Accelerators and the Regional Supply of Venture Capital Investment*

Daniel C. Fehder
Massachusetts Institute of Technology

Yael V. Hochberg
Rice University, Massachusetts Institute of Technology & NBER

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Recent years have seen the rapid emergence of a new type of program aimed at seeding startup companies. These programs, often referred to as accelerators, differ from previously known seed-stage institutions such as incubators and angel groups. While proliferation of such accelerators is evident, evidence on efficacy and role of these programs is scant. Nonetheless, local governments and founders of such programs often cite the motivation for their establishment and funding as the desire to transform their local economies through the establishment of a startup technology cluster in their region. In this paper, we attempt to assess the impact that such programs can have on the entrepreneurial ecosystem of the regions in which they are established, by exploring the effects of accelerators on the availability and provision of seed and early stage venture capital funding in the local region.

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Recent years have seen the emergence of a new institutional form in the entrepreneurial ecosystem: the seed accelerator. These fixed-term, cohort-based, "boot camps" for startups offer educational and mentorship programs for startup founders, exposing them to wide variety of mentors, including former entrepreneurs, venture capitalists, angel investors, and corporate executives, and culminate in a public pitch event, or "demo day," during which the graduating cohort of startup companies pitch their businesses to a large group of potential investors. The first accelerator, Y Combinator, was founded in 2005, quickly establishing itself in Silicon Valley as the first program of its kind. Techstars, one of the largest programs to emerge in the US, followed in 2007, when two local start-up investors in Boulder, Colorado founded an accelerator, hoping to transform the Boulder start-up ecosystem. Today, estimates of the number of accelerators range from 300+ to over 2000, spanning six continents, and the number is growing rapidly (Cohen and Hochberg 2014).

While proliferation of accelerators is clearly evident, evidence on the role and efficacy of these programs is scant at best. Many local governments have adopted the accelerator model, hoping to transform their local economies through the establishment of startup technology clusters. In this paper, we attempt to assess the impact that such programs can have on the entrepreneurial ecosystem of the regions in which they are established. We focus on a particular aspect of the ecosystem: the availability and provision of seed and early stage venture capital (VC) financing for startups.

Assessing whether accelerators affect the level and availability of VC funding in their region is non-trivial, as there is no source of guaranteed exogenous variation in the location of accelerators, and no natural experiments exist to help researchers in this task. While the locational choices of many accelerators are rooted in the birthplace of founders who found success in Silicon Valley and returned home hoping to transform their hometowns,[1] others are

[1] For example, Techstars, one of the first accelerators, was founded in Boulder, CO in 2007 by local entrepreneurs and investors for the purpose of starting a startup cluster in Boulder where none previously existed. Similarly, DreamIt was launched by Steve Welch in Philadelphia in 2008 simply because Welch at the time resided in Philadelphia and altruistically (in his words) wished to offer a service to local entrepreneurs; the Austin, TX branch

established for reasons we cannot directly establish. Given this challenge, our approach mimics that of other studies faced with similar program evaluation settings (e.g. Autor (2003)). First, we carefully match Metropolitan Statistical Areas (MSAs) that are 'treated' with an accelerator program to other MSAs that are very similar in terms of pre-treatment trends in the entrepreneurial ecosystem. We then employ a fixed effects difference-in-differences model, augmented by linear time trends to capture any pre-trends in funding patterns that might not be fully captured in the matching process.

Our matched, never-treated, MSAs are highly similar to their treated counterparts in financing trends and other characteristics in the years prior to treatment, which occurs in a staggered manner across multiple MSAs over the years 2005 to 2012. Post-treatment, however, MSAs that receive an accelerator program exhibit significant differences in seed and early-stage financing patterns. In our difference-in-differences model with a strictly matched sample, fixed effects and linear time trends, the arrival of an accelerator associated with an annual increase of 104% in the number of seed and early stage VC deals in the MSA, an increase of 289% in the log total $$ amount of seed and early stage funding provided in the region, and a 97% increase in the number of distinct investors investing in the region. This increase in the number of distinct investors comes primarily from an increase in nearby investment groups, rather than from entry of additional investors from outside the region. Regions with prior-existing formal angel groups experience a larger treatment effect than regions without such groups, suggesting that startup accelerators are also complementary to existing institutions in a region's innovation ecosystem. Moreover, the funding events themselves are not merely of accelerator graduates – much of the increase in funding events involves investments made in non-accelerated companies in the MSA. Taken together, these findings suggest that the presence of an accelerator leads to a shift in the general equilibrium of funding activity in the region, rather than merely to an effect of treatment on the treated.

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of DreamIt was subsequently launched after Welch and Kerry Rupp, another DreamIt director, both relocated to Austin for exogenous reasons.

Consistent with a causal interpretation of the estimates, these patterns are greater in the industry most likely to be "treated" by an accelerator: software and IT services. Estimating a triple-differences model that distinguishes between pre-and post-treatment funding availability patterns for the software and IT industry versus the semiconductor industry—an industry unlikely to be treated by accelerators—indicates that while funding events for startups in the software and IT segments increase dramatically post-accelerator arrival, early stage funding for semiconductor startups in the treated MSAs does not increase more substantially than funding in non-treated regions.

While the limited research on accelerators to date has primarily focused on the outcomes for 'accelerated' startups, we focus our study on the overall regional effects of such initiatives. Many studies of entrepreneurial policies and programs focus on firm-level dependent variables. Existing research suggests, however, that policies which seem "effective" at the individual firm level can have indeterminate or negative impacts on the regional economy (Davis, Haltiwanger, and Schuh 1998). Our research thus attempts to bridge programmatic evaluation of accelerators to a broader literature on the regional context of economic growth through innovation and entrepreneurship. Studying the effects of entrepreneurship-related initiatives on a region overall is particularly useful for policy makers, who often wish to pinpoint the mechanisms which underlie the development and success of productive entrepreneurial regions. In this particular case, the outcome variable we explore—early stage VC investment—is considered a critical element in the entrepreneurial ecosystem, and has been shown to be tightly tied to regional development (Samila and Sorenson 2011).

Our results contribute to a growing literature exploring the effects of regional features and initiatives on entrepreneurial activity. Researchers have long noted the localization of economic activity, especially inventive and innovative economic activity. Recent work has provided a rigorous confirmation of the clustering phenomenon for entrepreneurship (Glaeser and Kerr 2009) while also describing in more detail the shape and content of these clusters (Delgado, Porter and Stern 2010). A significant amount of scholarship has sought to account not only for the localization of innovation and entrepreneurship but also for the extreme differences in the level of activity across regions, and the role of the regional economic environment in shaping these differences (e.g. Saxenian 1994, Feldman 2001, Glaeser and Kerr 2009).

Existing work has stressed the highly localized flow of technical and market information (Jaffe, et al., 1994, Arzaghi and Henderson 2008), and has also noted the localization of the distribution of venture capital, rooted in the investor's monitoring function (Sorenson and Stuart 2001). Others have connected the presence of dealmakers to the rates of firm formation (Feldman and Zoller 2012), or have that current incumbents in the economic "ecosystem" of a region can have a large impact on a region's capacity for innovation and entrepreneurship for both the good (Agrawal and Cockburn 2003, Feldman 2003) and the detriment of a region (Chinitz 1961). Indeed, the composition of a region's economy in one period can have a long-term impact on the entrepreneurial capacity of a region moving forward (Glaeser 2012).

While it is important to understand the potential mechanisms that might explain the cross-sectional variation in the level of entrepreneurship and innovation in a region, another stream of research attempts to elucidate the dynamics of the growth of a region's capacity for entrepreneurship and innovation. A careful understanding of regional dynamics can have important policy implications. Despite significant allocations at the state and local level in the U.S. and globally, many entrepreneurship support programs have not produced significant returns (Lerner 2009). This may partly reflect a focus on characteristics of successful regions which are consequences, rather than determinants of, entrepreneurial capacity (Feldman 2001). While research has shown that an increase in venture capital allocation to a region can have a direct impact on economic growth (Samila and Sorenson 2011) and innovation (Kortum and Lerner 2000), less is known about the policies and interventions which shift venture capitalist's supply preferences across regions.

To the best of our knowledge, our study is the first to examine the local impacts of accelerator programs. The small number of emerging empirical papers on accelerators typically ask questions regarding the role of the accelerator for the accelerated or how companies that attend accelerators differ from those that pursue other financing or growth options. By focusing on local effects, we are able to provide initial evidence on the larger role played by accelerators in the regional entrepreneurial ecosystem. Our work thus informs the increasing academic and policy interest in the particular role in growth played by entrepreneurial activity (Davis, Haltiwanger, and Schuh 1998, Haltiwanger, Jarmin and Miranda 2013). The patterns we document may be useful for policy makers considering the benefits of accelerators for the local entrepreneurial economy and ecosystem, as our results suggest a clear role for accelerators in facilitating the emergence of a vigorous local early-stage investor community in their regions.

The paper proceeds as follows. Section I introduces the accelerator model and its relationship to local investment, and discusses the research available to date. Section II presents our methodological approach. Section III describes our data, and Section IV lays out the empirical analysis findings. Section V discusses and concludes.

I. Seed Accelerators

The formal definition of a startup or seed accelerator, first offered by Cohen and Hochberg (2014), is a fixed-term, cohort-based program, including mentorship and educational components, that culminates in a public pitch event, often referred to as a 'demo-day.' Many accelerator programs, though not all, provide a stipend or small seed investment ($22 thousand on average, with a range from $0 to $150 thousand) to their startups, and receive an equity stake in the portfolio company in return, typically 5-7%.[2] Most offer co-working space and other services in addition to mentorship, educational and networking opportunities. Some also offer a larger, guaranteed investment in the startup, in the form of a convertible note, upon graduation. While many accelerators are generalist across industries, others are vertically-focused (healthcare, energy, digital media). Despite the vertical or industry focus, careful examination of

[2] Summary statistics obtained from the Seed Accelerator Rankings Project (Gilani and Quann (2011), Hochberg and Kamath (2012) and Hochberg, Cohen, Fehder and Yee (2014)), which uses proprietary data collected annually from accelerator programs to assess the relative quality of U.S.- based programs.

the products/services provided by the portfolio companies of accelerators reveals that nearly all accelerator portfolio startups offer some form of software or internet services, though such software may be targeted towards use in a specific industry vertical.[3]

In practice, accelerator programs are a combination of previously distinct services or functions that were each individually costly for an entrepreneur to find and obtain: seed investment, value-added mentorship and advisement, co-working/co-location with other startup companies, capital introductions and exposure, network building, and the opportunity to pitch to multiple investors, a likely result of which is a reduction in search costs for the entrepreneur, and an increase in leverage vis a vis potential VC investors. Indeed, accelerators often attempt to be an organized version of the "dealmakers" described in Feldman and Zoller (2012), drawing the community together and creating social capital surrounding entrepreneurial efforts.

From the perspective of the VC investors, accelerators serve a dual function as deal sorters and deal aggregators. The accelerator application process screen among a larger population of startups to identify high-potential candidates, and the program aggregates these candidates in a single location, attracting investors who might otherwise find the costs of searching for opportunities in smaller regions too high to justify. Investors often serve as mentors, thus getting an early look at the startups, business plans, team dynamics and progress over the term of the program. The public demo day, or pitch event, allows them to observe multiple companies pitch in a single instance, and since they are already traveling to the region, non-local investors often choose to look at other opportunities in the area as well. The aggregation and sorting function performed by accelerators is thus believed to result in a reduction in search and sorting costs for the VCs when investing in smaller regions.[4]

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[3] The Seed Accelerator Rankings Project tracks the identity and focus of the portfolio companies for most established (2 cohorts +) accelerators.

[4] This deal aggregation, sorting and matchmaking underlies the financial model for most for-profit accelerators. The accelerator typically raises a fund in the form of a Limited Partnership, similar to the structure used for a VC fund. Here, however, the limited partners (LPs) are typically VC funds, rather than institutional investors. These VCs serve as mentors in the program. This mentorship role allows them early access to the portfolio companies; the best companies in each cohort often close funding before they ever reach demo day (Cohen and Hochberg (2014)). The

The emergence of accelerators has been facilitated by a significant fall in the costs of experimentation over the last decade (e.g. Ewens, Nanda and Rhodes-Kropf 2013). The capital requirements to seed a startup software company have fallen dramatically along with the cost of experimentation; where building a software company may have cost $5 million on average 10 years ago, today it can often be accomplished with $500 thousand, and startups can often accomplish with a $50 thousand seed investment what used to take $500 thousand to $1 million. This has allowed accelerators to provide meaningful funding and assistance to their startup portfolio companies with a seed investment or stipend as low as $15 thousand.

Notably, accelerators differ considerably from previously extant institutional structures in the entrepreneurial ecosystem, such as incubators. Incubators are primarily real estate ventures, offering startup co-working space at reduced rent. Incubators, unlike accelerators, lack a fixed term, and experience continuous entry and exit of startup groups, which stay resident for much longer periods of time (1-4 years on average versus 3-4 months for an accelerator). Most offer fee-based professional services. They do not offer investment or stipends, and their educational and mentorship offerings, if provided, are ad hoc at best. Incubators are primarily thought to shelter vulnerable nascent businesses from the harsh realities of the real world, while accelerators force startups to quickly confront those realities and determine whether the business is viable (Cohen and Hochberg 2014).[5]

Little prior research exists on the accelerator phenomenon, primarily due to the newness of the phenomenon and limited data availability. The definition of an accelerator amongst practitioners itself remains discordant. Some groups that would be defined as incubators based on the Cohen and Hochberg (2014) standardized definition refer to themselves as accelerators

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expectation is that the VCs will then make back their money on the larger investments they make in these accelerator graduates out of their primary funds, rather than generating direct returns on the small investment in the accelerator. Rather, the investment in the accelerator limited partnership is viewed as a fee to fund the deal screening and aggregation, with the costs split across multiple VC funds.

[5] Accelerators also differ from angel groups. While angel groups similarly offer small, seed stage investments to startups, they lack the co-location features and formal programming, and typically provide little to no value-added service or mentorship. Neither incubators nor angel groups offer the same simultaneous exposure to a large set of follow-on investors that is achieved in an accelerator demo day.

due to the current hype around the phenomenon, while others that meet the formal definition of accelerator still refer to themselves as incubators. As a result, researchers must manually identify and categorize programs. Complicating matters further is the significant heterogeneity that exists even amongst groups that meet the formal definition.

The data challenges are also significant. There is a general absence of large scale representative datasets covering accelerator programs. Researchers have little visibility into program features, the identity of the companies that enter and exit the programs, or the population of startups that apply to such programs but are not admitted. Most accelerators are small, lean organizations, with limited staff, and little organized data tracking. The participants themselves are small private companies, often unincorporated at the start, for who little data is available even if their identity were known. While some programs encourage their graduates to report to publicly available databases such as CrunchBase,[6] and other startups voluntarily report or are identified through CrunchBase's own data collection efforts, the data on accelerator graduates present in these databases is as yet incomplete.[7]

Existing research on accelerator programs is primarily conceptual. Cohen and Hochberg (2014) offer the first formal definition of an accelerator program, distinguishing accelerators from other programs that have similar or related goals, such as incubators or angel investment groups. Cohen (2013) utilizes an embedded multiple case study of nine U.S.-based programs to assess how accelerators accelerate the new venture process. Isabelle (2013) presents a comparison of accelerators to incubators, while Caley and Kula (2013) and Miller and Bound (2013) provide descriptions of the accelerator model. Radojevich-Kelley and Hoffman (2012) offer a multiple case study of how accelerator programs connect start-ups with potential investors, and Kim and Wagman (2012) present a game theory model of the accelerator as certification of start-up quality.

[6] Data on accelerator programs and graduates extracted through the CrunchBase API is aggregated at seed-db.com.
[7] The authors are actively working with CrunchBase to help identify and improve coverage in the database, as part of the Seed Accelerator Rankings Project (Hochberg, Cohen, Fehder and Yee (2014)).

An emerging set of empirical studies compare the startup companies that complete accelerator programs to other populations of startups that did not attend accelerator programs. Hallen, Bingham and Cohen (2013) compare accelerated startups that eventually raise venture capital to non-accelerated ventures that eventually raise venture capital. They find that graduating from a top accelerator program is correlated with a shorter time to raising VC, exit by acquisition, and achieving customer traction. Winston-Smith and Hannigan (2015) compare ventures that have participated in two of the leading accelerators, TechStars and Y Combinator, to similar ventures that do not go through these programs but instead raise angel funding. They find that startups that graduate from these top two programs achieve exit (acquisition or failure) faster than their matched, angel-funded counterparts, due to both higher acquisition rates and higher failure rates than for angel-funded startups. This increased speed of failure is also found in Yu (2014), utilizing a different sample of accelerated and matched controls. Winston Smith and Hannigan also demonstrate that attendees of these top two accelerator programs are more likely to come from educational backgrounds that include attendance at one of the institutions in the top 30 producers of computer science doctoral graduates, which suggests that there is a particular "type" of background that characterizes startups that choose to attend (or are accepted to) premier accelerator programs.

These early-stage studies are focused on the outcomes for accelerator portfolio companies. In other words, they are interested in the effect of treatment on the treated (do accelerators add value to the companies that attend them). Outcomes, however, are difficult to measure in this setting, and endogeneity issues are rife. Furthermore, if accelerators serve to shift the general equilibrium of the entrepreneurial ecosystem by improving outcomes or resources for both the treated and the non-treated in a region, studies of this nature will not be able to properly capture the full effects of accelerators. We therefore take a different approach in this study, examining the regional effects of programs on the general equilibrium in the entrepreneurial ecosystem, rather than the treatment effect of the accelerator on the treated startups.

II. Methodological Approach

Our research seeks to measure the impact of startup accelerator formation on the venture capital financing activity in a MSA region. As discussed above, startup accelerators lower the search costs for both entrepreneurs and investors seeking early stage investments. As such, startup accelerators are predicted to stimulate an increase in the level of startup investment activity in a region. At the same time, startup accelerators could be more likely to be founded in regions that have higher levels of startup activity or have experienced swift growth in that activity. Thus, we are interested in separating the causal impact of startup accelerator formation from the endogenous selection of startup accelerators into “hot” regions for startup activities.

Using a panel data set of US Census MSA regions across ten years, we exploit the fact that different accelerators were founded in different years in different MSA regions to assess the impact of accelerator foundation through a differences-in-differences model. Our baseline model takes the form:

$$VC_{t,MSA} = \propto_{MSA} + \gamma_t + \beta' X_{t,MSA} + \delta POST * TREATED + \varepsilon_{t,MSA} \quad (1)$$

which controls for time-invariant heterogeneity in the entrepreneurial capacity of different MSA regions with the MSA fixed effect, $\propto_{MSA}$, and for national level dynamics in the venture capital market with year fixed effects, γ_t. $POST * TREATED$ is a dichotomous variable that is set to 1 for MSAs that received accelerators for all years greater than or equal to the year of the accelerators first cohort. $X_{t,MSA}$ are time x MSA-specific controls. In this specification, $POST * TREATED$ measures the impact of the founding of an accelerator by comparing treated regions to untreated while controlling for fixed differences in regional levels of venture activity and time period specific shocks that are shared across all regions. If the founding of accelerators in a specific MSA can be assumed to be random and independent events, then equation (1) recovers an unbiased estimate of the causal impact of the founding of accelerators on venture activity in a region.

Unfortunately, the founding of an accelerator in a given MSA is potentially a function of variables that are unobserved by the econometrician. While any number of accelerator programs were established by former entrepreneurs for altruistic reasons such as a desire to support a hometown community or develop an ecosystem in an area that had none, a concern still remains that the regions in which they were established differ in a systematic fashion from regions that do not receive an accelerator. We address the potential for omitted variables bias in three ways. First, we create a set of matched control and treatment MSAs using a dynamic hazard rate model; second, for each model we run an additional regression with the inclusion of MSA-specific linear time trends; and third, we estimate a triple differences model using early stage investment into semiconductor startups as an untreated industry which adds industry variation within each MSA. Taken together, these three techniques allow us to examine the robustness of our regression models to different forms of misspecification. Each of these three approaches is discussed in turn below.

Our primary concern is that the decision to found an accelerator in one region versus another might be endogenous to short term fluctuations in the attractiveness of a region for early stage investors. In other contexts, researchers have found that short-term changes in outcomes, like a wage dip, can drive a treatment decision, like attending a job-training program (Ashenfelter, 1978; Abadie, 2005). To control for such short-term fluctuations that might drive the founding of an accelerator, we carefully match our treated MSAs to untreated MSAs that are substantially similar to the treated MSAs in pre-treatment year trends likely to affect the attractiveness of the region for early stage funding.

To create our matched sample, we estimate a dynamic hazard rate model of the form:

$$h(t, msa) = f(\varepsilon_{t,MSA}; \beta_0 + \beta_t VC_{t,MSA} + \beta_{t-1}\Delta_{t-1,MSA} + \beta_{t-2}\Delta_{t-2,MSA} + \beta_{t-3}\Delta_{t-3,MSA}) \quad (2)$$

In this regression, h(t) is the point hazard of an accelerator being founded in that MSA and in that year. $VC_{t,MSA}$ is the count of early stage venture capital deals in that MSA and in that year. The delta terms ($\Delta_{t-1,MSA}$, $\Delta_{t-2,MSA}$, and $\Delta_{t-3,MSA}$) measure the differences in the current number of early stage deals in that MSA to the levels one, two and three years previously respectively. Thus, our hazard rate model flexibly estimates how both the level and the short-term rate of change in funding events predicts the arrival of an accelerator in a given MSA region. We thus obtain an instantaneous probability, based on current levels of funding, that an accelerator will choose to locate in a specific MSA.

With our estimated dynamic hazard rate model, we then choose a match for each treated region by finding the untreated region with the most similar probability of founding an accelerator in that year when the treated region is on the common support. This matching procedure excludes certain regions, like Silicon Valley and the Boston/Cambridge region, which do not have a natural counterpart in the population of potential control MSAs. We believe that the exclusion of regions with disproportionately rich entrepreneurial ecosystems yields the proper counterfactual for the research question at hand. Consistent with this belief, each of the top five regions for total yearly venture capital allocations received startup accelerators relatively early in the diffusion of this organizational form (Cambridge, MA and Silicon Valley were the first two locations). Thus, we focus on understanding the causal impact of accelerators in regions with less developed startup infrastructure.

To further control for long term trends in each MSA, we augment our models with MSA-specific linear time trend controls, as in Autor (2003). For each model we estimate, we additionally estimate an alternative specification where we add an additional MSA-specific linear time trend. Specifically, we estimate the model:

$$VC_{t,MSA} = \propto_{MSA} + \gamma_t + \beta' X_{t,MSA} + \theta_{MSA} t + \delta POST * TREATED + \varepsilon_{t,MSA} \quad (3)$$

Here, θ_{MSA} measures the MSA-specific slope across all the years in the sample. With the addition of this term, the parameter of interest, δ, measures the average deviation from MSA-specific slope term observed after the arrival of an accelerator in an MSA. Thus, the θ_{MSA} parameter absorbs unobserved variation in the growth rate in venture financing in each MSA. Adding the MSA-specific time trend to our regressions tests how sensitive our estimates of the impact of accelerator founding are to the assumption that treatment and control groups are fundamentally similar.

Next, we attempt to control for unobserved changes in the quality of a MSA for startup activity by adding a counter-factual industry, semiconductors, which has been significantly less impacted by the emergence of accelerators. Human capital and lifecycle requirements of semiconductor startups are dramatically different than the software companies that populate accelerators. Founders and early employees of semiconductor startups are most often PhD-prepared scientists who are extending the findings of their earlier work into commercial applications. Thus, the work tends to be more proof-of-concept lab and manufacturing work than the quick customer development cycles emphasized by accelerators. Additionally, the capital requirements and time horizons are different for semiconductor startups: they require more time and money. For these reasons, accelerator programs have not attracted or solicited startups focused on the semiconductor space. We therefore argue that the ecosystem for semiconductor startups is less likely to be impacted by the arrival of a startup accelerator in their region, as the founders of a semiconductor company are unlikely to consider applying to the accelerator and the venture capitalists that specialize in investing in the software-as-service companies that populate accelerators are unlikely to invest in a semiconductor startup.[8]

Under the assumption that the semiconductor industry is a less-treated industry, we exploit this additional within-MSA industry variation to run the regression:

$$VC_{t,MSA,Ind} = \propto_{MSA} + \gamma_t + \phi_{Ind} + \beta' X_{t,MSA} + \theta_1 POST * IND + \theta_2 POST * TREATED \\ + \delta POST * TREATED * IND_{trat} + \varepsilon_{t,MSA} \quad (4)$$

In this equation, we add a number of terms from our baseline regression in equation (1). We add an industry specific fixed effect, ϕ_{Ind}, and the double difference terms, parameterized by $\theta_1$and θ_2, which measure the overall change treated industries after the introduction of an

[8] VC firms tend to be specialized to specific industries. See e.g. Sorenson and Stuart (2001), Hochberg and Westerfield (2012), Hochberg, Mazzeo and McDevitt (2014) for a discussion.

accelerator and the overall change to the treated region. In this equation, the parameter of interest is δ, the difference in treated regions in the treated industries after accounting for the shared inter-temporal variation within MSA and within industry.

Our last robustness check examines whether the arrival of an accelerator in a MSA changes the composition of investments in terms of both staging and industry within the region in a way that is consistent with our theorized impact of accelerator arrival. Specifically, we examine whether we see deal flow in a region shift toward accelerated industries, and towards early-stage investments in particular. In other settings, researchers have similarly used variation in a fractional dependent variable (like market share or test-passing rate) to identify the impact of investment and human-capital allocation in panel data (Papke and Woolridge, 2008; Hausman and Leonard, 1997).

We build upon these results by estimating a series of fractional logit models measuring changes in the composition of VC investment across two dimensions where we expect accelerators to have a differential impact: 1) stage of deal and 2) industry of deal. Specifically we estimate a series of models of the form:

$$\% \, VC_{t,MSA} = \propto_{MSA} + \gamma_t + \beta' X_{t,MSA} + \delta POST * TREATED + \varepsilon_{t,MSA} \quad (5)$$

Here, % VC measures the composition of venture capital investment along the two dimensions. First, we examine how the arrival of an accelerator in a region impacts the percentage of early stage deals funded (dollars invested) relative to later stage deals (total invested dollars), first within accelerated industries, and then within all other industries receiving VC investments. Next, we measure whether the arrival of an accelerator shifts the proportion of deals and total invested dollars in startups toward accelerated industries, first within early-stage deals and then within later-stage deals.

Our multiple empirical approaches alleviate much of the concern that unobserved variables might be driving both the founding of the accelerator and an observed increase in the number of startup financing events. Combining the matched sample, the inclusion of linear time trends in the difference-in-difference models, the triple difference model with treated and untreated industries, and the analysis of investment activity composition shifts addresses the set of obvious alternative explanations and concerns regarding the robustness of our results to potential unobserved changes at the MSA level.

Our last element of analysis examines the potential sources of an accelerator's impact. Here, we explore three potential sources of informative treatment heterogeneity. First, we explore whether the arrival of an accelerator stimulates more investment in local vs. distant investors, in order toisolate which segment is more influenced by the reduction in search costs or increase in inclinations to engage in entrepreneurship that is provided by the accelerator. Next, we examine variation in accelerator quality to examine whether the effectiveness of the program drives outcomes. Third, we explore whether potential complementary features of the region, specifically the existence of a formal angel groups, alters the impact of the accelerator on regional level investment patterns. Our final analysis examines the extent to which the increase in regional activity following accelerator arrival is attributable to startups that graduate from the accelerator, in order to ascertain whether the effect is driven by accelerator graduates or reflects a broader shift in the general equilibrium of the region.

In our examination of the local vs. distant investor margins, we estimate a series of regressions similar to (1) and (3) but each on a subsample of the data. We calculate the distance between the headquarters of the VC fund investing and the MSAand categorize each investor as *Near* or *Distant* based on this distance, using a variety of cutoffs. We then separately estimate models for the two populations.

For the next two sets of regressions, we focus on variation at the regional or accelerator level and examine how such variation drives aggregate levels of early-stage financing in that region. To do so, we estimate variations in equations (1) and (2) that allows us to incorporate regional/accelerator differences. Specifically, we estimate:

$$VC_{t,MSA,j} = \propto_{MSA} + \gamma_t + \beta' X_{t,MSA} + \delta_j POST * TREATED_j + \varepsilon_{t,MSA} \quad (6)$$

This model is similar to equation (1), but now allows a separate parameter estimate, δ_j, for each of the two dichotomous regional and accelerator-level variables we measure (i.e. high/low quality accelerators and formal angel programs/no programs). Additionally, we estimate models with MSA-specific time trends that are the same as (6) but with the inclusion of those time trends in a manner similar to equation (3).

III. Data

The initial of our sample is composed of 59 accelerators that were founded in 38 MSA regions in the United States between 2005 and 2012. We create an exhaustive list of accelerators from a number of sources, including thorough web searches and lists compiled through active engagement with the accelerator practitioner community by the Seed Accelerator Ranking Project. Our accelerator data set begins with the founding of the first accelerator (Y Combinator) in 2005 and thus contains the entire period of development for this new form of institution. The list of the accelerators included in our analysis is included in Table 1. Notably, many accelerators are located in regions that are not typically thought of as hot beds of startup or VC activity. For example, of the ten accelerators launched from 2005 to 2009, only two located in known startup clusters (Silicon Valley and Boston, MA). The remaining eight located in what were, at the time, relatively inactive locations, such as Boulder, CO, Philadelphia and Pittsburgh, PA, Dallas, TX and Providence, RI. Anecdotal evidence from books and interviews with accelerator founders suggests that this pattern emerges precisely because many programs were founded by hometown entrepreneurs who had made their money elsewhere and who wished to return to establish a startup cluster in their region.

For each of the accelerators in our list, we code a number of variables. First, we note the founding year as the year in which the first cohort of the accelerator graduated and had a demo day. We exclude accelerators from our analysis if they did not graduate at least two cohorts.

Next, we note the MSA region in which the accelerator is located. Third, we note whether the accelerator was ranked in the top fifteen in the 2013 Seed Accelerator Rankings.

For each MSA region in the United States, we create a dichotomous variable that indicates whether a startup accelerator has been established in the region (*TREATED*) and a variable that indicates when the region received its first accelerator (*TREAT YEAR*). We collect a range of outcome and control variables at the MSA-Year level. Table 2 describes each of the variables we collect and their sources. We obtain per capita income and employment at the MSA-year level from the U.S. Census. We obtain an annual count of utility patents issued to entities or individuals in the MSA from the United State Patent and Trademark Office. We obtain an annual count of Science, Technology, Engineering and Mathematics (STEM) graduate students in each MSA and annual University research and development spending in the MSA from the National Science Foundation. Finally, we obtain an annual count of new firms in each MSA from the U.S. Census Business Dynamics Statistics tabulation.

Our analysis contains three outcome variables each obtained from Thomson-Reuter's VentureXpert. First, we code the total sum of seed and early stage VC dollars invested each year at the MSA level (*FUNDS INVESTED*) in "Internet Specific" and "Computer Software" companies. We focus on these company classifications because all but two of the four hundred accelerator portfolio companies that we have records for are classified by VentureXpert in these two categories. Next, we measure the number of distinct seed and early stage VC deals that occur each year in each MSA (*NUMBER DEALS*) for companies in the two classifications. Last, we note the count of distinct investors making investments in each MSA each year (*DISTINCT INVESTORS*). We further break our total count of investors into separate counts of investors whose fund is headquartered more than 300 miles[9] from the startup company (*DISTANT*

[9] We calculate this distance as the geodetic distance between the geographic center of the zip codes reported for both the startup company and the investment firm. We chose 300 miles as a distance where a venture capitalist could fly there and back in a day or drive to the startup's office in a day. We obtain similar results when employing smaller radii.

INVESTORS) and investors whose fund is headquartered less than 300 miles (*NEAR INVESTORS*).

Our resulting sample is a panel with observations at the MSA x Year level. Panel A of Table 3 provides the descriptive statistics for our entire sample across all U.S. MSA regions and all years, segmented by ever-treated or never-treated status. Comparing the overall sample means of the never-treated regions to overall means of the treated regions reveals that treated regions exhibit statistically significant higher levels of venture financing activity both in terms of Funds Invested and Number of Deals. Treated regions also exhibit higher levels of other covariates associated with startup formation. In addition, comparison of the change in number of deals across treated and untreated regions over the course of the sample period reveals that treated regions differ significantly from untreated regions not only in terms of level but also growth rate of entrepreneurial financing events.

Panel B of Table 3 demonstrates the skewness of the distribution of entrepreneurial financing events by dropping the MSAs associated with the San Francisco Bay Area (Silicon Valley) and Boston from the summary statistics for the treated regions. Simply removing these regions from the summary statistics decreases the overall sample means for both Funds Invested and Number of Deals by roughly half in the treated column. The modal number of the funding events across all MSA-years is zero, while a few MSAs have a large number of yearly events. The differences between Panel A and Panel B of Table 3 underline the importance of finding the properly matched treatment and control groups so that our results are not driven by the large apparent differences in the level and growth rate of entrepreneurial financing events in treated and non-treated regions.

Table 4 explores the differences between the treated and non-treated regions in our matched sample. The matching procedure, which excludes accelerators in the San Francisco Bay Area and Boston, and requires matched and treated MSAs to be on the common support, leaves us with 23 treated MSAs that have substantially similar matched MSAs for the estimation. In contrast to the patterns exhibited in Table 3 for the full sample, the differences between the treated and untreated groups in the matched sample are far smaller. Indeed, when we compare the means for each of the variables in Table 4 for the pretreatment period of the treated and untreated MSA regions, we find no significant differences for any of the financing variables, though there remain some statistically significant differences between the two populations for the university R&D funding, firm births, and employment variables. In the subsequent regressions, we are careful to control for these differences by adding these variables as controls. Nevertheless and importantly, the matching procedure appears to purge these two populations of their differences in both the level and growth rate of entrepreneurial financing events.

IV. Empirical Analysis and Findings

Our empirical analysis begins with the estimation of the baseline specification described in Equations (1) and (3) of Section II. We estimate the model using our hazard-rate matched sample. Table 5 considers three outcome variables: the number of seed and early stage deals done in the region; the number of distinct seed and early stage VC investors active in the region; and the dollar amount of seed and early stage financing provided in the region. We estimate the models twice, adding an MSA-specific linear time trend in the second estimation.

The first two columns of Table 5 present our estimates of the baseline model where the outcome variable is the number of early and seed stage deals done in the MSA. The unit of observation is an MSA-year and we are interested primarily in the coefficient loading on the dichotomous variable that indicates whether an accelerator was active in the MSA in that year. Since the number of deals is a count variable, we estimate Poisson models. We report the coefficients in their exponentiated form, also referred to as the incidence rate ratio (or IRR), as it provides an intuitive interpretation as the multiplicative effect of the treatment on the count of the dependent variable in question. Column (1) estimates the baseline model. The coefficient on the *Accelerator Active* variable of interest is positive and statistically significant at the 1% level; the IRR estimate of 2.374 indicates that the region experiences an increase of 137.4% in the number of early stage venture deals in the years following the arrival of an accelerator in the MSA.

In column (2), we further add an MSA-specific linear time trend to absorb any unobserved variation in the growth rate in venture financing in each MSA. Once again we observe a positive and statistically significant coefficient on the variable of interest; the magnitude of the IRR estimate in this case is only slightly lower, suggesting an increase of 104.3% in the number of early stage venture deals in the years following the arrival of an accelerator in the MSA. The unconditional mean of financing events in the matched sample (treated and matched untreated) in the pre-treatment period is 1.75 deals per year. While this baseline level is low, the increase of over 100% in the number of deal represents a significant jump in activity for a region.

Figure 1 graphs the treatment effect for the treated regions by year relative to the control. Year 0 on the graph is the year of the accelerator founding. In the three years prior to the establishment of an accelerator, treated and matched control MSAs look virtually the same in terms of the number of deals done in the region; following the establishment of the accelerator, the number of deals jumps sharply for the accelerated MSAs as compared to the control MSAs. This pattern is evident in both models with and without inclusion of the MSA-specific linear time trend.

In columns (3) and (4) of Table 5, we present estimates from similar models, where the outcome variable employed instead measures the number of distinct seed and early stage venture investors active in the region in a given year. Estimating the model without the MSA-specific linear time trend (column (3)), we find a 98.6% increase in the number of distinct investors in treated MSAs following the arrival of an accelerator. In column (4), we explore whether this effect changes significantly with the inclusion of an MSA-specific linear time trend. The level of the IRR coefficient and the standard errors remain relatively similar with the inclusion of the linear time trend, addressing concerns that our coefficient estimates are being driven by differences in the growth rates of investors across the treated and untreated MSAs. The estimates in column (4) suggest an increase of 85.6% in the number of distinct seed and early stage investors in the region following the establishment of an accelerator. These increases are relative to the unconditional mean number of 2.66 distinct investors each year in the pre-treatment period.

In similar fashion to Figure 1, Figure 2 graphs the treatment effect for the treated regions by year relative to the control. Once again, in the three years prior to the establishment of an accelerator, treated and matched control MSAs look virtually the same in terms of the number of distinct seed and early stage investors active in the region; following the establishment of the accelerator, the number of distinct investors jumps sharply for the accelerated MSAs as compared to the control MSAs. Again, this pattern is evident in both models with and without inclusion of the MSA-specific linear time trend.

In columns (5) and (6) we repeat these estimations for the outcome variable measuring total dollar amount of seed and early stage software and IT VC investment in the region. We once again observe a significant effect of accelerator establishment on financing activity: with the arrival of an accelerator in the region, the MSA experiences an estimated increase of 196% (without linear time trend controls) to 289% (with MSA-specific linear time trend controls) in the natural logarithm of total $ seed and early stage capital invested in the region. Figure 3 presents the treatment effect graphically over time; once again, there is no apparent difference between the treated and matched untreated MSAs prior to the arrival of the accelerator, but after accelerator establishment, the treated MSAs experience a jump in total funding relative to the matched controls.

Notably, we observe little in the way of consistent statistically significant coefficients for the control variables included in the models, regardless of whether the models contain an MSA-specific linear time trend or not. The exception is Employment; across all but one model in column (2), the parameter estimates suggest a negative relationship between overall local employment levels and our measures of early stage funding activity (in the count models, the reported IRR coefficients are less than one, indicating a negative coefficient on the variable in the actual model estimation, and in the OLS models, the coefficients estimated are negative). Altogether, the models in Table 5 suggest a large and significant impact on entrepreneurial finance activity with the establishment of an accelerator in the region.

III.A Accelerated versus non-Accelerated Industries

Taking the estimates in Table 5 in sum, the baseline models in our study suggest that the founding of an accelerator has a large impact on the level of entrepreneurial finance activity in an MSA. The outcome variables we measure, however, capture seed stage investment activity in the software and IT segments alone. In Table 6, we provide a falsification test by adding to our models an industry that is less likely to be impacted by accelerators. Because of the length of the time to market and the differences in the human capital required of founders, startup accelerators have typically not included semiconductor companies in their portfolios. Thus, adding financing events from this “non-accelerated” industry to our data on “accelerated” industries within each MSA, we can control for trends across accelerated industries and shared trends within treated MSAs. Given the lack of focus by accelerators on the semiconductor segment, we would expect to see less of an effect of accelerator establishment on entrepreneurial finance activity in that industry.

Table 6 presents the estimates of the triple difference models for our three outcome variables. The coefficient of interest is that on the triple interaction *Treated Region X Treated Industry X Post-Treatment*. We observe significant and positive coefficients in the models for number of deals and number of distinct investors, both when we include MSA-specific linear time trends and when we omit them. Here, in Models 6-1 and 6-2, the model estimates suggest that the founding of an accelerator in an MSA produces a statistically significant 391% (336%) increase in the number of early stage software and IT deals in accelerated industries when omitting (including) the linear time trends. In models 6-3 and 6-4, we explore the impact of the arrival of an accelerator on the number of distinct investors while controlling for industry. We find that the arrival of an accelerator is associated with a 195% (169%) increase in the number of investors when omitting (including) MSA-specific linear time trends. Lastly, in models 6-5 and 6-6, we explore the impact of the arrival of accelerators on the total amount of dollars invested. In this set of models, we find no statistically significant differential impact of the arrival of an accelerator on software startups when compared to startups in the semiconductor industry.

Figure 4 graphs the treatment effect for the treated industry over time. There is no difference in financing patterns pre-accelerator founding between the groups; following the establishment of the accelerator, there is a jump in financing activity for the more-treated industry (software and IT) in the treated region, but not for the less-treated industry (semiconductors). Thus, our estimates of the positive impact of accelerator founding on regional entrepreneurial finance appear to be robust to controlling for whether the industry in question is likely to be more affected.

III.B Local versus Remote Investors

In Table 7, we build upon these results by asking whether the increase in the number of distinct investors active in the region is driven by an increase in investors located near the MSA or by investors located at a distance from the MSA. Column (1) of Table 7 provides the estimates for the model measuring the impact of accelerator founding on the count of number of early stage deals where at least one investor that participated in the round was headquartered more than 300 miles away from the headquarters of the startup company (distant investors). While the coefficients from this model suggest a statistically significant increase of 90% in the number of deals with at least one distant investor participating in the round after the arrival of an accelerator, when we add MSA-specific time trends in column (2), the coefficient loses statistical significance. In columns (3) and (4), we similarly explore the impact of accelerator founding on the number of deals where the investor syndicate is comprised entirely of investors headquartered within 300 miles of the company headquarters (local investors). Here, we observe a statistically significant 164% increase in the number of deals with entirely local investors, a result that is robust to the inclusion of MSA-specific linear time trends in column (4).

Columns (5) and (6) of Table 7 present estimates of the impact of accelerator founding on the count of distinct distant investors active in the region. While the coefficient in the baseline model in column (5) is statistically significant (85% increase in number of investors), once again when we add the MSA-specific linear time trends in column (6), the magnitude of the coefficient is substantially reduced and loses statistical significance. In contrast, in columns (7) and (8), when we examine the impact of accelerator founding on the count of number of distinct local investors, we find that the founding of an accelerator leads to a statistically significant increase of ~113% in the number of distinct local investors. This holds in both specifications with and without the MSA-specific linear time trend.

Lastly, we look at the impact of the arrival of an accelerator on the total number of dollars invested in a region by local and distant investors. In column (8) and (9), we explore the impact of accelerator founding on total investment from distant investors, finding no statistically significant relationship. In contrast, column (11) looks at the impact of accelerator founding on the total amount of early stage funding invested by local investors. Here, we find that the arrival of an accelerator is associated with a large and statistically significant increase in the amount of funding provided by local investors, and this result is robust to the inclusion of MSA-specific linear time trends in column (12).

Taken together, the estimates in Table 6 suggest that much of the increase in entrepreneurial finance activity in the region following the arrival of an accelerator stems not necessarily from the entrance of remotely-located investors into the region, but rather from new growth in investment groups local to the region itself. This is consistent with the idea that accelerators may serve as a catalyst for drawing together latent local forces to create an entrepreneurial cluster where it did not exist previously.

III.C Accelerator Quality

Taken together, the models in Tables 5 through 7 suggest that the founding of an accelerator has strong stimulative effect on the entrepreneurial financing environment in the region. In Table 8, we explore whether these effects are related to the quality of the accelerator, as measured by the annual accelerator rankings. We break the sample of accelerators founding into two subsamples—those ranked in the top 15 of the Seed Accelerator Ranking Project for 2013 and all others.[10] Columns (1) and (2) present the estimates for the models of the effect of accelerators on number of early stage deals in the region. Interestingly, we find a positive and significant effect for both highly-rated and non-highly rated accelerators, 91% and 123% respectively (though the two coefficients are not significantly different from each other in magnitude). Similarly, we find a statistically significant 84-86% increase in the number of distinct investors in the region for both groups in columns (3) and (4). The similarity in magnitude of the effect for both groups suggests that the founding of accelerators, regardless of quality (which is not known ex ante) may serve as a catalyst to attract attention to the region or to ignite latent tendencies towards entrepreneurship that might otherwise not have emerged.

Overall, our findings suggest a large and statistically significant impact of the founding of accelerators on the number of early stage venture deals and early stage investors in the accelerator's MSA. Our results are robust to a number alternative specifications. We note that as the average seed and early stage investment size has fallen in these industries over last 15 years, primarily due to reduction in the cost of experimentation (Ewens, Nanda and Rhodes-Kropf 2013), angels have begun to emerge as a viable substitute for VC seed and A round investment. While we do not observe angel funding, it is likely that the effects we see for VC investment are also present at the angel level, and may be many times the VC effects.

III.D Formal Angel Groups

[10] Future versions will consider prior year rankings rather than just 2013, as well as subsamples of groups ranked higher or lower on particular aspects, such as entrepreneur and investor appraisal of program quality.

In Table 9, we explore how the impact of the arrival of an accelerator varies depending upon the prior presence of a formal angel investment group in the MSA.[11] Columns (1) and (2) present the estimates for the models of the effect of accelerators on the number of early stage deals in a region. We find that the accelerator has a larger impact in regions that did not have prior angel investment groups than regions with prior angel groups, 388% versus 133%. The differences between these coefficient estimates are significant at the 5% level. Similarly, we find differences in the number of distinct investors in columns (3) and (4). Regions that had no prior angel group at the time of accelerator founding had a larger increase in the number of distinct investors at the time of accelerator founding (264% increase versus 96% increase). This difference between the coefficient estimates are significant at the 10% level. Lastly, we find less impact on the total amount of early stage financing raised in a region in columns (5) and (6). While we find a statistically significant increase of 167% in total funds raised in regions with angel groups, our point estimate for regions without angel groups is similar in magnitude, but not statistically significant. In addition, the difference between the point estimates is not statistically significant.

Overall, these results suggest that the impact of the arrival of an accelerator varies by the presence of formal angel groups in the MSA. Our results are robust to a number of alternative specifications. While we do not observe angel funding directly, our results suggest that accelerators might serve a similar role to formal angel groups in a region, allowing an outlet for the earliest outside financing for early stage startups. While accelerators might provide a substitute for formal angel groups in a region, the variation in the presence of formal angel groups across MSAs in our sample also suggests that accelerator founders are not sensitive to this particular feature of a startup ecosystem.

III.E Composition of Deals at the Regional Level

[11] We identified formal angel groups through extensive web searches. For each MSA, we searched for the words Angel, Investment and the names of each constituent city and town in the MSA. For an Angel group to qualify, it had to have both a formal process for startups to apply for funding and for potential investors to join the group.

In Tables 10 and 11, we examine how the arrival of an accelerator in a region impacts the composition of venture capital deals in that region along two dimensions: 1) stage of deal and 2) industry of deal. If investors begin funding more early stage deals or more deals in accelerated industries after the arrival of an accelerator, another result of accelerator arrival might then be a shift in the composition of deals invested in in the region. As accelerator programs provide an initial sorting of high quality ideas, and aggregate these deals into a single location, with easy, batched access for investors, accelerator programs have, for many angels VC firms, become a first line of attack both for the sourcing of deals and the due diligence process. Given the specific composition of companies that attend accelerators (primarily software and services), shifts in the composition of early stage VC financings are a distinct possibility.

Table 9 explores the impact of accelerator arrival on the proportion of early versus later-stage deals done in an MSA. Columns 1 through 4 of the table look at the impact of accelerators on the proportion of early stage deals in accelerated industries (Internet Specific and Computer Software). In column 1, the estimates suggest a 182% increase in the proportion of dollars allocated to early stage funding after the arrival of an accelerator in a treated region. Column 2 2 adds a MSA-specific linear time-trend to the previous model, reproducing the direction and magnitude of our estimate. In column 3, we explore the impact of accelerator founding on the proportion of deals funded in an MSA that are categorized as early-stage, with the estimated coefficients suggesting a 224% increase in the proportion of early-stage deals. Column 4 once again adds a MS-specific linear time trend, and finds similar results. Next, we turn our focus to the proportion of early stage funding in non-accelerated industries. Columns 5-8 demonstrate that within these industries, we find no impact of accelerator founding on the staging of deals either in terms of proportion of early stage dollars invested or count of deals.

In Table 10, we explore the impact of accelerator founding on the proportion of dollars and deals invested across industries in an MSA. We begin in Column 1 by estimating how the arrival of an accelerator affects the proportion of early-stage dollars that are invested in accelerated industries versus all other industries. The estimates suggest a 67% increase in the proportion of early stage funding dollars invested in software and IT deals after accelerator founding, but this result is not robust to the inclusion of MSA-specific linear time trends in Column 2. The lack of robustness to the inclusion of an MSA-specific linear time trend may be explained by the size differences in funding rounds between software companies and startups in semiconductors and other capital intensive industries. Next, in column 3, we explore the impact of accelerators on the proportion of total early stage deals that are investments into companies in the accelerated industries. Our estimates suggest that the arrival of an accelerator increases the proportion of early stage deals that are targeted towards accelerated industries by 167%. Column 4 indicates that this estimate is robust to the inclusion of MSA-specific linear time trends.

Columns 1 through 4 of Table 10 demonstrate that the arrival of an accelerator has an impact on the industry composition of early stage deals. Next, we look to see if the arrival of an accelerator has similar impacts on later stage deals. In contrast to the previous results, columns 5 through 8 of Table 10 show no statistically significant impact of accelerator founding on the industry composition of later-stage deals.

Thus, within the accelerated industry, we observe a shift towards earlier stage deals post-accelerator arrival, and within early stage deals, we observe a shift towards investments in the accelerated industries, consistent with accelerator arrival impacting the overall composition of companies funded by VCs in the region.

III.F Accelerated versus Non-Accelerated Companies

While Tables 5 through 8 suggest an increase in early stage VC activity in the region following the establishment of an accelerator, this increase in activity may be confined to the set of startups that went through the accelerator program. Alternatively, it may represent an effect on the general equilibrium of financing activity in the region, affecting both accelerated and non-accelerated startups alike.

To explore this issue, we use data on accelerator portfolio company identities obtained from the Seed Accelerator Rankings Project to match funding activity in the region to the companies that completed the accelerator program. In each region, we look at the average number of seed and early stage VC investments in the years following the establishment of an accelerator, and subtract from it the mean number of seed and early stage VC financings in the region in the three years prior to the arrival of the accelerator. This provides the average annual increase in the number of deals in the region after the arrival of an accelerator. We then ask how many of the deals post-accelerator arrival are financings of accelerated companies, and compare this to the increase in number of deals in the region. If the increase in activity is attributable solely to companies attending the accelerator, the number of deals involving accelerated companies should meet or exceed the increase in the number of deals in a region. If, instead, we observe that the number of deals post-accelerator founding that involve accelerated companies is only a fraction of the increase in number of deals in the region, it suggests a broader effect on the financing environment.

As an example, consider the MSA that includes Boulder, CO. TechStars Boulder was founded in 2007. In the period preceding the founding of TechStars, Boulder saw an average of 4.8 seed and early stage software and IT VC deals per year. Post-arrival of TechStars, from 2007-2013, the average number of deals in the Boulder MSA rose to 10.7 deals per year, a 5.9 deal increase. However, during this period, only 2.3 deals per year, on average, involved companies that had graduated from TechStars Boulder. Similarly, consider Cincinnati, OH, home of The Brandery, and accelerator founded in 2010. Pre-arrival of The Brandery, Cincinnati experienced, on average, 0.55 early stage VC deals per year – about one deal every two years. After The Brandery was established, in the period 2010-2013, Cincinnati averaged 4 deals per year—an increase of 3.45 deals per year. However, only 1.45 deals per year on average in this period involved a Brandery graduate startup.

We perform a similar tabulation for each of the treated MSAs for which we are able to obtain a list of portfolio companies from the Seed Accelerator Ranking Project. Across these MSAs, on average, seed and early stage financing deals of startups that graduated from the accelerator represent only 30.4% of the increase in the annual number of seed and early stage financing deals post-treatment. Thus, the effect of accelerators on entrepreneurial finance activity in the region is not a treatment effect for accelerated companies alone, but rather represents a more general effect on the general equilibrium of financing activity in the region, consistent with the notion that an accelerator program may serve as a catalyst to draw attention to the region more generally.

V. Conclusion

While the proliferation of accelerator programs over the last few years has been rapid, very little has been shown to date regarding their efficacy as institutions and intermediaries in the entrepreneurial ecosystem. With little information to inform decision-making processes, policy makers have struggled to determine how or if these programs should be supported or encouraged. This study provides some initial insights into the effect that accelerator programs can have on the entrepreneurial ecosystem, by exploring their effects on the entrepreneurial financing environment in the local region.

Our findings suggest that accelerators have regional impact on the entrepreneurial ecosystem. MSAs in which an accelerator is established subsequently exhibit more seed and early stage entrepreneurial financing activity, and this activity appears to not be restricted to accelerated startups alone, but spills over to non-accelerated companies as well, as attracting VCs to accelerator activities (mentorship, demo day) may increases the exposure of non-accelerator companies in area to investors.

Certainly, this increase in activity may simply represent a shift of investment dollars from other regions into the accelerator's region, possibly to the detriment of the other regions. Even if this is the case, however, if the presence of the accelerator increases activity in local region, this may meet the goals of both the accelerator founders and local policy makers. A second critique is that the companies being funded locally may simply be companies that would otherwise have gone to one of the coasts and been financed there, and now are instead financed in their original home regions. However, again, retaining companies locally is often a primary goal for local policy makers and for accelerator founders.

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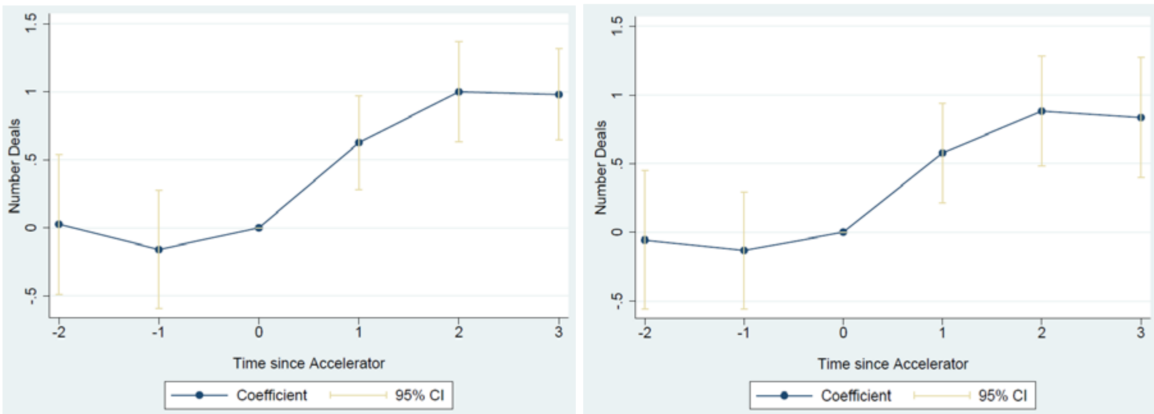
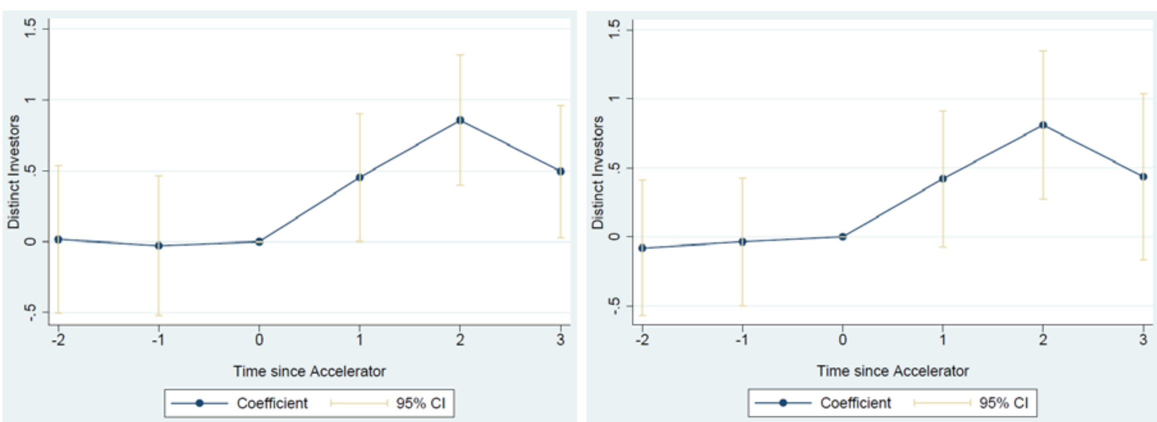
Figure1. Treatment Effect for Treated Region over Time—Number of Deals



Without MSA-specific linear time trend

With MSA-specific linear time trend

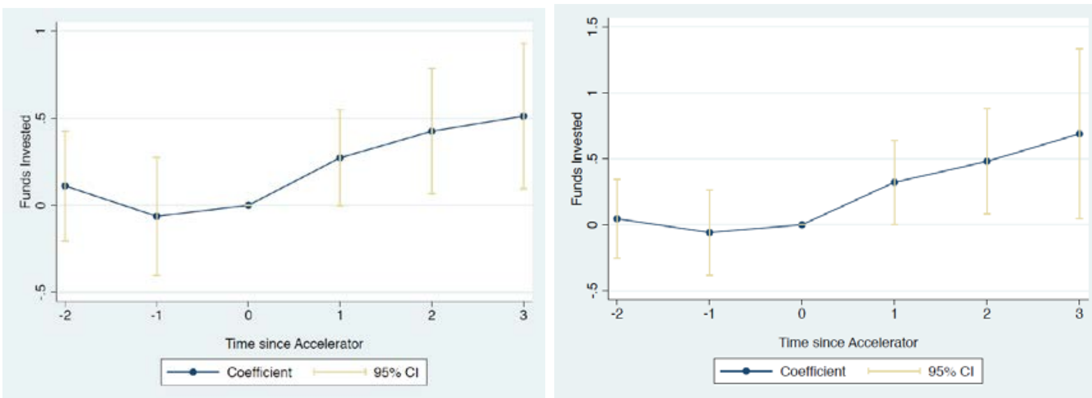
Figure 2. Treatment Effect for Treated Region over Time—Number of Distinct Investors



Without MSA-specific linear time trend

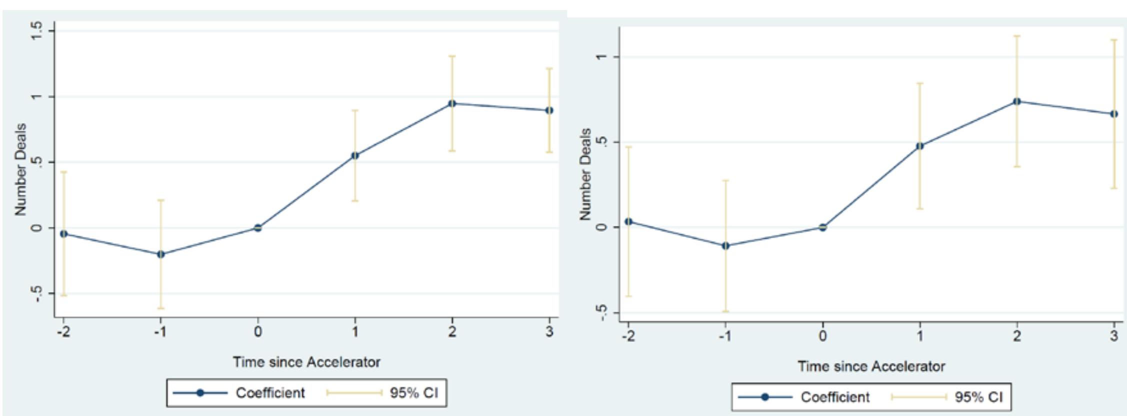
With MSA-specific linear time trend

Figure 3. Treatment Effect in Treated Region over Time—Total $ Funding



Without MSA-specific linear time trend	With MSA-specific linear time trend

Figure 4. Treatment Effect for Treated Industry in Treated Region over Time—Number of Deals (Triple-Diff)



Without MSA-specific linear time trend	With MSA-specific linear time trend

Table 1. U.S.-Based Accelerator Programs Founded 2007-2012

Accelerator Name	First Class Year	Location	Accelerator Name	First Class Year	Location
Y Combinator	2005	Silicon Valley, CA	Dreamit Ventures - NYC	2011	New York, NY
Techstars - Boulder	2007	Boulder, CO	gener8tor -- Milwaukee	2012	Milwaukee, WI
Dreamit Ventures - Philadelphia	2008	Philadelphia, PA	Hatch	2012	Norfolk, VA
AlphaLab	2008	Pittsburgh, PA	Blueprint Health	2012	New York, NY
Tech Wildcatters	2009	Dallas, TX	StartFast Venture Accelerator	2012	Syracuse, NY
Techstars - Boston	2009	Boston, MA	Accelerate Baltimore	2012	Baltimore, MD
Capital Factory	2009	Austin, TX	Telluride Venture Accelerator	2012	Telluride, CO
First Growth Venture Network	2009	New York, NY	Alchemist Accelerator	2012	Silicon Valley
Betaspring	2009	Providence, RI	LaunchHouse	2012	Cleveland, OH
Launchpad LA	2009	Los Angeles, CA	MindTheBridge	2012	Silicon Valley, CA
AngelPad	2010	San Francisco, CA	Techstars - Cloud	2012	San Antonio, TX
Brandery	2010	Cincinnati, OH	healthbox -- Chicago	2012	Chicago, IL
BoomStartup	2010	Sandy, Utah	StartEngine	2012	Los Angeles, CA
JumpStart Foundry	2010	Nashville, TN	SURGE Accelerator	2012	Houston, TX
Techstars - Chicago	2010	Chicago, IL	Triangle Startup Factory	2012	Durham, NC
Portland Incubator Experiment	2010	Portland, OR	Rock Health -- Boston	2012	Boston, MA
NYC Seed Start	2010	New York, NY	MuckerLab	2012	Santa Monica, CA
500 Startups	2010	Mountain View, CA	The Iron Yard	2012	Greenville, SC
Techstars - Seattle	2010	Seattle, WA	Bizdom - Detroit	2012	Detroit, MI
Entrepreneurs Roundtable Accelerator	2011	New York, NY	InnoSpring	2012	Santa Clara, CA
FinTech Innovation Lab	2011	New York, NY	New York Digital Health Accelerator	2012	New York, NY
NewMe	2011	Mountain View, CA	Co.Lab Accelerator	2012	Chattanooga, TN
Portland Seed Fund	2011	Portland, OR	Tandem	2012	Silicon Valley, CA
Techstars - NYC	2011	New York, NY	Blue Startups	2012	Honolulu, HI
Imagine K12	2011	Silicon Valley, CA	TechLaunch	2012	Montclair, NJ
Seed Hatchery	2011	Memphis, TN	ARK Challenge	2012	Fayetteville, AK
Rock Health -- San Francisco	2011	San Francisco, CA	gener8tor -- Madison	2012	Madison, WI
Amplify.LA	2011	Los Angeles, CA	Impact Engine	2012	Chicago, IL
Start Engine	2011	Los Angeles, CA	healthbox -- Boston	2012	Boston, MA
Capital Innovators	2012	St. Louis, MO			

Table 2. List of Data Sources for MSA Level Data

VARIABLE	DESCRIPTION	SOURCE
Funds Invested	Logged Yearly Sum of Early Stage VC Dollars in MSA	VentureXpert
Number Deals	Yearly Count of Early Stage VC Financing Events by MSA	VentureXpert
Distinct Investors	Yearly Count of Early Stage Investors in MSA	VentureXpert
Patent Count	Yearly Count of Utility Patents in MSA	USPTO
# STEM Grad. Students	Yearly Count of STEM Graduate Students by State	NSF
Firm Births	Yearly Count of New Firms by MSA	US Census BDS
University R&D Spending	Yearly Sum of University R&D Spending in MSA	NSF
Per Capita Income	Per Capita Income at MSA Level	US Census
Employment	Employment at the MSA Level	US Census

Table 3. Summary Statistics – Full Sample

Panel A: Summary Stats at the Year by MSA Level for Full Data

	Never-Treated	Ever-Treated	Treated, Pre-Treat	Treated, Post-Treat	Total
Funds Invested	1.45	11.78	9.64	14.91	2.53
	(4.44)	(7.64)	(7.93)	(5.95)	(5.80)
Number Deals	0.35	20.09	9.17	36.15	2.40
	(2.04)	(48.27)	(28.37)	(64.52)	(16.77)
Change in Number Deals (t-2)	0.05	5.22	2.52	9.20	0.59
	(1.22)	(18.11)	(11.64)	(24.24)	(6.14)
Change in Number Deals (t-3)	0.07	7.60	3.76	13.24	0.85
	(1.27)	(22.50)	(15.47)	(29.15)	(7.69)
Distinct Investors	0.51	23.58	10.78	42.42	2.91
	(2.58)	(53.28)	(30.12)	(71.48)	(18.69)
Patent Count	0.11	1.35	0.82	2.13	0.24
	(0.27)	(1.87)	(1.11)	(2.42)	(0.76)
# STEM Grad. Students	20.55	22.19	19.12	26.71	20.72
	(19.51)	(20.18)	(17.18)	(23.27)	(19.59)
Firm Births	1.06	7.64	6.48	9.34	1.74
	(2.16)	(11.04)	(9.67)	(12.64)	(4.56)
University R&D Spending	0.07	0.70	0.54	0.94	0.14
	(0.18)	(0.73)	(0.63)	(0.81)	(0.35)
Per Capita Income	34.78	42.34	40.24	45.43	35.57
	(5.99)	(9.31)	(9.67)	(7.81)	(6.81)
Employment	0.25	1.77	1.47	2.22	0.41
	(0.43)	(2.15)	(1.84)	(2.48)	(0.93)

mean coefficients; sd in parentheses

Panel B: Summary Stats at the Year by MSA Level excluding SF Bay Area and Boston

	Never-Treated	Ever-Treated	Treated, Pre-Treat	Treated, Post-Treat	Total
Funds Invested	1.45	11.07	9.23	14.09	2.38
	(4.44)	(7.55)	(7.81)	(6.02)	(5.60)
Number Deals	0.35	10.06	4.60	19.02	1.29
	(2.04)	(24.32)	(12.04)	(34.67)	(8.30)
Change in Number Deals (t-2)	0.05	2.84	1.41	5.19	0.32
	(1.22)	(9.46)	(6.43)	(12.67)	(3.26)
Change in Number Deals (t-3)	0.07	4.10	1.99	7.57	0.46
	(1.27)	(12.44)	(8.76)	(16.30)	(4.21)
Distinct Investors	0.51	12.10	5.89	22.29	1.63
	(2.58)	(28.19)	(13.77)	(40.38)	(9.70)
Patent Count	0.11	0.98	0.70	1.43	0.19
	(0.27)	(1.25)	(0.95)	(1.54)	(0.53)
# STEM Grad. Students	20.55	19.79	18.13	22.50	20.48
	(19.51)	(16.38)	(15.14)	(17.98)	(19.23)
Firm Births	1.06	7.49	6.23	9.56	1.68
	(2.16)	(11.45)	(9.78)	(13.56)	(4.52)
University R&D Spending	0.07	0.63	0.50	0.86	0.13
	(0.18)	(0.71)	(0.60)	(0.81)	(0.32)
Per Capita Income	34.78	41.06	39.59	43.48	35.39
	(5.99)	(8.50)	(9.24)	(6.47)	(6.54)
Employment	0.25	1.73	1.41	2.24	0.39
	(0.43)	(2.22)	(1.86)	(2.65)	(0.91)

mean coefficients; sd in parentheses

Table 4: Summary Statistics at the MSA-Year Level for Hazard-Rate Matched Sample

	Treated, Pre-treatment	Matched, Pre-treatment	Diff.	Treated, Post-treatment	Matched, Post-treatment	Diff.	Total
Funds Invested	8.67	7.93	0.74	13.25	9.30	3.95***	9.45
	(8.34)	(8.34)	(0.88)	(6.74)	(8.33)	(1.33)	(8.25)
Number Deals	1.58	1.93	-0.35	6.78	2.58	4.2***	2.88
	(2.41)	(3.36)	(0.31)	(7.80)	(3.45)	(1.09)	(4.79)
Change in Number Deals (t-2)	0.17	0.09	0.08	2.70	0.42	2.27***	0.68
	(2.11)	(2.14)	(0.26)	(4.15)	(2.67)	(0.63)	(2.89)
Change in Number Deals (t-3)	0.21	0.17	0.04	3.38	0.56	2.82***	0.88
	(2.20)	(2.57)	(0.31)	(4.72)	(2.67)	(0.69)	(3.26)
Distinct Investors	2.28	3.06	-0.85	6.61	4.34	2.26*	3.71
	(3.23)	(5.51)	(0.50)	(6.17)	(6.00)	(1.07)	(5.34)
Patent Count	0.56	0.48	0.08	0.83	0.76	0.07	0.62
	(0.62)	(0.63)	(0.07)	(0.73)	(0.89)	(0.14)	(0.71)
# STEM Grad. Students	19.39	20.96	-1.57	20.29	28.26	-7.96	21.54
	(14.60)	(18.25)	(1.74)	(14.41)	(23.42)	(3.38)	(17.67)
Firm Births	4.88	3.42	1.46**	5.52	3.55	1.97	4.33
	(3.98)	(4.43)	(0.44)	(4.54)	(4.08)	(0.77)	(4.32)
University R&D Spending	0.49	0.22	0.27***	0.66	0.38	0.27	0.42
	(0.54)	(0.35)	(0.04)	(0.58)	(0.46)	(0.09)	(0.51)
Per Capita Income	38.50	37.69	0.81	41.78	40.92	0.86	39.30
	(4.28)	(5.31)	(0.54)	(3.94)	(4.57)	(0.75)	(4.87)
Employment	1.22	0.75	0.47***	1.52	0.85	0.67	1.07
	(0.91)	(0.87)	(0.09)	(1.13)	(0.89)	(0.18)	(0.98)

mean coefficients; standard deviations in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Fixed Effects Models on Hazard-Rate Matched Subsample

	(1) Number Deals	(2) Number Deals	(3) Distinct Investors	(4) Distinct Investors	(5) Funds Invested	(6) Funds Invested
Accelerator Active	2.374***	2.043***	1.986***	1.856***	2.960**	3.899**
	(0.309)	(0.267)	(0.333)	(0.403)	(1.340)	(1.651)
Patent Count	0.678*	1.700**	0.647***	1.213	-5.114**	-4.743
	(0.139)	(0.421)	(0.104)	(0.465)	(2.443)	(2.854)
# STEM Grad. Students	1.015	1.110***	1.036	1.086	0.040	-0.116
	(0.024)	(0.037)	(0.034)	(0.067)	(0.206)	(0.350)
Firm Births	0.977	0.985	1.088	1.052	0.682	1.370
	(0.079)	(0.088)	(0.079)	(0.093)	(0.552)	(0.903)
University R&D Spending	1.841	2.563**	2.488**	3.468	7.843***	3.759
	(1.138)	(1.002)	(0.964)	(2.642)	(2.509)	(5.509)
Per Capita Income	0.881**	0.895	0.860***	0.894	-0.863***	-0.817
	(0.048)	(0.085)	(0.037)	(0.089)	(0.284)	(0.581)
Employment	0.075***	0.225	0.057***	0.068**	-12.093***	-31.075**
	(0.045)	(0.218)	(0.028)	(0.078)	(3.078)	(12.457)
Observations	451	451	451	451	451	451
R-squared					0.107	0.210
log-likelihood	-538.902	-486.561	-724.843	-662.893	-1357.225	-1329.485
MSA Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
MSA-Specific Linear Trend	NO	YES	NO	YES	NO	YES

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Triple Diff Models on Hazard-Rate Matched Sub-Sample

	(1) Number Deals	(2) Number Deals	(3) Distinct Investors	(4) Distinct Investors	(5) Funds Invested	(6) Funds Invested
Treated Region X Treated Industry X Post-Treatment	4.921*** (1.888)	4.326*** (1.601)	2.953** (1.311)	2.695** (1.204)	0.926 (3.447)	0.175 (3.667)
Treated Industry X Post-Treatment	0.984 (0.172)	1.153 (0.209)	1.242 (0.210)	1.386* (0.255)	2.947 (2.016)	3.819* (2.240)
Post-Treatment X Treated Region	0.526* (0.180)	0.456** (0.165)	0.624 (0.256)	0.570 (0.241)	-0.830 (0.971)	-1.672 (1.088)
Patent Count	0.662** (0.121)	1.600* (0.392)	0.596*** (0.099)	1.200 (0.380)	-2.148** (0.905)	2.720 (2.664)
# STEM Grad. Students	0.983 (0.021)	1.074** (0.031)	0.979 (0.032)	1.048 (0.048)	-0.290 (0.182)	0.148 (0.284)
Firm Births	0.918 (0.074)	0.952 (0.095)	0.999 (0.072)	1.019 (0.101)	0.079 (0.748)	0.579 (0.897)
University R&D Spending	1.635 (0.710)	1.309 (0.646)	1.817** (0.482)	1.237 (0.980)	1.258 (1.757)	-2.423 (3.237)
Per Capita Income	0.885** (0.044)	0.865 (0.079)	0.884*** (0.039)	0.872 (0.092)	-0.096 (0.173)	-0.384 (0.459)
Employment	0.109*** (0.059)	0.301 (0.347)	0.122*** (0.064)	0.115* (0.130)	-3.340 (5.732)	-5.056 (13.365)
Observations	902	902	902	902	902	902
					0.146	0.198
	-838.723	-782.321	-1233.391	-1156.923	-3008.356	-2980.025
MSA Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
MSA-Specific Linear Trend	NO	YES	NO	YES	NO	YES

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Fixed Effects Models for Near and Distant Investors

	(1) Number Deals, Far	(2) Number Deals, Far	(3) Number Deals, Near	(4) Number Deals, Near	(5) Distinct Investors, Far	(6) Distinct Investors, Far	(7) Distinct Investors, Near	(8) Distinct Investors, Near	(9) Funds Invested, Far	(10) Funds Invested, Far	(11) Funds Invested, Near	(12) Funds Invested, Near
main												
Accelerator Active	1.907***	1.369	2.647***	2.261***	1.857***	1.193	2.132***	2.130***	0.887	0.304	3.975***	4.849***
	(0.329)	(0.376)	(0.466)	(0.384)	(0.437)	(0.394)	(0.502)	(0.571)	(1.488)	(2.065)	(1.026)	(1.541)
Patent Count	0.528***	1.188	0.818	2.696*	0.557***	1.008	0.757	1.691	-5.398**	-6.487**	-2.788	3.600
	(0.085)	(0.503)	(0.260)	(1.431)	(0.112)	(0.554)	(0.208)	(0.921)	(2.057)	(2.664)	(1.685)	(3.160)
# STEM Grad. Students	1.022	1.098	1.009	1.178***	1.035	1.125	1.032	1.111	-0.376	-0.334	0.053	0.277
	(0.034)	(0.077)	(0.060)	(0.069)	(0.056)	(0.110)	(0.045)	(0.079)	(0.284)	(0.475)	(0.191)	(0.356)
Firm Births	1.095	1.129	0.895	0.998	1.039	1.026	1.056	1.075	0.166	0.453	0.423	0.290
	(0.084)	(0.164)	(0.080)	(0.108)	(0.088)	(0.145)	(0.099)	(0.117)	(0.563)	(0.955)	(0.545)	(0.956)
University R&D Spending	1.374	2.418*	1.655	1.909	1.993	5.330*	2.893***	2.633	6.551***	2.500	5.036***	4.539
	(0.552)	(1.240)	(1.407)	(1.152)	(0.982)	(4.591)	(1.192)	(2.671)	(2.169)	(4.661)	(1.608)	(3.271)
Per Capita Income	0.949	0.871	0.819***	0.798**	0.936	0.816	0.811***	0.914	-0.470*	-0.679	-0.778***	-0.416
	(0.046)	(0.121)	(0.052)	(0.077)	(0.061)	(0.125)	(0.041)	(0.097)	(0.262)	(0.650)	(0.186)	(0.445)
Employment	0.039***	0.017**	0.267	1.353	0.039***	0.022*	0.089***	0.185	-9.953**	-15.461	1.943	9.567
	(0.020)	(0.034)	(0.253)	(2.399)	(0.032)	(0.046)	(0.056)	(0.319)	(4.143)	(16.407)	(3.259)	(14.387)
Observations	407	407	396	396	407	407	418	418	451	451	451	451
R-squared									0.106	0.219	0.081	0.174
log-likelihood	-327.076	-299.782	-403.327	-355.358	-410.941	-366.817	-475.304	-435.849	-1350.776	-1320.103	-1346.762	-1322.686
MSA Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
MSA-Specific Linear Trend	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Fixed Effects Models with Accelerator Quality

	(1) Number Deals	(2) Number Deals	(3) Distinct Investors	(4) Distinct Investors	(5) Funds Invested	(6) Funds Invested
Highly Rated Accelerator	3.035^{***}	1.914^{***}	2.253^{***}	1.868^{**}	3.956^{***}	3.117
	(0.568)	(0.280)	(0.421)	(0.541)	(1.418)	(2.060)
Unrated Accelerator	1.771^{**}	2.239^{***}	1.712^{**}	1.840^{*}	1.791	4.605^{**}
	(0.401)	(0.484)	(0.409)	(0.577)	(1.624)	(2.213)
Patent Count	0.655^{**}	1.723^{**}	0.639^{***}	1.211	-5.185^{**}	-4.678
	(0.117)	(0.414)	(0.096)	(0.452)	(2.405)	(2.847)
# STEM Grad. Students	1.026	1.109^{***}	1.037	1.086	0.031	-0.129
	(0.022)	(0.038)	(0.036)	(0.067)	(0.211)	(0.354)
Firm Births	1.006	0.993	1.100	1.051	0.746	1.444
	(0.075)	(0.087)	(0.079)	(0.088)	(0.536)	(0.952)
University R&D Spending	2.017	2.547^{**}	2.565^{***}	3.470	7.605^{***}	3.897
	(0.925)	(0.991)	(0.855)	(2.634)	(2.429)	(5.534)
Per Capita Income	0.863^{***}	0.897	0.854^{***}	0.894	-0.876^{***}	-0.813
	(0.046)	(0.085)	(0.036)	(0.089)	(0.280)	(0.581)
Employment	0.047^{***}	0.193^{*}	0.047^{***}	0.069^{**}	-13.326^{***}	-32.590^{**}
	(0.029)	(0.190)	(0.024)	(0.077)	(3.003)	(13.869)
Observations	451	451	451	451	451	451
R-squared					0.195	0.282
log-likelihood	-534.116	-486.453	-723.156	-662.892	-1514.608	-1488.938
MSA Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
MSA-Specific Linear Trend	NO	YES	NO	YES	NO	YES

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Fixed Effects Models with Regional Angel Groups

	(1) Number Deals	(2) Number Deals	(3) Distinct Investors	(4) Distinct Investors	(5) Funds Invested	(6) Funds Invested
Accelerator Active X No Angel Group	4.886***	5.586***	3.694***	3.247*	2.807	3.336
	(1.684)	(3.198)	(1.546)	(2.022)	(1.948)	(2.113)
Accelerator Active X Angel Group	2.333***	1.998***	1.960***	1.830***	2.678**	3.236*
	(0.302)	(0.263)	(0.330)	(0.405)	(1.190)	(1.694)
Patent Count	0.683*	1.709**	0.650***	1.218	-4.494**	-4.090
	(0.141)	(0.428)	(0.105)	(0.468)	(2.161)	(2.463)
# STEM Grad. Students	1.010	1.110***	1.032	1.086	-0.094	-0.174
	(0.024)	(0.037)	(0.035)	(0.067)	(0.198)	(0.323)
Firm Births	0.973	0.986	1.084	1.053	0.503	1.099
	(0.078)	(0.088)	(0.079)	(0.093)	(0.503)	(0.787)
University R&D Spending	1.881	2.616**	2.526**	3.500	7.422***	3.842
	(1.155)	(1.035)	(0.970)	(2.670)	(2.296)	(4.800)
Per Capita Income	0.883**	0.896	0.861***	0.894	-0.772***	-0.720
	(0.049)	(0.085)	(0.037)	(0.090)	(0.260)	(0.566)
Employment	0.080***	0.221	0.060***	0.067**	-9.882***	-25.399**
	(0.048)	(0.214)	(0.030)	(0.077)	(2.827)	(9.642)
Observations	451	451	451	451	451	451
R-squared					0.107	0.210
log-likelihood	-537.951	-486.078	-723.905	-662.662	-1357.223	-1329.484
MSA Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
MSA-Specific Linear Trend	NO	YES	NO	YES	NO	YES

Table 10: Fractional Logit for Early Stage Funding as Proportion of Total Funding

	(1) Proportion Early Funding $	(2) Proportion Early Funding $	(3) Proportion Early Funding (# Deals)	(4) Proportion Early Funding (# Deals)	(5) Proportion Early Funding $	(6) Proportion Early Funding $	(7) Proportion Early Funding (# Deals)	(8) Proportion Early Funding (# Deals)
Industry Segment	Software/IT	Software/IT	Software/IT	Software/IT	All Other	All Other	All Other	All Other
Accelerator Active	2.822***	3.739**	3.244***	4.058***	0.518	0.728	0.366	0.252
	(1.123)	(2.115)	(1.186)	(2.063)	(0.317)	(0.469)	(0.269)	(0.390)
Patent Count	0.476	1.495	0.786	2.954	0.663	0.732	0.230	0.017
	(0.439)	(1.641)	(0.418)	(2.292)	(0.541)	(0.701)	(0.444)	(0.596)
# STEM Grad. Students	1.118	1.165	1.121**	1.222*	0.113	-0.076	0.102	-0.127
	(0.079)	(0.173)	(0.065)	(0.145)	(0.088)	(0.091)	(0.087)	(0.101)
Firm Births	1.055	1.141	1.072	1.125	-0.034	0.039	0.059	0.089
	(0.214)	(0.464)	(0.178)	(0.380)	(0.146)	(0.242)	(0.144)	(0.232)
University R&D Spending	1.413	0.233	4.575**	1.006	1.460***	0.319	0.960***	0.214
	(0.680)	(0.461)	(2.858)	(2.047)	(0.384)	(0.733)	(0.342)	(0.568)
Per Capita Income	0.769**	0.859	0.785**	0.877	-0.039	0.212	-0.037	0.070
	(0.092)	(0.198)	(0.077)	(0.152)	(0.081)	(0.168)	(0.065)	(0.127)
Employment	0.596	0.009	0.154	0.005	-1.797	-9.462**	-2.189	-6.888**
	(1.086)	(0.050)	(0.186)	(0.019)	(1.528)	(4.489)	(1.365)	(3.205)
Observations	484	484	484	484	484	484	484	484
log-likelihood	-176.317	-161.142	-187.439	-170.907	-175.930	-158.746	-187.263	-173.064
MSA Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
MSA-Specific Linear Trend	NO	YES	NO	YES	NO	YES	NO	YES

Table 11: Fractional Logit for Software/IT Funding as Proportion of Total Funding

	(1) Proportion Accel Funding $	(2) Proportion Accel Funding $	(3) Proportion Accel Funding (# Deals)	(4) Proportion Accel Funding (# Deals)	(5) Proportion Accel Funding $	(6) Proportion Accel Funding $	(7) Proportion Accel Funding (# Deals)	(8) Proportion Accel Funding (# Deals)
Stage	Early	Early	Early	Early	Later	Later	Later	Later
Accelerator Active	1.673*	1.442	2.671***	2.744***	-0.430	-0.249	-0.276	-0.095
	(0.507)	(0.696)	(0.666)	(1.031)	(0.374)	(0.444)	(0.332)	(0.340)
Patent Count	0.669	1.697	1.221	3.827*	0.399	2.100*	0.264	1.115
	(0.370)	(1.431)	(0.549)	(2.746)	(0.708)	(1.175)	(0.512)	(0.903)
# STEM Grad. Students	0.996	1.155	1.073	1.199	-0.128	-0.136	-0.119	-0.197*
	(0.078)	(0.166)	(0.088)	(0.146)	(0.102)	(0.144)	(0.089)	(0.117)
Firm Births	1.059	0.888	1.025	0.966	0.049	-0.254	0.167	0.005
	(0.208)	(0.274)	(0.173)	(0.251)	(0.148)	(0.222)	(0.138)	(0.161)
University R&D Spending	4.117**	5.797	6.907***	9.124	0.289	0.996	0.157	2.030**
	(2.877)	(11.910)	(5.165)	(18.897)	(0.616)	(1.068)	(0.548)	(1.003)
Per Capita Income	0.871*	0.798	0.842**	0.779	0.018	-0.112	0.006	-0.103
	(0.070)	(0.157)	(0.065)	(0.128)	(0.089)	(0.154)	(0.088)	(0.153)
Employment	0.559	29.432	0.274	1.094	-0.697	0.642	-0.895	-1.848
	(0.516)	(92.797)	(0.313)	(3.113)	(1.540)	(2.972)	(1.335)	(2.488)
Observations	484	484	484	484	484	484	484	484
log-likelihood	-178.286	-166.892	-176.697	-164.433	-187.699	-168.396	-185.758	-170.302
MSA Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
MSA-Specific Linear Trend	NO	YES	NO	YES	NO	YES	NO	YES