on firms' founding, sector, activities, milestones, and founders (Feldman & Lowe 2015). Firm lists were collected from a variety of sources, including universities and support organization archives. Lists were compiled, de-duplicated, and each firm individually researched for information on founding, and data were triangulated to ensure accuracy. Firm founding was verified with filings from the North Carolina Secretary of State. Our data gathering process has the benefit of including start-ups which fail early, before most available data sources can capture them, thus mitigating issues of selection bias. Firms were vetted by local veterans of the life sciences industry, providing us

[1] Comparison is available from the authors by request.
[2] There were 10 entrepreneurial firms operating in this region prior to 1980 but these firms were arguably not dedicated life science firms.
[3] Data was obtained from the PLACE: RTP database in February of 2019.

confidence that our dataset contains the full universe of entrepreneurial life science firms. The firm is our unit of observation: we match on firm name and prior alias used by the firm.

State-level funding data was obtained directly from the two funding sources: the North Carolina Biotechnology Center (NC Biotech) and NC IDEA. Both of these sources provide early stage seed funding. NC Biotech is a quasi-public entity dedicated to promoting biotechnology and the life sciences in North Carolina with a, "mission to accelerate life science technology-based economic development through innovation, commercialization, education and business growth," (NC Biotech 2019). Established in 1981, NC Biotech offers business and employment services, and hosts meetings and events to connect researchers and other industry stakeholders. Starting in 1989, NC Biotech Center has continuously provided small loans to new ventures. NC IDEA was created in 2006 to support high growth entrepreneurial firms, and was formed out of the break-up of the Microelectronics Center of North Carolina. NC IDEA began providing seed grants to entrepreneurial firms in North Carolina that year, and has continuously made such grants available. In 2015 the organization converted to a private foundation, and in 2016 made its 100th seed grant. For each seed grant, we collected the date and award amount.

To measure federal funding, we use SBIR and STTR awards from the Small Business Administration, combined with awards from NIH. Funding from these sources is focused on research the firm is performing, and awarded based on evaluations of that research. Dollar amounts of each award are typically larger than those of the State funding sources, but still much less than the quantities of private funding a firm might receive. Data were obtained from the NIH Federal RePORTER and SBIR.gov.

Data on private funding was gathered from CB Insights. Most private funding recorded in CB Insights comes from VC firms and angel funds. Other sources, added in the past decade, include start-up competition awards and funding from accelerator participation. This data includes information on the amount, date, and round of the investment, as well as the name of the investing entity. For some observations the dollar amount of the investment was missing. If the amount could not be determined from online press releases or other sources, we used $100,000 as a modest imputation.

Together state, federal, and private funding accounts for the majority of external finance a firm will receive.[4] Other possible external sources include foundation funding, but these awards are uncommon. Start-up founders might also "bootstrap" by not taking any type of finance that involves

[4] All dollar amounts are inflated to 2017 real dollars.

an exchange of equity. Bank loans and credit card debt are other means of financing but these data are not available.

Insert Figure 2 about here

Insert Figure 3 about here

Of the 933 firms, 179 received national funding, 162 received state funding, and 163 received private funding. A total of 264 firms have received public funding from state or federal sources. Figures 2 and 3 present annual counts of the number of firms receiving funding and the dollar amounts received by source, respectively. When examining the number of firms receiving funding from each source, it is apparent that most firms who have received funding receive it from the federal government. There is a general upward trend among all funding sources until the financial crisis, when all three sources allocate funds to less firms, with state funding experiencing the largest drop. When examining which source provides the most funding in terms of dollar amount, it is evident that private funding provides the most, followed by national support, and then state. Thus, even though the federal government supports the largest number of firms, private finance provides the greatest dollar amount of funding.

Insert Table 1 about here

Finally, we examined sectoral differences in the development of the region's life science cluster. Each firm was classified by the authors into one of the following six sectors, based on their technology focus: (1) dedicated biotechnology or biomaterials, (2) human therapeutics, (3) tools or diagnostics, (4) medical devices, (5) health IT/informatics, and (6) services. Table 1 provides definitions of these sectors. Classifications were verified in consultation with local industry experts. The largest concentration is human therapeutics (357 firms), followed by medical devices (152 firms). Our descriptive analysis, available upon request, revealed that services firms are quite different than other members of the life sciences industry, receiving their funding largely from federal sources, with little private sector investment. Furthermore, while these firms are part of the ecosystem, their activities are more service-oriented rather than research-related. For these reasons, we do not include these firms in the analyses. This reduces our sample of firms from 933 to 821.

METHODOLOGY

Our data allows deep, longitudinal exploration of emergence in one region. This data, combined with the exploratory nature of our research questions, lends itself to a methodology that follows an exploratory, empirical analysis. We therefore employ five different techniques to examine how an industry emerges and develops in a particular local ecosystem, and investigate the role of start-up finance. Here we present an overview of these methods, which we explicate mathematically in subsequent sections.

First, appealing to theory on industry and cluster life cycles we examine the emergence and development of the industry by empirically distinguishing stages. There is no agreed upon way in the literature to measure different life cycle stages in this context (Wang et al. 2014) so we introduce the use of threshold regression analysis to help with this task. An exception is the discriminant method, which Agarwal & Bayus (2002) implement to detect the shift from growth to maturity.

After we establish the dates upon which the regional ecosystem moved between phases, we provide a chronicle of the region's development, relying on detailed qualitative information we gathered over several years of interviewing entrepreneurs, support organization managers, entrepreneurial service providers, public officials, and other individuals with first-hand knowledge of the regional ecosystem. This data provides a qualitative argument for why phase changes occurred when they did, providing support for quantitative analysis.

Next, we examine how multi-level public and private start-up funding influenced the region's development. First, we establish the relationships between federal, state, and private finance, and examine how these differed among stages using a dynamic random effects probit model with unobserved heterogeneity and regime-switching analysis. With these two techniques we are also able to examine how receipt of one type of funding is related to prior funding from the same source, and other sources, and how this relationship changed across the ecosystem lifecycle.

Third, we examine how funding influences ecosystem development through firm survival. To answer this question, we employ discrete event history analysis to see how the source, or combination of funding, influences firm survival. Start-up survival is of paramount importance to ecosystem development.

DETECTING EMERGENCE

The ecosystem life-cycle model builds on the industry and product life cycle theory's logistic S-shaped curve characterized by different underlying functions that specify slope or rate of change (Agarwal & Bayus 2002; Argyres & Bigelow 2007; Moeen & Agarwal 2017). The curve is characterized by changing functions, with varying degrees of convexity during emergence. When a system enters a period of decline, the function then becomes concave. Our intent is not to map the Research Triangle's ecosystem to the life cycle curve, rather to use the cycle and its derivative elements to characterize the nonlinearity of ecosystem emergence.

Our method uses the distribution of firms to detect discontinuities in the growth of firms in the region. Building on derivative elements of the life cycle, we detect the dates when the sign of the second partial derivative changes with respect to time. We thus write the industry dynamic as a second order polynomial function of time, that is:

$$y_t = \alpha t + \beta t^2 + \varepsilon_t \qquad (1)$$

which translates into the following first difference model:

$$\Delta y_t = y_{t+1} - y_t = \alpha + \beta(2t+1) + u_t\,. \qquad (2)$$

We can further simplify this expression by demeaning the first difference model, and obtain:

$$\Delta y_t - \overline{\Delta y_t} = \beta\left[(2t+1) - \overline{(2t+1)}\right] + v_t \qquad (3)$$

With this expression, we need only estimate one parameter, β, which corresponds to the second partial derivative of the industry dynamic with respect to time. Consequently, by identifying the structural change in the β value, we are able to precisely detect different industry life-cycle transition points and phases.[5]

We employ a threshold model to detect break points in the regional industry life-cycle. Hansen (2000) argues that threshold models can capture abrupt breaks or asymmetries observed in most time series data. Threshold models are flexible in that they allow specification of a known number of thresholds or let the software find the optimal number of thresholds through different efficiency criteria (Hansen 2001 provides a survey of threshold regression models).

Consider first our empirical specification for the dynamic of the industry,

$$\Delta y_t - \overline{\Delta y_t} = \beta x_t + v_t \qquad (4)$$

[5] Additional details are available upon request.

where y_t represents the number of active firms in region at time t. Let x_t represent our first difference demeaned variable of time $\left[(2t+1) - \overline{(2t+1)}\right]$. In our case, the empirical specification does not include any stage-invariant covariates. The dynamics of the industry life-cycle are only a function of time, which is also our threshold variable. Therefore, we estimate the following threshold model:

$$\Delta y_t - \overline{\Delta y_t} = \sum_{j=1}^{n+1} x_t \beta_j I_j(\lambda_j, t) + \varepsilon_t \qquad (5)$$

Here, λ_j represents the threshold value in t, that is, the break point dates in the industry life-cycle. Estimation uses the *threshold* command in StataSE 15.1.

Insert Table 2 about here

Threshold Estimation Results

Table 2 presents three different threshold estimations using different specifications. The typical life cycle specification is 4 stages but we are not sure a priori that the region has experienced decline. Model 1 set the number of stages to 3 stages while Model 2 specifies 4 stages. Model 3 uses the Bayesian Information Criteria (BIC) to decide the optimal number of thresholds.

Models 1 and 3 provide identical estimation. According to the BIC, the optimal number of thresholds is two, which results in three threshold phase changes. This is what was imposed in Model 1. The results suggest that the Research Triangle's life science industry has experienced three different stages from 1980 to 2016. The initial phase, which exhibits a positive convex dynamic (*β=0.445),* began in 1980 and lasted until 1997. The next stage is estimated between 1998 and 2009 with a stronger convex dynamic (*β=0.899)*, indicating higher growth. Finally, we estimate that the industry entered into a third stage in 2010, marked by a significant change in the industry dynamics as the curve becomes more concave (*β=-0.065)*.

Model 2 imposes four different stages for the industry life-cycle. An important artifact is that we still detect the same time period for our three main stages: an initial phase (1980-1997), followed by higher growth (1998-2009), and then slower growth (2010-). By imposing another threshold, we detect the turning point of the second phase–the date when the dynamic becomes less convex. Model 2 highlights a strong dynamic during the first part of this stage (1998-2004) with a β estimated at 1.4767, whereas the second part (2005-2009) has a β estimated at 0.775, which is approximately half the former.[6] Overall these results are robust and confirm the existence of three ecosystem phases from 1980 to 2016.

Insert Figure 4 about here

Qualitative Mapping of Regional Life Cycle Phases

We examine these quantitative results with a qualitative mapping of events in the region. Over time, the Research Triangle region slowly nurtured an entrepreneurial ecosystem, thanks to mergers and layoffs from high-profile multinational firms (like GlaxoSmithKline), a more aggressive technology transfer stance from the region's research universities, and the development of a plethora of support institutions. The result is a steadily growing number of entrepreneurial firms and the presence of intermediary entrepreneurial support institutions. Notable events in the development of the Research Triangle region’s life science industry are chronicled in the timeline in Figure 4. Specifically, we examine events that preceded the discontinuities that occurred in 1997 and 2009. Within this complex system it is impossible to establish causality, however we are interested in events that coincide with moving the ecosystem from one phase to the next.

The three universities, University of North Carolina at Chapel Hill (UNC), Duke University (Duke), and North Carolina State University (NCSU) were important for anchoring the region and providing access to skilled labor and collaborations. IBM and the National Institute of Environmental Health Sciences (NIEHS) were early tenants in the Park, moving in 1965. Becton Dickinson and Wellcome were the first life science firms, becoming Park tenants in the early 1970s.

During the Phase 1, state support of biotechnology strengthened. During the early 1980s policymakers and civic leaders initiated a concerted effort to build the biotechnology industry in the region as they believed the region’s research universities could be leveraged for competitive advantage in knowledge-intensive industries. The universities had already demonstrated considerable success in bringing in federal research funding but in this time period they established technology transfer offices to streamline commercialization efforts. Duke and NCSU opened tech

[6] Using industry turnover as the dependent variable with sales data is confirmatory of the breaks identified with industry density presented here, but data problems limit their explanatory power. Therefore, whatever the dependent variable, it seems that using our empirical specification with threshold regression allow us to precisely determine the date of the life-cycle transition points. Results are available from the authors upon request. Data on sales was obtained from the National Establishment Time Series (NETS) for the years 1990-2014 (Walls & Associates 2013). We supplement NETS with more recent data from Lexis Nexis[6] and used Stata’s *mipolate* command to interpolate across missing years as this data was usually available for one year between 2014 and 2018 for our firms.

transfer offices in the mid 1980s, with UNC following later in the mid 1990s. The Council for Entrepreneurial Development (CED) and the NC Biotech Center were both founded in 1984. The NC Biotech Center is a state-funded industry development organization. CED was founded by the Raleigh Chamber of Commerce, along with several important stakeholders in the industry, to support high-tech entrepreneurship in the Triangle region. Both organizations are still active today. During the 1980s, a series of federal policies also helped strengthen researchers' ability to perform and commercialize life science research. This deepening sociopolitical legitimation of the new industry laid important groundwork for its continued development (Aldrich & Fiol 1994)

When Glaxo moved its headquarters to the Triangle in 1983 it was well positioned to take advantage of possible collaborations with the universities. As large firms moved to the Triangle, spin-outs from the university started to become more common. Quintiles, now the international firm IQVIA, was founded by two UNC professors in 1981. Sphinx Pharmaceuticals, a Duke spin-out, was the region's first initial public offering (IPO) in this industry in 1991, and the largest in state history at the time ($70 million). Intersouth Partners, the region's first VC firm, provided Sphinx's seed funding and original incubation space, and Sphinx founders received a $3 million grant that they used to start the company. Sphinx was ultimately bought by Eli Lilly & Company in 1994. After this acquisition, Eli Lilly established an RTP presence. Today, Intersouth Partners boasts over 30 companies in the region that can be traced to Sphinx's founders. This story highlights the deep connections between incumbents, universities, and spinouts in the Research Triangle region (Intersouth Partners 2019).

The early success of a few home-grown start-ups (including PPD, Quintiles, Sphinx, Embrex) brought national attention to the region. Furthermore, the nature of these early start-ups (Quintiles, PPD) and the attraction of large corporations (Glaxo, Fujifilm Diosynth) meant start-ups had flexibility to easily outsource activities to high-profile, neighboring contact research organizations and contract manufacturing organizations, while also exploiting networks within these organizations and universities. Several IPOs and large VC deals likely increased the amount of funding going to firms as the Triangle region achieved more notoriety in the life sciences.

These activities laid the foundation for the cluster to expand and move from Phase 1 to Phase 2. The 1990s saw a takeoff of spinout companies in the Research Triangle region. This trend of an increasing number of start-ups was enhanced by a series of spin-outs created from former Glaxo and Burroughs Wellcome employees after layoffs caused by the 1995 merger of the two companies left employees jobless, but with ideas for new firms. Several more local VC funds were founded during the 1990s as well, and the decade witnessed more IPOs and some larger VC deals.

UNC and NSCU established a joint biomedical engineering department in 2003, just a few years after NCSU created its Centennial Biomedical Campus with lab and office space for life science start-ups. Interestingly, the timing of entry into Phase 2 comports with an early prediction made by Aldrich and Zimmer (1986) that significant entrepreneurial activity would not occur in the Research Triangle region until the mid 1990s because of the lack of density in social networks and low start-up rates when considering the time it took for Silicon Valley and Route 128 in Boston to mature.

The beginning of Phase 3 begins in 2009, which corresponds with the financial crisis. While we might call this period "Maturity" because of the decrease density of of spin-outs, we actually cannot be sure. Most life cycle theories attribute the onset of the Maturity stage to a period of industry "shakeout" due to competition, saturation, or the like (Agarwal et al. 2002). With the onset of the region's third phase so closely matching an exogenous economic shock, it is likely that this break point which brought an apparent downturn only periodically stunted the development of the region, which may already be experiencing a renewal as new technological advancements are made that bring new market opportunities. Still, the results indicate a structural break from the prior period.

The number of start-ups continues to increase annually, and the ecosystem continues to be successful along other performance measures. During post-recession the region witnessed an influx of entrepreneurial support organizations including incubators and accelerators from outside the region. Interestingly these organizations have already experienced much turnover. IPOs are rare events, but local start-ups consistently go public and the number of IPOs continues to increase in this stage. A recent acquisition of Bamboo Therapeutics by Pfizer brought much attention. With a $150 million price mark, the deal had the potential to reach over $600 million depending on how the start-up technology developed. G1 Therapeutics completed an IPO in 2017 for $105 million, after receiving $1 million in loans from NC Biotech and over $95 million in venture capital. Other start-ups' stories demonstrate the embeddedness of the entrepreneurs and technologies in the region. Advanced Liquid Logic, which spun-out of Duke, was sold to Illumina in 2013 for $96 million. The founders then licensed the technology back from Illumina and started Baebies, a company that develops newborn screenings. It is important to note that the number of local VC firms supporting the life sciences has declined over the past decade, though sources indicate RTP start-ups are becoming more adept at acquiring non-local VC (personal interview, 2019).

Insert Table 3 about here

FUNDING SOURCES & EMERGENCE

While the number of firms funded and the amount provided by federal sources increases throughout the three stages, the number supported by private sources sees a dramatic increase from Stage 1 to Stage 2 (see Table 3). State funding is significantly lower than federal and private in terms of dollar amount but has seen more growth than the other two sources going from Stage 2 to Stage 3.

Dynamic Random Effects Probit Model with Unobserved Heterogeneity & Regime-Switching

We estimate a dynamic random effects probit model with unobserved heterogeneity to examine the relationships between funding sources across the entire panel and then implement a regime-switching analysis on the same model to see how these results change depending on the stage. We perform this analysis separately for each funding source (state, federal, and private). Table 3 demonstrates variation across funding sources for the three stages

The dynamic random effects probit model is appropriate for several reasons. First, our setting is dynamic where lagged values of funding from each source are needed to estimate the probability of funding from that source in the current time period. We are most interested in the probability of securing funding, given the prior distribution of sources. As such, we must account for state dependent processes. Second, we do not use the value of funding because we are more interested in the links between funding sources in the ecosystem and want to avoid a value-effect from funding caused by noise related to large or erratic values. Thus we have a binary outcome variable. For example, if a start-up received funding from the same source in every year, but the amount decreased we would see a negative effect even if the probability of receiving funding is high. Third, the relationships between state, federal, and private funding are nonrecursive. It is for this reason we cannot estimate for each type of funding simultaneously. Due to the nonrecursive and binary nature of the data, a structural equation model is inappropriate. We follow Grotti & Cuturi (2018) and Rabe-Hesketh & Skrondal (2013) in estimating a model of the following form:

$$y_{it}^{*} = \rho y_{it-1} + \gamma Z_{it} + c_i + u_{it} \qquad (6)$$

Here y_{it}^* is the probability of firm i receiving funding at time t. It is a function of funding received in the previous period, y_{it-1}, which accounts for state dependence, and covariates Z_{it}, which control for firm-level bias. c_i is the firm-specific unobserved effect, while u_{it} is an idiosyncratic error term.

The firm-specific unobserved effect accounts for heterogeneity between firms and is written as:

$$c_i = \alpha_0 + \alpha_1 y_0 + \alpha_2 \bar{X} + \alpha_3 X_0 + \alpha_4 \qquad (7)$$

While α_0 and α_4 (the firm-specific time-constant error) are purely random, y_0 represents the initial value of the dependent variable, while X_0 is a row matrix of the initial value of the time varying explanatory variables for all firms, $X_0 = \{X_{01}, X_{02}, \ldots, X_{0n}\}$. Here, this is the initial value of the other two sources of funding. For example, if y_{it}^* is the probability a firm received private funding in time t, X_0 accounts for the initial value of state and federal funding. Similarly, $\bar{X}$ is a row matrix of the mean value of the time-varying covariates (in the example, state and federal funding) for all firms, $\bar{X} = \{\bar{X}_1, \bar{X}_2, \ldots, \bar{X}_n\}$. Specifically, it is the within-firm average based on all time periods. c_i then accounts that the probability of receiving one type of funding is likely influenced by other funding sources in prior periods (Grotti & Cutuli 2018; Rabe-Hesketh & Skrondal 2013; Wooldridge 2005). The X are a subset of Z. All models are heteroskedastic robust.

The dynamic random effects probit model assesses state dependence in the probability of receiving funding but does not account for differences across life cycle stages. We estimate a regime-switching regression analysis, which is a generalization of the linear model that accounts for temporal breaks in the effects of the variables (Elhorst & Fréret 2009; Montmartin et al. 2018). We expect the influence on funding is not linear with time and therefore consider the break points we identified in the threshold analysis. The model allows us to estimate stage-specific coefficient values.

We estimate one dynamic random effects probit model with regime-switching for each funding source, including stage specific indicators and interactions that represent the transitions. For example, the model for private funding is as follows:

$$\begin{aligned} PRIV_{it} = {} & \alpha_1 + \beta_{11} PRIV_{it-1} + \Delta\beta_{12} PRIV_{it-1} + \Delta\beta_{13} PRIV_{it-1} + \beta_{21} State_{it-1} + \Delta\beta_{22} State_{it-1} \\ & + \Delta\beta_{23} State_{it-1} + \beta_{31} Federal_{it-1} + \Delta\beta_{32} Federal_{it-1} + \Delta\beta_{33} Federal_{it-1} + \Delta\alpha_2 \\ & + \Delta\alpha_3 + Z_{it} + c_i \qquad (8) \end{aligned}$$

Here, the β_{1i} represent the focal funding source and coefficients of key interest (private funding in this equation), with β_{2i} and β_{3i} representing lagged values of the other two funding sources. The β_{i1} represent coefficients for Stage 1, which we choose to be the base effect, while the $\Delta\beta_{i2}$ represent the change of the effect from stages 1 to 2 and the $\Delta\beta_{i3}$ represent the changing effect in stage 3 with respect to stage 1.[7] For the regime analysis, the c_i unobserved effect covariates include only state and federal funding. All models are heteroskedastic robust.

Insert Table 4 about here

Insert Table 5 about here

Insert Table 6 about here

Our estimation includes several firm and industry level covariates (Z_{it}). These are listed in Table 4 with the literature that included these control variables. We include firm-level controls for founding team size, founder human capital, sector, and establishment date, as well as the region-level industry density. Covariates describing founders' human capital are commonly used controls for start-up quality, since start-ups generally lack data on other metrics such as sales that would measure this. Summary statistics and correlations are provided in Tables 5 and 6.[8]

Insert Table 7 about here

Dynamic Random Effects Probit Estimation with Regime Switching Results

Results from the dynamic random effects probit estimation are provided in Table 7, while Tables 8, 9, and 10 present the dynamic random effects probit result with regime switching analysis. We present tables showing the total effects and their significance by stage. The full table of regime-switching estimation results can be found in the Appendix Table A1.

[7] We calculate the net effect by stage by adding the coefficient of the base effect and the coefficient of the associated change for stages 2 and 3. We calculate standard errors using the covariance matrix of the coefficients and calculate a t-statistic to discern statistical significance at the usual levels.

[8] For 31 firms it was impossible to determine values for some of these variables. Eight firms are missing all founder data. The other 23 firms had founders with some missing details of their work experience and/or educational background. For these firms we used either the minimum or average value to replace the missing values, whichever would cause any bias to be in the direction a null funding. In the case of the same prior industry experience variable, we inflated the count by how many founders there are in the founding team for firms for which only some founders were missing this variable.

Table 7 demonstrates that, even without considering the influence of life cycle stage, there are differences in the dynamic relationships between funding sources. Model 4 considers the influence of lagged indicators for whether a firm received private, state, and/or federal funding (time t-1) on the probability of receiving private funding in time t. We detect a positive influence of private funding (t-1) and a positive influence of state funding (t-1) on private funding in time t. We do not, however, find an influence of federal funding in time t-1 on private funding in time t. These findings indicate overall that private sources may use state funding as a signal. Furthermore, prior private funding is a predictor of future private funding. There is no influence of any type of funding in the prior time period (t-1) on state funding in the current period (time t) (Model 5). We argue this provides confirmation of what we know about state funding—that it is awarded at a very early stage, usually before other funding sources are available to firms, and that it is rare that state grants and loans are awarded to the same firm more than one time. Finally, in Model 6, considering the dynamic random effects probit model across the whole panel for the influence on federal funding in time t, we detect a positive effect of federal funding (t-1), a positive effect of state funding (t-1) and a positive effect of private funding (t-1). This means firms federal sources rely on signals from other funding sources and invest in firms likely that are nearing the end of seed-stage. Furthermore, federal funds are likely to go to firms that have already received some federal funding.[9]

Insert Table 8 about here

Insert Table 9 about here

Insert Table 10 about here

The stage based model results in Table 8 provide a deeper understanding of these relationships for private funding. We find that the positive effect of private funding in time t-1 on private funding in time t is only present during Stage 1 and disappears in later stages. Interestingly, the positive influence of state funding is present in Stages 1 and 3. By Stage 3, state funding sources are encouraging firms to go after private sources and using their own networks to help the firms

[9] While the federal SBIR/STTR programs grant funds in phases, with Phase II and Phase III follow-on on funds, this structuring is not sufficient to explain this finding as it is unlikely a firm will receive a Phase I grant in year t-1 and Phase II in year t. Firms are receiving different grants for different projects.

make connections and access new funding sources. The impact of federal funding is not strong. We detect no effect in Stage 1 and only a slightly negative effect during Stages 2 and 3. This finding could be driven by a few firms that rely on federal research grants to fund their work rather than trying to attract private funding—a practice which has earned the nickname "SBIR mills."

When considering North Carolina State funding in time t (Table 9), we find no influence of prior state funding or prior federal funding in year t-1, regardless of life cycle stage. This finding therefore most closely aligns with the results for the full panel. We do, however, see a positive influence of private funding in year t-1 in Stage 3. As the private funding mechanism has evolved over time we have begun to see more angel funding and more sources of private funding being directed to early stage firms, such as accelerators and competitions. It then makes sense why private seed funding might pre-date public seed funding and even act as a signal to state-level funding sources for more recent start-ups. We know from our own experiences and interviews in the region that state agencies which support biotech devote considerable attention to developing networks and relationships with local VC and angels.

If we consider federal funding in time t (Table 10), we see it is strongly influenced by all three sources in time t-1 during the first stage. While this influence drops for private funding in the second stage, it is maintained for state and federal funding. However, the influence of federal and state funding in time t-1 on federal funding in time t disappears in the third stage. This indicates that early in the emergence process federal funding may rely heavily on signals from other funding sources and be more likely to re-invest in firms which show promise. As the industry matures, however, federal funding sources may be more likely to be directed to firms developing more high-risk and untested technologies which private may not be interested in supporting and state does not have the bandwidth to support..

Overall these results demonstrate it is important to consider the wide variation in the relationships between funding sources, considering each source separately and considering the life cycle stage. Interestingly as well, we find across all regime models that the initial value of other funding does not well explain future funding, while the mean value is consistently statistically significant.

FUNDING SOURCES & FIRM SURVIVAL ACROSS THE ECOSYSTEM LIFE CYCLE

We develop a complementary loglog (cloglog) model including non-parametric frailty and a logarithmic duration dependence to model the hazard rate for survival of the Research Triangle region entrepreneurial life science firms. Our survival analysis begins in 1980 and ends in 2016 with an interval of one year for grouping. Therefore, we cannot consider that the ratio of the interval length to the typical spell length is low, as many entrepreneurial life science firms die in their first 5-10 years. Consequently, though survival occurs in continuous time our data are grouped and the observations on the transition process are summarized discretely rather than continuously. Thus we use econometric methods dealing with discrete survival time data and a complex dynamic for the hazard rate concerning entrepreneurial life science firms.

The cloglog model is best suited for our data (see Jenkins 2005). The discrete time hazard rate is modeled as:

$$h(t, X) = 1 - exp[-\exp(\beta' X + \gamma_t)] \qquad (9)$$

where X are the covariates influencing the hazard rate and γ_t summarize the pattern of duration dependence in the interval hazard. There are two main ways to model γ_t, either by not placing any restrictions on how the γ_t vary from interval to interval (in which case the model is a type of semi-parametric one) or by specifying a parametric functional form. The most common duration dependence specifications are the logarithm dependence $[\gamma_t = log(t)]$, polynomial dependence $\left[\gamma_t = z_1 t + z_2 t^2 + \cdots + z_p t^p\right]$, or assume that γ_t is piecewise constant, that is groups of years are assumed to have the same hazard rate but the hazard differs between these groups. In order to investigate this point, we take the hazard rate value obtained from the life-table method and test which of these three duration dependence specifications is able to explain the hazard rate. Efficiency criteria indicate the polynomial dependence is most useful to model the duration dependence, followed by logarithm dependence and the piecewise constant dependence.

We include the same covariates used in the prior analysis. Another important consideration is the potential presence of unobserved heterogeneity in the hazard rate. We may face some problems with omitted variables. Indeed, we do not have, for instance, employment data that would consider the size of the entrepreneurial firm. And as shown by Bruderl and Schussler (1990), Ortiz-Villajos and Sotoca (2018), and others, size matters for the survival of entrepreneurial firms. Thus, we need to take into account the presence of unobserved heterogeneity, or “frailty”, as it is called in the literature.

We thus now consider the following generalized cloglog model:

$$h(t, X|u) = 1 - exp[-\exp(\beta' X + \gamma_t + u)] \qquad (10)$$

where u represents the unobserved individual effects. There are three main ways to model these unobservable variables: using a normal distribution $[u \sim \mathcal{N}(0, \sigma^2)]$, a gamma distribution $[u \sim \Gamma(1, \sigma^2)]$ or a non-parametric approach which fits an arbitrary distribution using a set of parameters. These parameters comprise a set of mass points and the probabilities of a person being located at each mass point. The graph showing the hazard rate is not helpful to discriminate between these three possibilities.[10] Consequently, we choose the best specification for frailty by comparing the relative performance of each estimation.

Insert Table 11 about here

Discrete Event History Analysis Results

Our first survival estimation results can be found in Table 11. Information criteria from estimations comparing the normal distribution, non-parametric approach, and gamma distribution indicate the non-parametric approach is preferred. We present results from the non-parametric estimation only. For comparison, results from the Gaussian and gamma estimations can be found in Appendix Tables A2 and A3, respectively. The robustness of this model is confirmed by the similar results found when modeling heterogeneity with Gaussian and gamma distributions. Table 11 presents four models, each with a different functional form of the main dependent variable. Model 16 displays the results using the logged cumulative dollar amount of funding a firm receives separately from state, federal, and private sources. Model 17 estimates instead the logged cumulative number of investments a firm receives from each source separately. Model 18 again uses the logged cumulative dollar amount invested and adds a squared term for each funding source. Model 19 presents the preferred specification, which uses the logged cumulative dollar amount, with a nonlinear effect of private funding.

Overall, we find that firms that received federal funding experience less chance of failure, and this effect is nonlinear with the cumulative amount received. Importantly, the effect of federal funding is statistically significant across all specifications. The value of the coefficient for federal funding in Model 19 indicates that if federal funding is increased by 1%, the probability of failure is reduced by 0.034%, which provides support for the argument that federal funding plays a role in industry emergence. This funding helps firms extend research lines by hiring staff or outsourcing. Of course these grants depend on the quality and promise of the research, but by modeling the unobserved heterogeneity in our discrete time models we alleviate concerns of cross-firm heterogeneity.

[10] Additional details are available upon request.

We also find that firms that received private funding experience less chance of failure, and the effect is non-linear with the cumulative amount received. In increase of 1% in private funding reduces the risk of failure by 0.044% which is slightly larger than the influence of federal funding. This result confirms prior literature on the importance of VC and other private funding sources to emerging ecosystems. Private funding generally comes in larger amounts than state and federal, though as mentioned previously such trends have changed, and focuses on building the firm. Private therefore should help firms survive and have a larger magnitude influence than federal funding. Private funding from VC and angels generally comes with mentorship and accesss to the funders networks of resources which further help firms develop.

Finally, however, we find that firms that received North Carolina state funding do not experience less of a chance of failure, as results are not significant, controlling for the amount of federal and private funding. This finding does not suggests state funding is inconsequential. Instead, state funding is likely to impact firms in many ways, not just on their ultimate survival. The smaller dollar amount of state funding may be too small to have an ultimate impact on survival. As show in previous results, state funding does influence the probability of later private and federal funding, which do show a positive relationship to firm survival.

Concerning controls, a higher level of competition in the industry and region, as measured by industry density, has a significant effect on the risk of failure, decreasing the risk of failure. In contrast, being a newer firm with a later establishment actually increases the probability of failure. The fact that a firm has an entrepreneur that has already worked in the same industry decreases the risk of failure. Also, firms with more co-founders have a decreased probability of failure. Finally, firms who have more serial entrepreneurs have an increased probability of failure. This finding is at odds with theory about the benefits of prior entrepreneurial experience but could suggest that these entrepreneurs are better at knowing how to fail fast.

Insert Table 12 about here

We examined further variations on the functional forms of the state, federal, and private funding variables. These results are presented in Table 12 (Gaussian and gamma specifications in Appendix Table A4). Here we include all possible varieties of funding that a firm might receive as a series of indicator variables, with the reference category being firms that received no support. These results confirm the previous ones and improve our understanding of the effect of funding an emerging ecosystem. Receiving only private funding or any combination of sources decreases the probability of failure. Receiving only state funding or only federal funding has no effect, while receiving state and federal funding, even without private funding, does decrease the probability of failure. However, an important finding from these models is that firms that received both private and federal funding and firms that received all three sources of funding have the lowest magnitude chances of failure.

When examining the controls, we again see that being a newer firm in the ecosystem increases the probability of failure. Results also indicate that firms whose founder(s) have some prior industry work experience have a lower chance of failure, as well as firms with team founded firms. Again we see that firms who have more serial entrepreneurs have an increased probability of failure.

Insert Table 13 about here

Discrete Event History Analysis with Regime-Switching

We also implement a regime-switching regression analysis to investigate the stage-specific influence of each funding source on the survival prospects of firms. The results are provided in Table 13. We apply the same regime method here as for the prior dynamic probit model and calculate stage specific coefficients the same way. The full estimation can be found in Appendix Table A5.

Findings indicate there exist important differences in the influence of funding on firms' probability of failure across ecosystem life cycle phases. This is an important finding as it indicates looking at the industry over the entire time period overlooks important differences across regimes. In terms of private funding the regime findings accord with our previous finding that private funding is not significant overall in decreasing the probability of firm failure without a square term (see Table 11 for reference), because this effect is changing over time due to industry dynamics. In Stage 1, private funding is not helping firms survive. This could be due to the fact that these firms were entering a new industry and may have been very high risk. Furthermore, the private funders may not have yet developed expertise in identifying more promising technologies and start-ups as dominant forms in the new industry are still undiscovered. In Stage 2, private funding becomes associated with a decreased probability of firm failure, but this is not statistically significant. In the third stage (Model 23), however, we see a decreased probability of failure and this is stronger in magnitude and statistically significant. In contrast, federal funding is associated with a decreased probability of firm failure across all stages. The statistical strength of this effect decreases in the third stage, but the magnitude increases. This means federal funding decreases the probability of firm failure in Stage 3 with a higher probability than in Stages 1 and 2. When considering state funding we do not see an influence until Stage 3, when the funding begins to reduce the probability of firm failure.

These results demonstrate that all three funding sources become more efficient in their funding allocations over time so that by the third phase these sources are all associated with a decrease in firm failure above prior stages. Ultimately, this method improves our understanding of how the funding that is available to firms in an ecosystem is related to their survival, and how this influence differs depending on industry dynamics which define the ecosystem life cycle.

DISCUSSION & CONCLUSION

Surprisingly little research examines how financing that supports entrepreneurial businesses indeed promotes regional growth and influences the emergence of new industries. Studies tend to examine one program in isolation, either venture capital or specific government programs, with a focus on the degree to which the receipt of that particular funding affects firm performance. Yet the combined impact on a regional economy—the sum of effects on individual firms—remains unexplored. There is general consensus that the social rate of return to public R&D investment is high (Toole 2012), which is used as a justification for government funding. Another related stream of literature considers the degree to which public funding affects private funding or the extent of crowding-out versus crowding-in. This topic has been debated since the 1960s (see Zuniga-Vicente et al. 2014, for a survey of this vast empirical literature). The empirical evidence suggests that government R&D subsidies lead to an additionality effect and induce private investment at the firm level. For example, Howell (2017) finds that a government Small Business Innovation Research (SBIR) award doubles the likelihood of the subsidized firm to subsequently receive venture capital. The literature is relatively silent on the relationship of government financing to other sources of financing at the aggregate regional level.

We find emergence and the ecosystems view of the region to be a useful extension of the theory for explaining how regions, through myriad small efforts of firms and ecosystem stakeholders, develop capabilities through public and private financial resources that help them grow and develop new industries. In order to empirically explicate the region's development, we employ several new techniques which allow us to assess varying temporal relationships within the region over a long-time horizon.

First, through threshold analysis we find that the Research Triangle region's life science cluster has experienced two distinct ecosystem life cycle transition points corresponding to three phases. The first phase, lasting until 1997 coincides with a period of capability building dominated by state and federal sources. Then, the region enters a period of dramatic growth characterized by a higher number of start-ups entry and the availability of greater amounts of private finance as the region gained prominence in the US. This period of growth began to slow with the start of the financial crisis as shown by the industry dynamic beginning to exhibit a concave dynamic with respect to time. Time will tell whether this is actually a downturn for the region or rather the result of an exogenous economic shock if the start-up entry rates regain momentum. Our contribution is not mapping the life cycle stages onto an ecosystem, rather we are arguing that an ecosystem goes through different phases and funding has a different influence over the phases.

Second, the dynamic random effects probit model depicts the relationships between funding sources at the firm level over time. We find prior state and private funding (time t-1) influences private funding in time t, while no prior sources influence state funding in time t. However, we see a relatively strong influence of prior funding from all three sources on federal funding in time t. Combined with regime analysis, we are able to show that these relationships actually differ across different life cycle stages of the ecosystem. In the initial phase of emergence, private funding is strongly influenced by prior private and state funding, while federal funding is strongly influenced by prior funding from all three sources. Moving to a phase of higher growth we see a consistent influence of prior federal and state funding on federal spending, but we lose the influence of private and state funding on state spending. The trends change again during the third phase, when state funding actually influences private spending, a finding that would be overlooked with an analysis of the full panel alone. We also find the converse, that prior private funding influences state spending.

Finally, discrete event history analysis provides evidence that the mix of multi-level public and private funding of these firm matters for firm survival, and therefore ecosystem emergence. Necessarily, firms in an emerging industry much be able to reach a point of viability in order for an ecosystem to develop around them. Notably our results show the importance of having a strong base of federal funding. Private funding, which provides substantially more funds to Research Triangle firms in terms of dollar amount than both public sources combined, also decreases the chances of firm failure. Contrary to expectations, we do not find an effect for state funding, which typically provides the least funding in terms of dollar amount. Still, our results show the interrelationship between funding sources as firms that receive funding from a variety of sources experience the greatest magnitude decrease in probability of firm failure. Furthermore, findings from the application of the regime model to the survival analysis have direct policy implications and improve the overall survival model. We find an increased efficiency of state funding and private funding over time, and a consistent influence of federal funding.

Our results shed light on the process by which new industries and ecosystems develop and emerge in a regional context. They have direct implications for policymakers and for firms. The results suggest the firms may benefit from strategically considering the sources of funding they seek depending on the phase of the ecosystem. Furthermore, policymakers interested in growing their economies by the development of a new industry ecosystem should not merely copy the current actions of already successful regions, as they would essentially be following the old idiom of comparing apples and oranges. Our results show that the industry dynamics of the Research Triangle ecosystem changed in important ways over the ecosystem life cycle. The private, state, and federal funding sources exhibited differing relationships to each other depending on the stage, and firm survival was more influenced by different sources also depending on the stage. Consequently, the paper also makes a methodological contribution to the literature by using innovative methods to show how results from a full panel mask these dynamics.

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APPENDIX

Table A1: Dynamic random effects probit model with regime switching

	Private Funding in Time t (Model A1)	**State Funding in Time t** (Model A2)	**Federal Funding in Time t** (Model A3)
Private funding$_{(t-1)}$ (ΔStage 1)	0.798***	-0.085	0.319**
	(0.156)	(0.190)	(0.147)
Private funding$_{(t-1)}$ (ΔStage 2)	-0.708***	-0.176	-0.181
	(0.200)	(0.207)	(0.194)
Private funding$_{(t-1)}$ (ΔStage 3)	-0.699**	0.622**	-0.368
	(0.274)	(0.265)	(0.357)
State funding$_{(t-1)}$ (ΔStage 1)	0.458***	-0.070	0.349**
	(0.172)	(0.383)	(0.166)
State funding$_{(t-1)}$ (ΔStage 2)	-0.323	0.072	0.169
	(0.201)	(0.426)	(0.179)
State funding$_{(t-1)}$ (ΔStage 3)	0.722**	-0.083	-0.030
	(0.305)	(0.442)	(0.350)
Federal funding$_{(t-1)}$ (ΔStage 1)	-0.091	0.058	0.743***
	(0.138)	(0.155)	(0.210)
Federal funding$_{(t-1)}$ (ΔStage 1)	-0.283	-0.050	0.040
	(0.188)	(0.180)	(0.254)
Federal funding$_{(t-1)}$ (ΔStage 1)	-0.847	0.000	-0.719**
	(0.524)	(0.321)	(0.349)
Sector	0.081***	-0.031	0.022
	(0.029)	(0.026)	(0.029)
Total Founders	0.200*	-0.112	-0.384***
	(0.103)	(0.090)	(0.110)
Max Founder Age	0.007	-0.001	-0.001
	(0.005)	(0.005)	(0.006)
Cumulative Education	-0.006	0.020**	0.068***
	(0.010)	(0.010)	(0.010)
Establishment Date	0.080***	0.124***	0.004
	(0.018)	(0.021)	(0.016)
Industry Density	-0.002***	-0.005***	-0.002***
	(0.000)	(0.001)	(0.000)
Same Prior Industry Experience	-0.110	-0.094*	-0.129**
	(0.072)	(0.057)	(0.064)
Prior Entrepreneurial Experience	0.053	-0.019	0.072
	(0.070)	(0.061)	(0.067)
ΔStage 2	-0.206	0.089	0.248
	(0.217)	(0.169)	(0.231)
ΔStage 3	-0.518	0.376	0.294
	(0.341)	(0.292)	(0.352)
Private funding initial	1.895***	-0.286	-0.388
	(0.149)	(0.228)	(0.244)
Federal funding initial	0.133	-0.143	1.430***

	(0.350)	(0.331)	(0.158)
State funding initial	-0.196	1.259***	-0.367
	(0.268)	(0.132)	(0.239)
Private funding mean		0.633**	0.668*
		(0.319)	(0.384)
Federal funding mean	1.386***	1.473***	
	(0.426)	(0.325)	
State funding mean	1.117*		2.092***
	(0.594)		(0.581)
Constant (ΔStage 1)	-162.446***	-248.766***	-10.076
	(36.362)	(41.206)	(32.532)
Observations	8,057	8,057	8,057
LogL	-1145.898	-565.169	-1205.356

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01. LogL is the log of the likelihood function.

Table A2: Results of Gaussian frailty duration models for firm survival

	Model A4	**Model A5**	**Model A6**	**Model A7**
Log (Cumulative Private Funding)	-0.003		-0.026***	-0.027***
Log (Cumulative Federal Funding)	-0.013**		-0.015	-0.014**
Log (Cumulative State Funding)	0.004		0.027	0.010
Total Founders	-0.274*	-0.426	-0.264	-0.264
Max Founder Age	0.012	0.019	0.012	0.011
Cumulative Education	0.008	0.008	0.006	0.007
Establishment Date	0.165***	0.251***	0.171***	0.171***
Industry Density	-0.004***	-0.005***	-0.004***	-0.004***
Same Prior Industry Experience	-0.179	-0.388*	-0.177	-0.177
Prior Entrepreneurial Experience	0.143	0.320	0.153	0.153
Log (Cumulative Number of Private Fundings)		-0.110		
Log (Cumulative Number of Federal Fundings)		-0.313**		
Log (Cumulative Number of State Fundings)		0.015		
Square of Log (Cumulative Private Funding)			0.000***	0.000***
Square of Log (Cumulative Federal Funding)			0.000	
Square of Log (Cumulative State Funding)			-0.001	
Constant	-334.906***	-511.683***	-346.127***	-345.950***
lnsig2u	-1.049***	2.145***	-1.073***	-1.072***
Logarithmic Duration Dependence	Yes	Yes	Yes	Yes
Observations	8,881	8,881	8,881	8,881
LogL	-910.743	-902.223	-905.920	-906.128
AIC	1847.487	1830.446	1843.839	1840.256
BIC	1939.678	1922.638	1957.306	1939.539

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01. LogL is the log of the likelihood function. AIC is the Akaike Information criteria, while BIC is the Bayesian Information Criteria.

Table A3: Results of gamma frailty duration models for firm survival

	Model A8	ModelA9	Model A10	Model A11
Log (Cumulative Private Funding)	-0.017		-0.043**	-0.036***
Log (Cumulative Federal Funding)	-0.043**		-0.029	-0.018**
Log (Cumulative State Funding)	-0.011		-0.002	0.019
Total Founders	-0.252	-0.251	-0.167	-0.254
Max Founder Age	0.001	0.001	0.004	0.012
Cumulative Education	-0.018	-0.018	-0.017	0.005
Establishment Date	0.183**	0.180**	-0.167***	0.168***
Industry Density	0.000	0.000	-0.001	-0.004***
Same Prior Industry Experience	-0.544	-0.546*	-0.427	-0.215
Prior Entrepreneurial Experience	-0.447	0.445	0.408	0.204
Log (Cumulative Number of Private Fundings)		-0.242		
Log (Cumulative Number of Federal Fundings)		-0.533**		
Log (Cumulative Number of State Fundings)		-0.109		
Square of Log (Cumulative Private Funding)			0.000	0.000***
Square of Log (Cumulative Federal Funding)			-0.000	
Square of Log (Cumulative State Funding)			-0.000	
Constant	-372.896**	-366.507**	-341.076***	-341.068
ln_varg	2.834***	2.830***	2.461***	0.992***
Logarithmic Duration Dependence	Yes	Yes	Yes	Yes
Observations	8,881	8,881	8,881	8,881
LogL	-896.322	-896.794	-894.796	-904.444
AIC	1818.645	1819.588	1821.592	1834.888
BIC	1910.836	1911.779	1935.058	1927.079

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01. LogL is the log of the likelihood function. AIC is the Akaike Information criteria, while BIC is the Bayesian Information Criteria.

Table A4: Detailed funding: Gaussian and gamma frailty duration models for firm survival

	Model A12: Gaussian	**Model A13: gamma**
Received State Funding Only	0.121	0.717
Received Federal Funding Only	-0.862*	-1.064
Received Private Funding Only	-1.727***	-2.188***
Received State & Federal Funding	-1.616**	-3.126**
Received State & Private Funding	-1.078	-2.477**
Received Federal & Private Funding	-4.540**	-7.151***
Received State, Federal, & Private Funding	-0.995	-2.045*
Reference Group: Received No Funding		
Total Founders	-0.333	-0.256
Max Founder Age	0.018	0.003
Cumulative Education	0.013	-0.005
Establishment Date	0.239***	0.181***
Industry Density	-0.005***	-0.001
Same Prior Industry Experience	-0.389**	-0.537
Prior Entrepreneurial Experience	0.387*	0.667**

Constant	-486.923***	-369.915***
lnsig2u	1.939***	
ln_varg		2.737***
Logarithmic Duration Dependence	Yes	Yes
Observations	8,881	8,881
LogL	-890.902	-885.777
AIC	1815.803	1805.553
BIC	1936.362	1926.112

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01. LogL is the log of the likelihood function. AIC is the Akaike Information criteria, while BIC is the Bayesian Information Criteria.

Table A5: Discrete Event History Analysis with Regime Model Estimation Output

	Model A14:
Log (Cumulative Private Funding) (ΔStage 1)	0.026*** (0.007)
Log (Cumulative Federal Funding) (ΔStage 1)	-0.041*** (0.013)
Log (Cumulative State Funding) (ΔStage 1)	0.034 (0.031)
ΔStage 2	1.631*** (0.476)
ΔStage 3	3.909*** (0.744)
Log (Cumulative Private Funding) (ΔStage 2)	-0.041*** (0.012)
Log (Cumulative Private Funding) (ΔStage 3)	-0.108*** (0.036)
Log (Cumulative Federal Funding) (ΔStage 2)	-0.020 (0.022)
Log (Cumulative Federal Funding) (ΔStage 3)	-0.097 (0.063)
Log (Cumulative State Funding) (ΔStage 2)	-0.012 (0.041)
Log (Cumulative State Funding) (ΔStage 3)	-0.121** (0.054)
Total Founders	-0.756*** (0.221)
Max Founder Age	-0.003 (0.013)
Cumulative Education	0.030 (0.021)
Establishment Date	0.107** (0.043)
Industry Density	-0.005*** (0.001)
Same Prior Industry Experience	-0.402**

	(0.161)
Prior Entrepreneurial Experience	0.555***
	(0.169)
Log(t)	3.259***
	(0.373)
Constant (ΔStage 1)	-223.442**
	(85.028)
m2	4.744***
	(0.348)
logitp2	-1.413***
	(0.130)
Observations	8,881
LogL	-873.289
AIC	1790.578
BIC	1946.595

Notes: * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$. LogL is the log of the likelihood function. AIC is the Akaike Information criteria, while BIC is the Bayesian Information Criteria.

TABLES & FIGURES

Table 1: Sector Classifications

Sector	Definition	No. Firms
Dedicated Biotechnology / Biomaterials	Basic biomaterials research, including agricultural biotech	124
Human Therapeutics	Treatment of disease; drug development; clinical trials; includes some veterinary drug development	357
Services	Specialized service providers for the life sciences, including staffing and management firms, which are not involved in scientific or technological development	109
Health IT	Health and life science related software and information technologies; health informatics	87
Tools / Diagnostics	Biotechnology tools and diagnostics tests; use biomarkers	104
Medical Devices	Instruments and machines for medical purposes	152

Table 2. Threshold regression

	3 Stage Specification (Model 1)	**4 Stage Specification** (Model 2)	**No Stage Specification** (Model 3)
Stage 1	0.445***	0.445***	0.445***
Stage 2	0.899***	1.467***	0.899***
Stage 3	-0.065	0.775***	-0.065
Stage 4		-0.065	
Break Dates	1997 & 2009	1997, 2004, & 2009	1997 & 2009

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01.

Table 3. Firms funded and amount of funding by Stage and Source

	Number of Firms Funded		
	Stage 1: 1980-1997	***Stage 2: 1998-2009***	***Stage 3: 2010-***
Private	24	106	115
Federal	31	72	96
State	20	108	68
	Total $ Amount to Firms		
Private	$346M	$2.54B	$2B
Federal	$52.90M	$421M	$413M
State	$3.78M	$13.70M	$18.40M
	Average $ Amount to Firms		
Private	$14.42M	$23.96M	$17.39M
Federal	$1.71M	$3.90M	$4.30M
State	$0.19M	$0.19M	$0.27M

Table 4. Description of Covariates

Covariates	**Measurement**	**Prior literature**
Total Founders	Number of founders of firm; proxy for early size of firm as employment unavailable	Hyytinen, Pajarinen, & Rouvinen (2015); Wojan, Crown, & Rupasingha (2018)
Max Founder Age	Maximum age of any founder at time of founding	Boden & Nuccie (2000); Ortiz-Villajos & Sotoca (2018)
Founder Cumulative College	Cumulative years of college among all founders	Boden & Nuccie (2000); Dencker, Gruber, & Shah (2009); Ortiz-Villajos & Sotoca (2018)
Establishment Date	Firm establishment year	Kalleberg & Leicht (1991); Wojan, Crown, & Rupasingha (2018); Wooley (2018)
Industry Density	Number of active, entrepreneurial life science firms in the Research Triangle region by year, as measure of competition	Hyytinen, Pajarinen, & Rouvinen (2015); Wooley (2018)
Founder Same Prior Industry Experience	Count of founders of firm with prior work experience in life science industry	Delmar & Shane 2004; Dencker, Gruber, & Shah (2009); Hyytinen, Pajarinen, & Rouvinen (2015); Ortiz-Villajos & Sotoca (2018)
Prior Entrepreneurial Experience	Count of founders of firm with prior experience as an entrepreneur	Delmar & Shane (2004); Hyytinen, Pajarinen, & Rouvinen (2015)
Sector	Categorical for all sectors except services as described in Table 1	Bruderl & Schussler (1990); Wooley (2018)

Table 5. Summary Statistics, all firms

	All Firms			
	Mean	Std.Dev.	Min	Max
Duration (years)	8.61	6.54	1	37
Log (Cumulative Private Funding)	4.11	13.65	0	159.5
Log (Cumulative National Funding)	6.91	22.70	0	364.4
Log (Cumulative State Funding)	2.24	6.47	0	66.41
Total Founders	1.83	0.99	1	10
Max Founder Age	46.91	10.35	19	74
Cumulative College	13.26	9.68	0	89
Establishment Date	1999.53	8.08	1980	2016
Industry Density	504.41	199.18	11	711
Same Industry Experience	0.92	0.90	0	9
Entrepreneurial Experience	0.54	0.81	0	4
Firm-Year Observations	10,545			

Table 6. Correlations between covariates

	Total Founders	Max Founder Age	Cum. College	Estab. Date	Industry Density	Same Industry Experience	Entrepren-eurial Experience
Total Founders	1.000						
Max Founder Age	0.304	1.000					
Cumulative College	0.852	0.323	1.000				
Establishment Date	0.106	0.254	0.158	1.000			
Industry Density	0.080	0.151	0.109	0.632	1.000		
Same Industry Experience	0.518	0.297	0.447	0.147	0.106	1.000	
Entrepreneurial Experience	0.460	0.300	0.411	0.208	0.136	0.526	1.000

Table 7. Dynamic random effects probit with unobserved heterogeneity estimation results

	Private Funding in Time t (Model 4)	**State Funding in Time t** (Model 5)	**Federal Funding in Time t** (Model 6)
Private funding$_{(t-1)}$	0.291***	-0.111	0.328**
	(0.108)	(0.192)	(0.144)
State funding$_{(t-1)}$	0.411**	-0.030	0.334**
	(0.174)	(0.159)	(0.164)
Federal funding$_{(t-1)}$	-0.084	0.041	0.708***
	(0.134)	(0.156)	(0.115)
Sector	0.081***	-0.035	0.022
	(0.028)	(0.025)	(0.029)
Total Founders	0.176*	-0.103	-0.390***
	(0.103)	(0.089)	(0.110)
Max Founder Age	0.008	-0.001	-0.000
	(0.005)	(0.005)	(0.005)
Cumulative Education	0.002	-0.019*	0.068***
	(0.010)	(0.010)	(0.010)
Establishment Date	0.081***	0.123***	0.005
	(0.018)	(0.021)	(0.016)
Industry Density	-0.002***	-0.005***	-0.002***
	(0.000)	(0.006)	(0.000)
Same Prior Industry Experience	-0.123*	-0.088	-0.136**
	(0.073)	(0.057)	(0.064)
Prior Entrepreneurial Experience	0.054	-0.020	0.069
	(0.068)	(0.060)	(0.067)
Stage 2 constant	-0.328	0.082	0.246
	(0.204)	(0.162)	(0.232)
Stage 3 constant	-0.605*	0.480*	0.152
	(0.315)	(0.285)	(0.350)
Private funding initial	1.855***	-0.316	-0.349
	(0.145)	(0.226)	(0.236)
Federal funding initial	0.156	-0.119	1.396***
	(0.328)	(0.352)	(0.149)
State funding initial	-0.259	1.260***	-0.381
	(0.264)	(0.132)	(0.237)
Private funding initial		0.833***	0.486
		(0.289)	(0.329)
Federal funding mean	0.933**	1.399***	
	(0.407)	(0.290)	
State funding mean	1.391***		2.055***
	(0.507)		(0.528)
Constant	-165.104***	-246.499***	-12.361
	(35.104)	(41.095)	(32.353)
Observations	8,057	8,057	8,057
LogL	-1161.413	-569.192	-1210.406

Notes: * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$. LogL is the log of the likelihood function.

Table 8. Summary of dynamic random effects probit models with regime analysis for private funding

Private funding in time t	**Stage 1** (Model 7)	**Stage 2** (Model 8)	**Stage 3** (Model 9)
Private funding (t-1)	0.798***	0.081	0.099
State funding (t-1)	0.458***	0.135	1.180***
Federal funding (t-1)	-0.091	-0.374*	-0.938*
Covariates	Yes	Yes	Yes
Observations	8,057	8,057	8,057

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01.

Table 9. Summary analysis of dynamic random effects probit models with analysis for state funding

State funding in time t	**Stage 1** (Model 10)	**Stage 2** (Model 11)	**Stage 3** (Model 12)
State funding (t-1)	-0.070	0.002	-0.153
Private funding (t-1)	-0.085	-0.261	0.537***
Federal funding (t-1)	0.058	0.008	0.058
Covariates	Yes	Yes	Yes
Observations	8,057	8,057	8,057

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01.

Table 10. Summary analysis of dynamic random effects probit models with regime analysis for federal funding

Federal funding in time t	**Stage 1** (Model 13)	**Stage 2** (Model 14)	**Stage 3** (Model 15)
Federal funding (t-1)	0.743***	0.783***	0.024
Private funding (t-1)	0.319**	0.138	-0.049
State funding (t-1)	0.349**	0.518**	0.319
Covariates	Yes	Yes	Yes
Observations	8,057	8,057	8,057

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01.

Table 11. Non-parametric duration models for business survival

Non-parametric heterogeneity	Model 16	Model 17	Model 18	Model 19 (preferred)
Log (Cum. Private Funding)	-0.006		-0.045***	-0.044***
	(0.007)		(0.014)	(0.013)
Log (Cum. Federal Funding)	-0.028**		-0.040***	-0.034***
	(0.011)		(0.015)	(0.011)
Log (Cum. State Funding)	-0.017		0.017	-0.008
	(0.023)		(0.046)	(0.021)
Total Founders	-0.770***	-0.879***	-0.759***	-0.760***
	(0.271)	(0.297)	(0.255)	(0.255)
Max Founder Age	0.002	0.024	0.000	0.003
	(0.016)	(0.016)	(0.014)	(0.013)
Cumulative Education	0.033	0.050*	0.029	0.030
	(0.022)	(0.027)	(0.022)	(0.023)
Establishment Date	0.160***	0.161***	0.215***	0.213***
	(0.056)	(0.000)	(0.044)	(0.042)
Industry Density	-0.002	-0.002***	-0.004**	-0.004**
	(0.002)	(0.001)	(0.002)	(0.002)
Same Prior Industry Experience	-0.353*	-0.417**	-0.289*	-0.297*
	(0.181)	(0.166)	(0.164)	(0.164)
Prior Entrepreneurial Experience	0.362*	0.273	0.277	2.909***
	(0.186)	(0.172)	(0.175)	(0.171)
Log (Cum. Number of Private Fundings)		-0.126		
		(0.094)		
Log (Cum. Number of Federal Fundings)		-0.318**		
		(0.124)		
Log (Cum. Number of State Fundings)		-0.355		
		(0.256)		
Square of Log (Cum. Private Funding)			0.000***	0.000***
			(0.000)	(0.000)
Square of Log (Cum. Federal Funding)			0.000	
			(0.000)	
Square of Log (Cum. State Funding)			-0.000	
			(0.002)	
Constant	-328.463***	-330.409	-438.385***	-434.837***
	(112.470)	(.)	(88.494)	(84.480)
m2	4.548***	4.688***	4.683***	4.666***
	(0.444)	(0.381)	(0.368)	(0.359)
logitp2	-1.585***	-1.601***	-1.591***	-1.596***
	(0.146)	(0.133)	(0.135)	(0.135)
Logarithmic Duration Dependence	Yes	Yes	Yes	Yes
Observations	8,881	8,881	8,881	8,881
LogL	-896.343	-898.025	-889.722	-890.028
AIC	1820.686	1822.049	1813.445	1810.056
BIC	1919.969	1914.241	1934.003	1916.431

Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01. LogL is the log of the likelihood function. AIC is the Akaike Information criteria, while BIC is the Bayesian Information Criteria.

Table 12. Duration models for business survival by funding source(s)

Non-parametric heterogeneity	**Model 20**
Received State Funding Only	0.191
	(0.471)
Received Federal Funding Only	-0.929
	(0.623)
Received Private Funding Only	-1.319**
	(0.537)
Received State & Federal Funding	-2.222**
	(1.081)
Received State & Private Funding	-1.638**
	(0.638)
Received Federal & Private Funding	-4.756***
	(1.132)
Received State, Federal, & Private Funding	-1.915***
	(0.580)
Reference Group: Received No Funding	
Total Founders	-0.730***
	(0.278)
Max Founder Age	-0.005
	(0.015)
Cumulative Education	0.041
	(0.026)
Establishment Date	0.165***
	(0.062)
Industry Density	-0.003
	(0.002)
Same Prior Industry Experience	-0.310*
	(0.183)
Prior Entrepreneurial Experience	0.408**
	(0.199)
Constant	-336.727***
	(123.491)
m2	4.554***
	(0.371)
logitp2	-1.445***
	(0.170)
Logarithmic Duration Dependence	Yes
Observations	8,881
LogL	-884.927
AIC	1805.854
BIC	1933.504

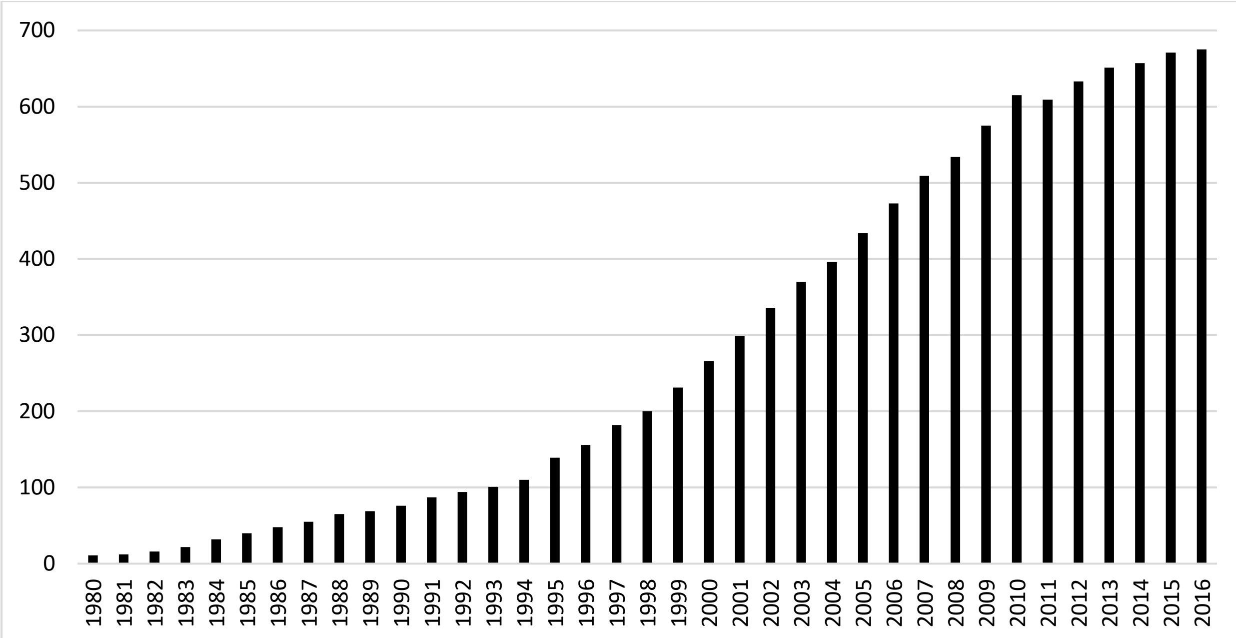
Notes: * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01. LogL is the log of the likelihood function. AIC is the Akaike Information criteria, while BIC is the Bayesian Information Criteria.

Table 13. Summary analysis of discrete event history models with regime analysis

	Stage 1 (Model 21)	**Stage 2** (Model 22)	**Stage 3** (Model 23)
Log (Cum. $ Private)	0.026***	-0.015	-0.082***
Log (Cum. $ Federal)	-0.041***	-0.061***	-0.138**
Log (Cum. $ State)	0.034	0.022	-0.087*
Logarithmic Duration Dependence	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
Observations	8,881	8,881	8,881

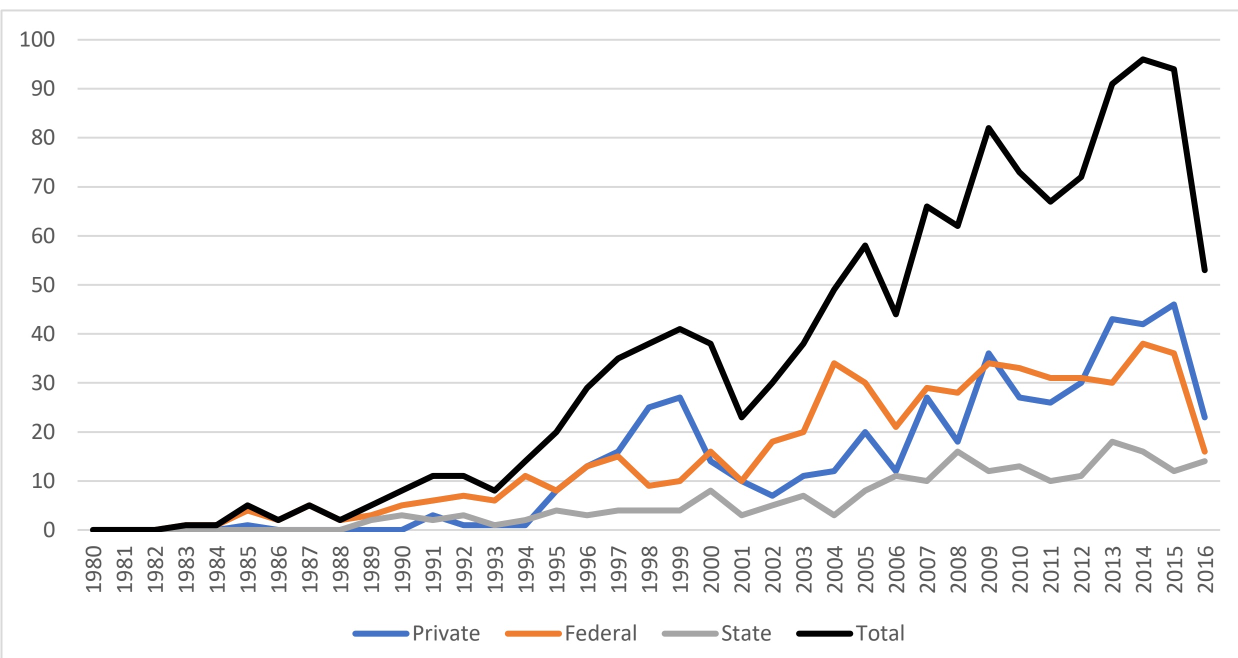
Notes: * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Figure 1. Annual No. of Active RT Region Entrepreneurial Life Science Firms



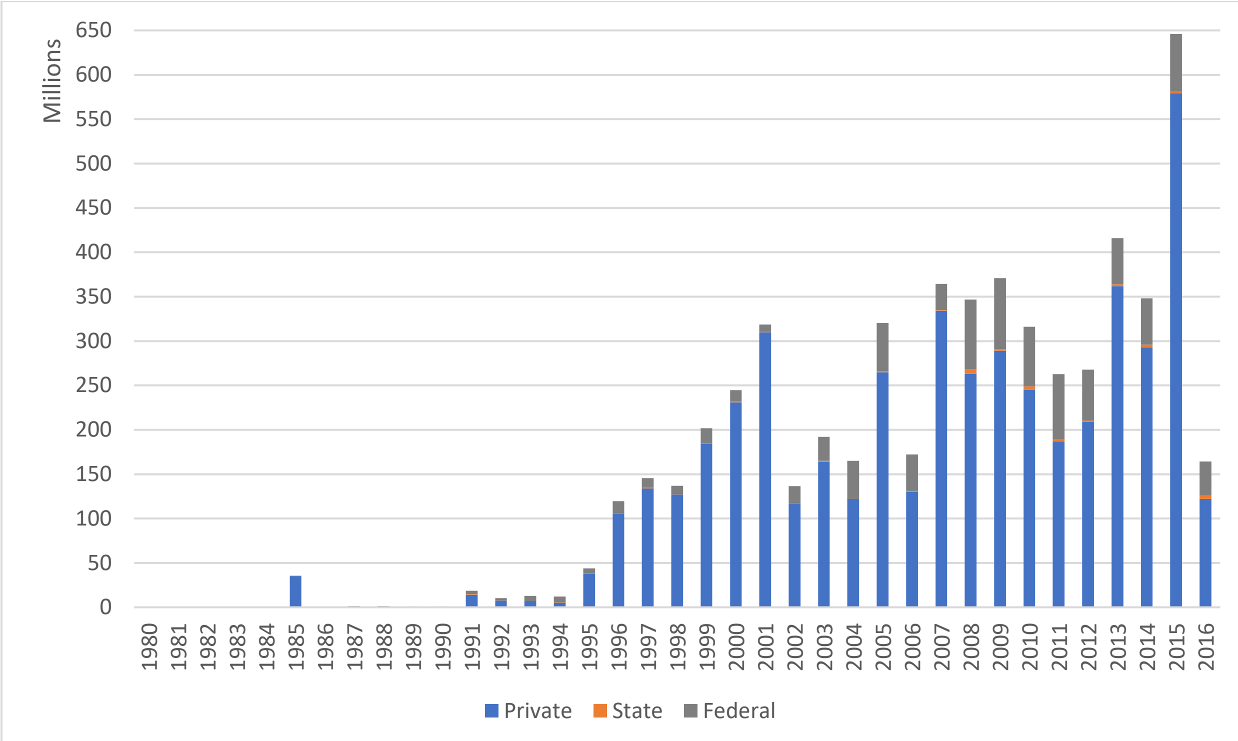
Source: PLACE: RTP Database.

Figure 2. Annual No. of RT Entrepreneurial Life Science Firms Receiving Funding by Source



Source: PLACE: RTP, adapted from CB Insights, NIH Reporter, SBA, NC IDEA, NC Biotech Center.

Figure 3. Annual Real Dollar Amount of Funding to RT Entrepreneurial Life Science Firms by Source



Source: PLACE: RTP, adapted from CB Insights, NIH Reporter, SBA, and NC Biotech Center.

Figure 4. RT Region Life Science Industry Timeline.

1980 - 1997

- NC Biotech Center, 1981
- Quintiles founded by UNC prof, 1981
- Glaxo HQ move, 1983
- Council for Entrepreneurial Development, 1983
- NC State TTO, 1984
- Syngenta move, 1984
- Intersouth Partners founded as first local VC firm, 1985
- PPD founded by UNC prof, 1985
- Sphinx Pharmaceuticals, 1986
- Duke TTO, 1986
- BASF Corp. Agricultural Products, 1986
- NC Biotech Center offers first business loans, 1989
- First Flight Venture Center, 1991
- Embrex IPO ($16.7M), 1991
- Sphinx IPO ($75M), 1991
- Biotechnology Industry Organization (BIO), 1993
- LabCorp move, 1993
- Sphinx sold to Eli Lilly, 1994
- The Aurora Funds and Pappas Capital (VC), 1994
- UNC TTO, 1995
- Burroughs Wellcome & Glaxo merger, 1995, freed talent
- Fujifilm Diosynth (CMO) move, 1995
- Aeolus Pharmaceuticals & Quintiles IPOs, 1996
- Mycosearch sold to Onogene ($4.7M)

1998 - 2009

- NC ranked #4 in biotech VC investment, 1998
- Eno River Capital (VC), 1998
- BD BioVenture Center, 1999
- Icagen raises $19M in VC, 1999
- Inspire Pharmaceuticals IPO ($69M), 2000
- Glaxo-Wellcome & SmithKline Beecham merger, 2000
- Hatteras Venture Partners (VC), 2000
- NC State Centennial Biomedical Campus, 2000
- Triangle Pharmaceuticals raises $75M in VC, 2001
- Trimeris IPO ($102M), 2002
- Southeast TechInventures, 2003
- Icagen IPO, 2005
- One NC SBIR Match Fund, 2006-2011, 2016-present
- Dara Biosciences IPO, 2008
- Hamner Bioscience Accelerator, 2008
- Cempra Pharmaceuticals raises $50M Series F, 2009

2010 - Present

- Significant expansion and turnover in ESOs
- Quintiles IPO-II ($947M) & LipoScience IPO ($45M), 2013
- Advanced Liquid Logic sold to Illumina ($96M), 2013
- KBI BioPharma (CMO) move, 2013
- Humacyte raises $150M Series B, 2015
- Bamboo Therapeutics sold to Pfizer ($150-645M), 2016
- 10+ other IPOs including Liquidia ($50M) and G1 Therapeutics ($105M)
- University Angel Networks: CAN, DAN, WIN
- BioLabs NC, 2018
- Firms successful in getting nonlocal VC

Source: Information taken from Smilor et al. (2007), Hardin (2008), Feldman & Lowe (2011), Lowe & Feldman (2015), McCorkle (2012), a variety of online sources, and interviews with local entrepreneurs and ecosystem members.

Note: Green font indicates a funding relate event. Red font indicates a university related event. Blue font indicates public event.

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