Financing Entrepreneurship through the Tax Code: Angel Investor Tax Credits

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Abstract

Many jurisdictions seek policy tools to stimulate high-growth entrepreneurship. Angel investor tax credits, which subsidize startup investment by wealthy individuals (i.e. "angels"), are an attractive option because they allow the market to "pick winners" and have relatively low administrative burdens. This paper studies these programs using state-level event studies and a within-program comparison of tax credit beneficiary firms with their rejected counterparts. We find no evidence that angel tax credits have significant effects on local entrepreneurial activity. The programs may have a limited effect in part because a large share of investor-company pairs benefiting from the tax credits do not suffer from the severe information asymmetry that is believed to cause financial constraints among early stage, risky, and potentially high-growth startups. Indeed, just 9.5 percent of beneficiary companies did not previously raise external equity, have no executive receiving an investor tax credit, and have activities related to the IT/Web/Computer sector.

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"We need policies that get capital flowing to the whole country, not just for select cities. One idea is to create a fund for states to plow money into entrepreneurship....[There are] tax breaks for investors and special interests...We need a tax code that recognizes that investors are not the only engine of growth."

- Vice President Joe Biden, March 2018[1]

1 Introduction

Many local governments are eager to encourage high-growth entrepreneurship as a means to create high-skill jobs and foster economic growth. Subsidies could be effective if financial frictions leave promising early stage startups financially constrained, which may be more often the case outside of the major hub cities (Kerr & Nanda 2011).[2] One policy tool at the state level is to subsidize angel investment in local ventures through the tax code. Angel investors are high-net worth individuals who provide private early-stage capital for startups, and are often a startup's first source of outside capital.[3] Since the 1990s, 30 U.S. states have implemented angel investor tax credits, which are deductions from income taxes owed (not from taxable income).

Subsidizing investors through the tax code has several attractive features relative to alternatives such as direct grants to firms. First, there is no need for the government to "pick winners," which might lead to regulatory capture (Lerner 2009). Tax credits retain market incentives, in theory leaving expert investors with some skin in the game. Second, the administrative burden of tax subsidies is relatively low. Keuschnigg & Nielsen (2002) show that by lowering the cost of starting a new business, investment subsidies should in theory increase entrepreneurship and success conditional on entry. As a targeted subsidy, angel investor tax credits avoid the blunter instrument of lowering capital gains taxes, which applies to a much broader set of investments (Poterba 1989).

Yet there are challenges to implementing angel tax credits. First, a tax credit will only

[1]https://bidenforum.org/geography-can-shape-opportunity-joe-biden-wants-to-change-that-1617d07f02c6

[2]See also Chen, Gompers, Kovner & Lerner (2010) and Krishnan, Nandy & Puri (2014)

[3]See The American Angel, a report from the Angel Capital Association, for details on angel investing. https://www.angelcapitalassociation.org/data/Documents/TAAReport11-30-17.pdf?rev=DB68

be effective if the company whose investor received a tax credit (henceforth "beneficiary company") would not otherwise receive financing. If the company would obtain financing regardless, then the policy is simply a transfer from the government to investors or other company stakeholders. In such a case, the subsidy crowds out alternative funding sources. Second, the tax credit must target companies with the potential to grow or innovate. That is, there will be few economic benefits such as jobs or real investment if the target company is extremely low quality. In sum, to be useful angel tax credit programs must reach companies with positive NPV investment opportunities that nonetheless face external financing frictions.

This paper provides the first evaluation of U.S. state angel investor tax credit programs. Are these tax subsidies a means to "get capital flowing to the whole country"? Or are they "tax breaks for investors" that fail to stimulate the engines of growth? While this study does not aim to provide a definitive answer to these questions, our analysis may provide useful insights to further the debate. At both the aggregate state level and the applicant company level, we find no evidence that the programs have positively affected local entrepreneurial activity or angel investment. Considered individually, many of our null estimates do not allow us to rule out the presence of a small positive effect. However, the results together provide compelling evidence in support of the conclusion that these programs have not been particularly effective. In the last part of the paper, we document features of these programs that may explain our findings, and conclude that the tax credits are often allocated to company-investor pairs that do not depend on the credit; in other words, in many cases beneficiary companies appear likely to have received financing regardless of whether an investor obtained a tax credit.

The absence of an effect is in striking contrast to evidence that other policies to encourage innovation and entrepreneurship are useful. Bloom, Griffith & Van Reenen (2002), Wilson (2009), and Rao (2016), among others, show that R&D tax credits stimulate innovation investment. Higher corporate and income taxes deter new business formation and superstar inventor mobility, respectively.[4] Bronzini & Iachini (2014) and Howell (2017) demonstrate

[4]On the former, see Mukherjee et al. (2017), Serrato & Zidar (2018), and Curtis & Decker (2018) in the U.S., and Da Rin et al. (2011) in Europe. Relatedly, Zwick & Mahon (2017) show that small firms are especially sensitive to temporarily lower investment tax rates. On the latter, see Akcigit et al. (2016) and

positive effects of grant programs for high-tech startups. Finally, accelerator participation and winning new venture competitions – both of which often benefit from public funds – are also useful for startups (McKenzie 2017, Gonzalez-Uribe & Leatherbee 2017 and Howell 2019). The above policies are diverse, yet they have a notable feature that distinguishes them from investor subsidies: they target firms or individuals performing real activities, not the financial intermediary.

We begin by providing comprehensive and systematic information about all 30 state programs, based on examination of each state's tax codes (Table 1 and Appendix Table A.1). The programs are quite generous, as the share of qualified investment that can be deducted from the investor's income taxes, or reimbursed as a cash grant to out-of-state investors, is 33 percent on average and 28 percent at the median. Suppose an angel invested $100,000 with the expectation of a "2x multiple," or 200 percent cash-on-cash return (alongside IRR, this is the standard industry return metric). The median tax credit transforms this into a 2.8x multiple. There is wide variation in the amount of money states allocate to the programs, with the smallest program at $0.75 million and the largest at $50 million. While these numbers are a small share of total tax revenue, they are large relative to state funding for entrepreneurship, both public and private, as well as to total state angel investment (see Section 2.1).

We assess whether these programs spur subsequent financing and small firm activity growth at the state and company levels. At the state level, we use a difference-in-differences design to assess whether program introductions were associated with changes in local angel financing and high-tech new firm formation. In the main analysis, we compare states that introduced the tax credit post-2001 to nearby states. The primary outcome is high-tech young firm employment, though we also consider alternative industry and age definitions, including all small firms. We consistently find economically small effects that are never significantly different from zero. For example, the coefficient on employment in high-tech new firms is 4 percent, with a 95 percent confidence interval between -15 percent and 10 percent. Furthermore, we find no significant effects on the amount and number of angel or VC investments in the state. While the we cannot rule out a small positive effect, evidence

Moretti & Wilson (2017).

that the tax-credit caused a meaningful increase on entrepreneurial activity is extremely weak.

However, it is possible that the programs had positive effects, but were too small relative to the state economy to influence aggregate measures. To examine the effect at the company level, we hand-collect annual information for 12 states about applicant companies between 2005 and 2018. For all but two of these states, we also observe companies that were certified for an investor to receive a tax credit but for which no tax credit was ever issued ("failed applicants"). Our main outcome variables are subsequent financing, employment, and exit (experiencing an acquisition or IPO), based on matching applicant firms to external commercial databases.[5]

Failed applicants are a useful comparison group to the beneficiary companies because they are in the same state and indicated interest in the tax credit. However, they are also systematically different. There are two reasons that a certified company would fail to have an investor claim a tax credit. One is that no investment deal occurred, in which case the company may have sought but failed to raise angel investment or raised money from a source that did not claim the state tax credit. The other is that the company applied after the state ran out of funding. Late applicants could be more poorly managed. There is, in sum, no reason to think that failed applicants will be higher quality than beneficiary companies. Indeed, failed applicants raised less previous financing, and they had lower pre-application employment. We therefore expect that any bias in the analysis will be towards finding a positive effect of having an investor receive a tax credit.

Consistent with positive bias, beneficiary companies are on average more successful than their rejected counterparts. However, after controlling for previous financing, this relationship disappears. In our preferred specifications, we find fairly precise zero effects on financing, employment, and exit. For example, the relationship between receiving a tax credit and having at least 25 employees in the second year after the tax credit year is -0.021 percentage points in our preferred specification, with a 95 percent confidence interval ranging from -0.5 to 0.5 percentage points, relative to a mean of about three percent. Consistent with the aggregate analysis, we cannot detect any evidence that the

[5] We use Crunchbase, CB Insights, VentureXperts, and Dunn & Bradstreet.

tax credit programs positively affect beneficiary company financing or growth. As a robustness test, we find similar results using a matching estimator in which control companies are those that received similar amounts of previous financing, but are in a different state in the same Census division that never had a tax credit program.

Why did the programs fail to significant raise start-up activity in the local market? To begin to answer this question, it is important to clarify the conditions under which we would expect to observe large effects. The main motivation for subsidizing angel investment is that financing frictions inhibit optimal investment (Jensen & Meckling 1976, Stiglitz & Weiss 1981, Myers & Majluf 1984). Information asymmetry and agency conflicts between managers and investors reduce the investor's willingness to provide capital despite the company having deserving investment opportunities. Information asymmetry is especially severe among startups (Gompers & Lerner 1997, Gompers & Sahlman 2001). Longstanding research shows these financing frictions can translate into reduced real expenditure on investment by the company (Hoshi, Kashyap & Scharfstein 1991, Hubbard 1998). This literature suggests that subsidies should target those young, entrepreneurial firms facing the most severe information asymmetries. In this framework, a tax credit will foster entrepreneurial activity if it reduces the cost of external financing sufficiently to induce an investor to put money into a local business who would not have otherwise invested.

In light of this theoretical motivation, we document three facts that may shed light on the null effects. First, beneficiary companies tend to already be well-financed. This contrasts with a common perception that angel investor tax credits target a company's initial external investment. We find that 37 percent of beneficiary companies previously received external financing, with large dollar amounts relative to the average angel deal. This suggests that a significant share of firms that received the tax credit may have been able to raise funding independently from the program. Second, beneficiary companies are less likely to be in the IT/web/computer sector than VC-backed startups in general. This sector is important, as it comprises 65 percent of VC-backed companies and is strongly associated with innovative, high-tech, high-growth firms. We find that just 27 percent of beneficiary companies are in the IT/web/computer sector, where we try to be as generous as possible in assigning companies to this sector. This appears to be somewhat in contrast with program rules in many states that seek to limit eligibility to high-growth industries; it seems that a wide variety of companies successfully claim in their application that some aspect of what they do is, for example, "IT-related." The industry composition may help explain our results for two reasons. First, high-tech sectors likely face more severe financing frictions than traditional industries. Second, these sectors are more likely to have a positive impact on economic activity, either through direct growth or indirectly by generating positive externalities on the local market (Griliches 1992, Acs et al. 1994).

Third, we show that investors benefiting from the tax credit are often insiders of the firm. For five states, we observe the identities of investors who received a tax credit linked to the beneficiary company. We find that 33 percent of the companies for which we observe the investor-company link have at least one investor who is also a company executive. (This rate may be an underestimate, as it is not straightforward to identify insiders.) Insider investors by definition do not face information asymmetry, which may help explain why subsidizing them would have a limited impact.

In sum, our data suggests that the programs have a limited effect on entrepreneurial activity and angel investment because they tend to target companies and investment that do not suffer from the financial constraints we associate with early stage, risky, and potentially high-growth startups. Indeed, just 9.5 percent of beneficiary companies have no insider investment, are in the IT/Web/Computer sector, and did not previously raise external equity. To the degree that beneficiary companies would have been able to raise additional financing if their investors had not received a tax credit, the subsidies crowd out private investment.

One contribution of this paper is to describe state investor tax credit programs, which to our knowledge have not been characterized comprehensively or studied academically. In doing so, we also shed light on the makeup of over 5,600 individuals who receive angel tax credits in states where we observe investor names. For example, 79 percent are in-state, 87 percent are male, and 95 percent are white. The majority of the data on beneficiary companies and their investors have not previously been public and were hand-collected, but we can make complete, identified data available for future use.[6] Understanding the angel

[6]Complete data with firm and investor identities will be available on the authors' websites.

investor ecosystem is important, as angel investors fund far more new ventures than venture capital firms; for example, in 2017, they invested about $24 billion in 61,560 startups, while in 2016, VCs invested $69.1 billion in 7,751 U.S. firms.[7] Our paper joins a growing new literature focusing on angel investment, which includes Kerr, Lerner & Schoar (2011), Bernstein, Korteweg & Laws (2017), Ewens & Townsend (2018), and Lerner, Schoar, Sokolinski & Wilson (2018), and Lindsey & Stein (2019).

Potentially consistent with our results, Gonzalez-Uribe & Paravisini (2019) find what they describe as "low take-up" of a UK angel investor subsidy program that eliminated capital gains taxes, lowered income taxes, and lowered capital gains taxes, and subsidized after-tax losses. They ascribe the low take-up to large costs to startups of issuing equity.[8] Our study is different both in its agenda and methodology. We evaluate whether a policy to subsidize angel investment crowds out private investment, while their objective is to understand how firms respond to the cost of equity.

Research in entrepreneurial finance has demonstrated the importance of frictions, especially information asymmetry (Duchin et al. 2010, Acharya & Subramanian 2009, Cornaggia et al. 2015, Bernstein, Giroud & Townsend 2016, Hombert & Matray 2016, Howell 2019). These frictions appear to be unevenly distributed, with some areas benefiting from innovation clusters and others suffering from an absence of new firms (Baumol 1990, Foster, Haltiwanger & Syverson 2008, Gennaioli et al. 2012, Haltiwanger et al. 2013 Decker et al. 2014). Public policies to promote entrepreneurial activity have the potential for large social welfare gains. The specific nature of our analysis implies that we cannot assess how angel investor tax credits might operate outside our context. However, our result that the programs have no discernible effect is at a minimum relevant to U.S. state-level policymakers. While the funding dedicated to angel investor tax credits is generally small relative to the total state budgets, there are meaningful opportunity costs: The programs are typically a large share of state entrepreneurship funding and there are

[7] UNH Center for Venture Research Angel Market Report 2017, https://paulcollege.unh.edu/sites/default/files/resource/files/2017-analysis-report.pdf and NVCA 2017 Yearbook, https://nvca.org/blog/nvca-2017-yearbook-go-resource-venture-ecosystem/

[8] There is less evidence and it is more mixed on how tax rates affect VC investments; while Cullen & Gordon (2007) and Bock & Watzinger (2017) find that higher capital gains taxes reduce investment, Jeng & Wells (2000) find no effect and Da Rin et al. (2006) find economically small effects. Poterba (1989) points out that most investors in VC funds, such as endowments and pension funds, are in any event tax exempt.

well-established positive effects of other policy tools.

2 Angel Tax Credit Programs

This section explains how angel tax credit programs work (Section 2.1). For a subset of the programs, we observe identities of angel investors. We discuss their characteristics in Section 2.2.

2.1 State Angel Tax Credit Programs

Since 1998, 30 states have employed angel investor tax credit programs to encourage local high-growth entrepreneurship. To our knowledge, no similar program existed in previous years; they appear to have been motivated by the rise of Silicon Valley and the Dotcom boom. The typical motivation is to raise economic activity locally, in particular through an increase in firms employing high-skill, high salary workers. For instance, a typical motivation is as follows: "Wisconsin established the Qualified New Business Venture (QNBV) Program in 2005 to drive investment into early-stage companies with the promise of creating next-generation economic opportunity in Wisconsin...the QNBV Program helps companies create high-paying, high-skill jobs throughout Wisconsin."[9] As nearly all programs in cite job creation and additional investment as the central goals, the analysis in subsequent sections focuses on employment and financing outcomes.

A contribution of this paper is to provide – to our knowledge – the first systematic and comprehensive documentation of U.S. state angel tax credits, based on examination of the original legislation. A few key variables are in Table 1: the year that the program went into effect, the expiration year, the share of an investment the investor may claim as a deduction from his tax liability (note these are not deductions from taxable income), and the total allocated funding. The investment share varies dramatically, from 10 percent in New Jersey to 100 percent in Hawaii. Some programs are larger than others; for example, Wisconsin permits 50 percent of the investment to be deducted and allocates \$30 million to the program, while New Mexico permits 25 percent to be deducted and allocates just \$2

[9] Wisconsin Economic Development Corporation 2013 Qualified New Business Venture Program Report.

million. There appears to be some competition across states; for example, Iowa increased its investment deduction from 20 to 25 percent for most investors in order to on par with nearby Minnesota and Wisconsin.[10] Similarly, Wilson (2009) shows that while state R&D tax credits do increase local R&D, the effect largely reflects reallocation from other states.

While the programs are typically small relative to overall state budgets, they are significant portions of the funding allocated to supporting entrepreneurship or small businesses. For example, funding in Ohio, Minnesota, and Wisconsin are respectively 19, 58, and 86 percent of annual state funding for high-tech jobs or small businesses, most of which takes the form of grants.[11] The state funding amounts are also in many cases large relative to total annual angel investment in the state, averaged across years where the program is in force (Appendix Table A.1 column 6). For example, dedicated funding is 47 percent of total angel investment in North Carolina and 163 percent in Maine. In many cases, programs do not exhaust allocated funds.

Complete rules and eligibility requirements are listed in subsequent columns of Appendix Table A.1. Where a cell is blank, it means that the state's rules do not explicitly address the criterion. Most states allow angel groups or VCs to benefit as well as individuals. Further, many states use a refundable credit, such that investors may receive a cash grant in lieu of a tax liability deduction if they are out of state or otherwise do not qualify. Most programs have a first-come-first-serve policy in the event funding runs out. In many states the tax credit can be transferred, sold, or carried forward. All but two programs have a maximum company size, defined in terms of revenue, assets, employees or some combination. Fourteen have a maximum age for eligibility, most often five years. Importantly, because of the nature of tax-credit, these programs should not directly relax investor financing constraints, because they do not receive the credit until after they have completed the investment.[12] This

[10] Based on interview with program officials.

[11] The other programs considered for Ohio are the Pre-Seed/Seed Plus Fund Capitalization Program, The Technology Validation and Start-up Fund, The Ohio Third Frontier initiative and the JobsOhio Research and Development Center Grant Program. The other programs considered for Wisconsin are the Seed Accelerator Program, SBIR/STTR Matching Grant Program, Entrepreneurial Micro-Grant, Capital Catalyst, Entrepreneurship Support Program. The other programs considered for Minnesota are the Innovation Voucher Program and the Minnesota Job Creation Fund.

[12] In principle, investors could borrow against the future tax credit. However, this is very unlikely because in any case the investment has to be completed before the tax-credit is issued. Anecdotal evidence seems to confirm this hypothesis.

is different than programs such as direct grants that provide companies with money upfront.

Programs consistently require the business to be tied to the local economy. For instance, Illinois requires that at least 51 percent of a company's employees be located in-state and the "principal place of business" to be in Illinois. Most states have some industry or "innovation" condition, but these are are often broad and subjective. Illinois demands that a beneficiary company have "the potential for increasing jobs, increasing capital investment in Illinois, or both" and be "principally engaged in innovation." Some features may be surprising; for example, 22 programs explicitly permit the investor to be employed by the company, while only six programs forbid this. We will return to this in Section 5.

The average investment amount is \$376,000, which is very close to the average angel deal size in the U.S., but much larger than survey data on the average individual angel investment.[13] However, states with tax credit programs do not include the major entrepreneurial finance hubs of California and Massachusetts. In 2016, total angel investment in tax credit states was \$1.97 billion, with a state average of \$70 million, compared to a total of \$4.89 billion and average of \$223 million in non-tax credit states. This difference appears to have been growing over time. For example, in 2013 states with tax credits averaged \$65 million in angel investment, compared to \$158 million in non-tax credit states.[14]

2.2 Angel investor characteristics

We collected information about angel investor identities for seven states; in some cases, this is publicly available, and in other cases it was provided to us directly by program officials. We can make all of it, as well as the company-level information introduced in Section X, publicly available. For the seven states, we observe all investors, though the years from which we begin to have data vary. In total, there are 5,637 unique individual investors in these seven states (this excludes group investors, such as VC firms) described in Table 2.

[13]The average angel deal size in recent years is about \$390,000, according to the UNH Center for Venture Research Angel Market Report 2017. available at https://paulcollege.unh.edu/sites/default/files/resource/files/2017-analysis-report.pdf. Huang et al. (2017) find in survey data that the average angel check is around \$35,000.

[14]Statistics based on angel and seed financing compiled from CB Insights and Crunchbase.

They are skewed towards Minnesota, which comprises 39 percent of the data.

Subsequent statistics in the data have sample sizes that reflect the number of investors for which the variable could be identified.[15] As information asymmetry may be more severe when investors are geographically far away (Chen et al. 2010, Bernstein, Giroud & Townsend 2016), it is possible that there is inadequate angel investment outside of entrepreneurial hubs such as Silicon Valley. Table 1 shows that the states that employ angel investor tax credit programs tend not to have significant entrepreneurial financing activity. As VCs are known to be quite concentrated in cities while angels are more dispersed (e.g. Huang et al. 2017), local angels could act as a bridge to the VC market. Consistent with this, we find that 79 percent of subsidized angel investors are located in the same state as the tax credit program; this varies from 23 percent in New Jersey to 91 percent in Illinois (see A.3).

We find that 87 percent of the angel investors are male. This gender ratio is in line with existing research on angel investors. Ewens & Townsend (2018) find that 92 percent of angel investors on AngelList are male. In a wide survey of U.S. angel investors, most of whom are members of the Angel Capital Association, Huang et al. (2017) report that 80 percent are male. Gompers & Wang (2017) find that around 90 percent of VCs are male.We coded the ethnicity or race using pictures, and found that 95 percent of investors appear to be white.[16] In Huang et al. (2017)'s data, 87 percent of respondents are white. Panel 2 of Table 2 shows that the average angel investors is 42 years old. The average age is higher in Huang et al. (2017)'s data, at 58 years old.

We also categorized job titles or descriptions: The majority of investors are corporate executives (e.g., the Vice President of a company). The next-highest group is doctors, at 7.3 percent, with relatively few professional investors or entrepreneurs. Among survey participants in Huang et al. (2017), 55 percent report being executives at for-profit companies, and 55 percent also report experience with entrepreneurship. Therefore, our

[15] Based on manual research of publicly available (i.e. before logging in) information on LinkedIn.

[16] **ADD LINK** We also coded as Hispanic individuals that our web researchers identified as "white" but who had names among the top 20 Hispanic names in the U.S. (https://names.mongabay.com/data/hispanic.html).

data appear more heavily weighted towards executives at older companies and away from entrepreneurs.

Together, these statistics paint a novel portrait of angel investors in non-hub states. This provides an alternative window into the sector, contributing to existing survey evidence in Huang and data about AngelList platform participants in Bernstein et al. (2017), and Ewens & Townsend (2018). Angel investors who receive tax credits in non-hub states appear younger, less entrepreneurial, and whiter than the average U.S. angel investor.

3 State Level Analysis

The tax credit program aims to increase employment through fostering local entrepreneurship in the state. Therefore, the first step in our analysis is to test whether aggregate employment in young, entrepreneurial firms increased following the policy.

3.1 State-level Data

We test whether aggregate employment in young entrepreneurial firms has increased following the policy using data from the Quarterly Workforce Indicators (QWI). The QWI allows us to measure both aggregate and industry employment for firms of different ages and sizes. We construct the data at the quarterly state level since the policy variation is at the state-level. Table A.5 reports a summary of the QWI data. The main outcome we examine is startup employment in high-tech industries, as these industries have been shown to be the focus of angel investment.[17] We also look at several alternative outcomes, including employment across all industries, small businesses, and a different definition of start-up firms.[18]

[17]QWI data is provided with a breakdown by industry and we define high-tech industry following the definition in Appel et al. (2017). This definition covers both life-science and IT and it contains the following NAICS: 3254 3341 3342 3344 3345, 3346, 3353, 3391, 5112, 5141, 5171, 5172, 5179, 5182, 5191, 5413, 5413, 5415, 5416 and, 5417.

[18]According to the UNH 2017 Angel Market Report, 30 percent of all angel deals are in software, and 29 percent are in life sciences; see https://paulcollege.unh.edu/sites/default/files/resource/files/2017-analysis-report.pdf.

3.2 Empirical Approach

We use a difference-in-differences model in event-time to identify the effect of the tax credit program on the state's economic activity. In particular, we estimate the effect of the introduction of a tax credit program by comparing how economic activity changes across states that introduce the policy and states that do not introduce the policy in the same region (Census division). We identify the start of a tax credit program using information contained in state program documentation, where we define the beginning of a program as the year the program starts, or the year after if the program start date is in the second half of the year (see Table 1 and Appendix Table A.1). For states with a tax credit program, we use data in a six-year window around the program introduction.[19]

The timing of policy change across states and the variation in the introduction of the tax credit across states within a Census division provides the source of identifying variation. We estimate the following equation:

$$ln(y_{st}) = \alpha_{Dt} + \alpha_s + \beta TC_{st} + \theta X_{st} + \varepsilon_{st}$$

In this case, s identifies the specific program, and t is the quarter, D represents the Census division. In most cases, the program is introduced only once, and then s is simply the state. α_{Dt} is a fixed-effect at census-division by period level. This fixed effect means that the comparison is within Census division across states that have and have not introduced the angel tax credit program. We also include state fixed effects (α_s). In some specifications, we include a set of state-by-year controls, X_{ts}. In particular, we control for the log of population, the log of personal income, the level of corporate income tax, and the unemployment rate. We include the whole sample available in QWI since 2002. To interpret our key parameter as a growth rate, we log-transform the outcomes (more discussion of interpretation is below). Standard errors are clustered at state level, which is the level of the treatment.

[19]For the few cases in which tax-credit were introduced more than once, each event will be in the data as a separate experiment.

3.3 Effects on Aggregate Employment

Table 3 Panel 1 focuses on start-ups defined as a firm that is less than a year old. Among this set of firms, we construct three different measures of employment: total employment, manufacturing employment, and high-tech employment. While we focus on employment in high-tech industries, the lack of stringent formal industry requirements in some tax credit programs resulted in the participation of non-high-tech companies in addition to high-tech companies.[20] We present baseline results in columns 1, 3 and 5 for the effect of tax credit programs on total employment, manufacturing employment, and high-tech employment, respectively. Columns 2, 4, and 6 present results controlling for additional time-varying state-level characteristics.

Across different specifications, we find that the introduction of a tax credit program does not cause an increase in start-up activity at the state-level. In particular, the coefficients of interest β across various employment outcomes tend to be negative, albeit small in magnitude and non-significant with large confidence intervals. The introduction of a tax credit program is linked to a 0.8 percent decline in total employment, with the 95 percent confidence interval ranging from about -5 percent to +3 percent. We find consistent results when the outcome examined is employment in high-tech firms but with a larger magnitude, where the introduction of a tax credit program is linked to a 4 percent decline in start-up employment in high-tech industries and a 95 percent confidence interval from -16 percent to +10 percent. Estimates with manufacturing employment as outcomes also present similar results. While the results are rather imprecise to make a strong claim of zero effects, the results seem to at least suggest that the introduction of tax credit programs did not lead to a strong positive effect in start-up activity.

Panels 2 and 3 present results with an alternative definition of start-up (firms less than five years old) and looking at small firms instead of start-ups (firms with less than 20 workers).[21] In both panels, we find results that are consistent with above as we document small and non-significant average effects. However, relative to the conventional definition of a start-up

[20]Looking at total employment may also have the advantage of accounting for potential spillovers from angel start-up to the rest of the economy.

[21]In an unreported regression, we find essentially the same results looking at small defined as with fewer than 50 workers.

(less than one year of activity), examining an alternative definition of start-ups and small firms yield slightly more positive results with smaller confidence intervals. For start-ups defined as firms with less than five years of activity, the introduction of a tax credit program is linked to a 3 percent increase in total employment and a 95 percent confidence interval of -5 percent and +11 percent. For small firms, the introduction of a tax credit program leads to only a 0.2 percent increase in total employment.

Altogether, this evidence fails to provide support to the claim that tax credit programs were associated with meaningful increases in local entrepreneurial activity. However, there are three limitations that merit discussion. First, a causal estimate of the policy would require an assumption that tax credit program introductions were exogenous to the local economy. One concern is that the tax credit might be introduced during a state economic downturn. To explore this hypothesis, we present the dynamic counterpart of our main estimation, where we explore the effects of introducing the tax credit program year-by-year in a six year window around the shock.[22] We normalize the year before the introduction of the tax credit to be zero so we can interpret the point estimate as the change in employment growth relative to the previous period. These results are not driven by a lack of parallel trends between treatment and control states prior to the introduction of tax credit programs. The key identifying assumption of this difference-in-differences model is that without policy intervention, treatment and control groups would have followed a similar trend in start-up employment growth.

Figures **??** and **??** reports the results from estimating the dynamic counterpart of our main estimation for the one- and five-year start-up definitions, respectively. In both figures, we find no statistical difference in employment growth for tax credit states and non-tax-credit states before the introduction of the policy. This is consistent with the parallel trends assumption and suggests that the zero effect is not driven by differential trends among the

[22] In other words, we estimate:

$$ln(y_{st}) = \alpha_{Dt} + \alpha_s + \beta_t TC_{st} + \theta X_{st} + \varepsilon_{st}$$

which is identical to the previous equation but for the fact that β_t is estimated separate for each year around the shock. TC_{st} is a vector of dummies that takes value of 1 in each period around the window (-2, -1, 0, +1, +2, +3). Consistent with the literature using this type of model, for the control group the TC_{st} is always equal to zero, since the tax-credit is never introduced.

treatment and control states. Consistent with the results above, the tax credit programs have small and non-significant effects on employment one, two, and three yeas after program introduction. These results are not driven by a lack of parallel trends between treatment and control states prior to the introduction of tax credit programs. While the parallel trend assumption is fundamentally untestable, this evidence provides supportive evidence.

The second concern is that while the tax-credit may have had an effect, they are too small to be detected at state level. Two results limit this concern. First, below we also find no effects on local angel investment, which should be a first-order effect of the policy. Second, we show in Section 4 that there are also no effects at the firm level.

3.4 Effects on Aggregate Investment

The results in **??** suggests that these tax credit programs likely failed to generate large waves of growth in high-tech start-ups. Yet, it could be that the null results are consequences of the program not being large enough to scale up employment—despite fostering entrepreneurship—in the start-ups during this period. To partially address this concern, we focus on whether the introduction of tax credit programs has affected angel or VC firm investments. If the program still fostered entrepreneurship despite not realizing employment growth, then the program should lead to an increase in investments from angels or VC firms.

We employ th same empirical strategy as above, but instead of of looking at employment outcomes, we examine three different measures of angel and VC investments as outcomes: total funding in seed investments by angels, total investment by angels, and total VC investment. We collect data from CB Insights, Crunchbase, and VentureXpert to create state by quarter measures of investment by angels of VCs. While the previous sample starts from 2002, this sample starts from 2008.

Table 4 reports results similar to the results on employment outcomes in **??**. Across all three outcomes, the effects of the tax credit is non-significant and small in magnitude. The introduction of a tax credit program leads to a 3 percent decline in seed investment and a 3.7

percent increase in total angel investments. Relative to previous estimates on employment outcomes, the confidence intervals are rather wide. While we cannot make a strong claim about null results in this context, the evidence seems to exclude the existence of any large increase in investments in start-ups following the introduction of a tax credit program.[23]

In general, tax credit programs do not appear to have spurred more angel investments in the state. This result is important because it provides further evidence that the programs were not particularly successful in fostering new start-up activity. Furthermore, the result helps us understand that the policy did not appear to increase the amount of investment in start-ups. Given the subsidy embedded in the tax credit, the evidence suggests that investors did not increase their investment in response to this subsidy; if anything, the policy seems to have crowded out private funding in favor of state funding.

4 Firm-level Analysis

As mentioned above, it is possible that the programs do positively affect beneficiary companies, but are too small to have an observable effect at the state level. To address this, we use data at the firm level about the specific beneficiary companies. We expect that if the tax credits enable them to raise more seed money than they would have otherwise, or raise money where they would not have been able to at all, they will subsequently perform better in terms of follow-on VC financing and employment. In this section we first present data on the sample of applicant companies that we use (Section 4.1), and then use two estimation approaches to analyze the relationship between being a beneficiary company and outcomes (Sections 4.2 and 4.3).

4.1 Data on applicant companies

We obtained data on beneficiary companies for 12 states either from public records or from privately from state officials. For 10 of these states, we also observe companies that were certified to have an investor benefit from a tax credit, but for which no investor actually was awarded a tax credit. We term these "failed applicants." Within a given year, the data are

[23]Figures 3 and 4 confirm this result in a graphical setting.

comprehensive, though we do not always observe all years from program inception. Table 5 Panel 1 shows the number of unique companies by state. The state with the largest number of companies is Ohio, with about 900, and the smallest is New Mexico, with 72. In total, there are 1,823 beneficiary companies, for which an investor received a tax credit, and 1,404 failed applicants.

There are two reasons that a company would be certified yet no investor would claim a credit. First, it is possible that no investment deal occurred.[24] Second, the company may have applied after the state ran out of funding but before it closed its application portal. If no deal occurred, the company may have sought but failed to raise angel investment, or raised it from some other source that is not eligible or chose not to claim the state tax credit. If the company was later than other startups in applying and the state had run out of money, there is no reason to expect that it is better quality. If anything, we expect such companies to be less well-managed. Therefore, we should assume that if there is bias in comparing these groups, the bias is in the direction of finding a positive effect.

We merged unique tax credit recipients to two external datasets. The first is a dataset of angel and VC equity financing events, which we refer to as the "financing data." These financing data combine deal-level data from VentureXpert, Crunchbase, and CB Insights. We match startups in the tax credit data to the financing data by name and state location. The second external dataset is Dun & Bradstreet (D&B), which is a panel dataset at the company-year level.[25] Startups in the tax credit data are matched to startups in the D&B data by name, state, and city of headquarters location (if available). We matched 808 companies to D&B and 1,227 to the financing data. There are 608 firms that matched to both. We developed startup sector classifications based on market and industry variables in the financing and D&B data, as well as hand-coding.

Table 5 Panel 2 shows that beneficiary companies are on average more successful than their rejected counterparts. Any Financing Pre-TC indicates whether a startup received financing before its tax credit year. Any Financing 2 Years Post-TC indicates whether a

[24] In some states there is no time limit on when a qualified business can receive a investment that can claim a tax credit, while in other states it is limited to one year (see column 25 in Appendix Table A.1).

[25] The original D&B is at the establishment level. We merge the tax credit data to establishment names, then aggregate to the company-level for analysis. Most companies in the tax credit data have only one establishment in D&B.

startup received financing within two or three years after its tax credit year, including the tax credit year. The amount of financing is defined analogously. Beneficiary companies raise previous financing at nearly twice the rate of failed applicants. The dollar amount of previous financing is $3.3 million for beneficiary companies, relative to $2.5 million for failed applicants. We return to the subject of past financing in Section 5.1, where we discuss the mechanisms behind our results. After the tax credit year, beneficiary companies are more likely to raise additional financing, raise more money, and are more likely to exit than failed applicants.

Employment data comes from D&B. We are primarily interested in whether the number of employees at a startup exceeds various thresholds during a tax credit year and in the years that follow. We create indicators for whether startups employ greater than 10 or 25 employees, which are reasonable benchmarks for small businesses, and whether the number of employees exceeds the sample's 75th percentile. One reason we bin the employment outcomes is that not all D&B is precise, and imputation can create bias (Decker and Crane 2019). D&B provide flags for the source of employment data: true value, range, impute. In our data, employment is "true" data for 72 percent of firms. (Our results are robust to alternative definitions.) Emp $> x$ in Credit Yr indicates whether the number of employees exceeds x in the company's first tax credit year. Thirteen percent of companies have more than 10 employees and 4 percent have more than 25 employees. These numbers rise somewhat in the second year after its first tax credit year (Emp $> x$ 2yrs Post-TC). Table 5 Panel 2 shows that there is no difference in employment between beneficiary companies and failed applicants either before or after the tax credit year.

4.2 Within-program analysis

This section uses data only on certified companies – companies that demonstrated interest in having an investor receive a state angel investor tax credit – to assess whether being a beneficiary company is associated with better outcomes.

4.2.1 Empirical Approach

We estimate the effects of angel investment tax credits on startup success by comparing financing and employment outcomes for beneficiary companies and companies that were certified but failed to have an investor receive a tax credit ("failed applicants", see Section 4.1 for details). The sample is restricted to the 10 states in which we observe all certified companies, including failed applicants. For beneficiary companies, we measure outcomes with respect to the number of years after the startup received the tax credit, which is usually the same as the application year. For failed applicants, we measure outcomes with respect to the number of years after they first applied for the credit.

$$Y_{i,t+k} = \alpha_{tc} + \alpha_{ts} + \beta TC_i + \delta' \mathbf{X}_{it} + \varepsilon_{i,j}$$

The dependent variable $Y_{i,t+k}$ is an outcome for startup i in year $t+k$, for $k = 1, 2, 3$, where year t is the "tax credit year" — the year the startup either received its first tax credit or first unsuccessfully applied for a tax credit. The outcomes for startup i are measures for financing, employment, and sales revenue. TC_i is an indicator for whether startup i received a tax credit or was denied a tax credit. In $\mathbf{X}_{it}$, we control for the pre-existing level of the outcome variable, which is either previous financing or employment in the application year. Our most stringent specification further includes sector-year fixed effects (α_{tc}) and and state-year fixed effects (α_{ts}) . In all cases, we cluster standard errors by state-year.[26] However, the results are very similar with other approaches, including robust standard errors.

4.2.2 Results

The relationship between receiving a tax credit and subsequent financing is shown in Table 6. Our preferred outcome is simply an indicator for raising VC within two years following the tax credit application year (Panel 1). With no controls whatsoever, as predicted in the summary statistics, beneficiary companies are about ten percent more likely to raise VC (column 1). However, this relationship disappears when previous financing is controlled for (columns 2-5). In our preferred specification with state-year and sector-year fixed effects in

[26] There are too few clusters to cluster by state.

column 5, the coefficient is -0.88 percentage points, with a 95 percent confidence interval ranging from -4 to 2 percentage points. The average rate of subsequent VC is 21 percent, so even the top of the confidence interval would be just 10 percent of the mean.

In column 6 we interact all the covariates with the share of companies in the state overall that previously received external financing. The negative significant coefficient (-0.16) on Got Tax Credit interacted with the previous financing rate indicates that in states where more companies previously raised external finance, beneficiary companies have lower chances of subsequently raising more money. The positive coefficient on "Got Tax Credit" represents the effect in states with zero previous financing instances, which does not exist in the data, so should be interpreted with caution. This regression suggests that states have better subsequent financing outcomes when their beneficiary companies were less likely to have received previous financing.

Table 6 Panel 2 considers other financing outcomes: the log amount of external financing raised in the two years after the tax credit year (columns 1-2), the level amount (column 3), and the chances of an exit through IPO or acquisition (columns 4-5). In all cases, we find effects that are not significantly different from zero after controlling for previous financing.

We next turn to employment, which is a primary goal states by policymakers for implementing angel investor tax credits. It is also useful because while subsequent financing is a commonly used measure of early stage startup success, it is possible that the angel round is all the external finance a company needs, in which case it is not a good proxy for success. Table 6 Panel 1 examines our preferred outcome, which is an indicator for having at least 25 employees in the second year after the tax credit year, which has a mean of about three percent. The effect is 1.1 percentage points with no controls (column 1), but is -0.021 percentage points in our preferred specification, with a 95 percent confidence interval ranging from -0.5 to 0.5 percentage points (column 5). Across the range of specifications with alternative controls, we find persistently negative coefficients that are very close to zero. Panel 2 demonstrates that the same is qualitatively true using alternative outcomes: at least 10 employees (columns 1-3), and employment greater than the 75th percentile among certified companies (columns 4-6). In sum, for both financing and employment, we can rule out economically meaningful positive effects of being a beneficiary company.

These results are consistent with the aggregate results above. While firms receiving the tax credit seem to outperform the control group, this is entirely driven by positive selection. After including controls for past fundraising, beneficiaries do not raise more funding or grow more than certified companies for which no investor received a tax credit. This result is particularly surprising since any bias should go in the direction of finding a positive effect among beneficiary companies relative to failed applicants.

4.3 Matching estimator

This section provides an alternative approach to assessing the performance of beneficiary companies. We use a different control group in a matching estimator. Specifically, we consider firms in nearby states without tax credit programs, which therefore couldn't plausibly apply for a tax credit.

4.3.1 Empirical Approach

We estimate the effects of Angel investment tax credits on startup success by comparing outcomes of treatment group startups against outcomes of control group startups. For this analysis, the treatment group consists of tax credit recipients and the control group consists of startups that have never applied for a tax credit and are located in states that do not have established Angel tax credit programs. We restrict the analysis to startups observed in both the financing data and the D&B data. We match each treatment group startup with up to five similar control group startups through a nearest neighbor matching procedure. To match with a treatment group startup, the control group startup(s) must be located in a different state but the same census division, belong to the same sector/market, have a similar age, and have a similar amount of previous financing relative to the year of the treatment startup's first tax credit. Based on the within-program analysis above, it is clear that having raised a similar amount of previous investment is a crucial control, so we match on this first, and do not consider it as an outcome, as it is inappropriate to match on the outcome variable. After this match, the age of each control group startup must be within two years of the treatment group startup's age, and each startup belongs to one of eighteen narrowly defined sectors. Covariates before and after matching are shown in Appendix Table A.2.

Within the nearest neighbor match group consisting of one treatment startup and up to five control group startups, we measure outcomes with respect to the year of the treatment group startup's first tax credit; we refer to this as the "tax credit year" for both treatment and control group startups in a match group.

$$Y_{i,t+k} = \alpha + \beta_1 TC_i + \beta_2 Y_{i,t} + \delta' \mathbf{X}_{it} + \varepsilon_{i,j}$$

The dependent variable $Y_{i,t+k}$ is an outcome for startup i in year $t + k$, for $k = 1, 2, 3$, where year t is the tax credit year. The outcomes for startup i are measures for financing, employment, and sales revenue. $GotTaxCredit_i$ is an indicator for whether startup i belongs to the treatment group or the control group. We control for startup i's pre-tax credit year performance with $Y_{i,t}$, and in some models startup-specific characteristics with $\mathbf{X}_i$. These include sector-year fixed effects as well as an indicator for whether the startup previously raised private investment.

4.3.2 Results

Like the within-program analysis, the matching estimator finds near-zero and often negative coefficients on the relationship between receiving a tax credit and subsequent employment or startup exit. The results are in Table 8. Our preferred specification for employment, in Panel 1 column 4, finds an effect of -0.64 percentage points relative to a mean of three percent, again indicates the absence of a meaningful positive effect, though the result is somewhat less precise than the within-program analysis. In this case, the 95 percent confidence interval ranges from -2.5 to 1.2 percentage points. The rest of the table confirms these findings, showing near-zero effects on employment higher than ten or higher than the 75th percentile (Panel 1 columns 1-2 and Panel 2 columns 1-2), and on the chances of exit (Panel 2 columns 4-5).

5 Mechanisms

The results thus far present a puzzle. Despite being quite generous – recall that the average deduction from tax liability is 33 percent of the investment amount – we can find no evidence that angel tax credits promote entrepreneurial activity, nor do they increase angel investment in the state. This points to the possibility that the programs crowd out private investment, that is, the investments benefiting from tax subsidies might still have occurred in their absence. In this section, we hypothesize that the limited impact of the angel tax credit programs are a result of their design. In particular, we present evidence suggesting that the programs do not target the companies and investors that we expect to benefit most from the tax credit.

5.1 Pre-existing investment

Our first observation is that beneficiary companies tend to already be well-financed. As shown in Table 5, nearly forty percent of the beneficiary companies previously received external financing, with an average of \$3.7 million conditional on having received previous financing. These dollar amounts are large relative to the average angel deal size, which was \$390,000 in 2017.[27] Startups seeking financing on AngelList request on average \$700,000, and just 2.6 percent of these startups are successfully funded (Ewens & Townsend 2018). In our data, the match rates may be biased downward as the financing data do not comprehensively cover early stage, especially angel, investment. Furthermore, the average investment amount in our data, at \$376,000, is much higher than the average U.S. angel check, which according to Huang et al. (2017)'s survey is \$35,000. This evidence suggests that a sizable share of firms that received the tax-credit may have been able to raise funding independently from the program.

If these firms were indeed able to raise funding independently from the program, then the tax-subsidy should not have any real effect for the business. [28] Rather than being the "first

[27] See UNH Center for Venture Research Angel Market Report 2017, available at https://paulcollege.unh.edu/sites/default/files/resource/files/2017-analysis-report.pdf.

[28] It seems unlikely that there are no financially constrained and eligible startups in states that adopt the tax credits, given the abundant evidence of constraints (e.g. Kerr & Nanda 2011, Howell 2019).

money in," the investment that benefits from the tax credits tends to come after substantial funding. Furthermore, it is not immediately obvious that even beneficiary companies without no previous investment are constrained, because when we restrict the sample to this group, we continue to find no effect.

5.2 Sector composition

Our second observation concerns industry composition, which does not appear oriented towards the types of companies that we might expect to be especially sensitive to the tax credit. Figure 5 groups beneficiary companies into five sectors and compares their sector distribution to that of VC-backed companies.[29] Since the tax credit data span 2005-2018, this is the same period we use to identify unique VC-backed companies. We require them to have a first VC deal date in the same period. The sector most strongly associated with VC backing and Silicon Valley is what we term "IT/Web/Computer," which includes companies whose activities are primarily related to software, mobile, web, or computer hardware. Sixty-five percent of VC-backed companies are in this sector, according to their primary categorizations in the financing data. We try to be as generous as possible in assigning applicant companies to this sector, assigning them if there is any evidence of activity in this area from any of the sector/market/industry variables in the financing and D&B data, as well as by manual search. Among beneficiary companies, just 27 percent are in the IT/Web/Computer sector[30] The other sector with a large difference is "Other," with 25 percent of companies. This includes local businesses in sectors that are not typically associated with growth, innovation, or angel investment. Examples of companies in this category include a hoof trimming business in Ohio and an art store in Wisconsin.

Many companies in our data – including some in the "Other" category – are potentially high-growth businesses. However, these businesses tend to have raised previous financing before the round in which they had an investor benefit from a tax credit. When the sample is restricted to companies without previous financing, the share in IT/Web/Computer declines

[29] We use the Crunchbase and CB Insights databases.

[30] Table 5 shows that beneficiary companies are somewhat more likely to be in this sector than failed applicants, again pointing to the potential for positive bias in the within-program analysis.

to just 16 percent, while the share in Other rises to 35 percent. Furthermore, applicant companies in the high growth sectors are much more likely to have had previous financing, and thus are likely less constrained than companies seeking to raise a first round. Among all applicant companies, 26 percent had previous financing before their tax credit year. Among IT/Web/Computer companies, 51 percent raised previous financing. The analogous percentages for beneficiary companies are 37 and 64 percent. In sum, it appears that the tax credit programs tend to be used by companies that are either not in especially high growth sectors or had previous financing.

5.3 Insider investment

A third observation is that a large share of investors receiving tax credits are employees or executives of the beneficiary companies. There are several reasons why subsidizing insider investment may be suboptimal from the perspective of fostering additional economic activity. First, this type of investor should in general face smaller financing frictions than external investors because there are no information asymmetry or agency problems. If an insider investor would behave optimally in the absence of the tax credit, the subsidy becomes a transfer from the local government to the investor. Second, since the subsidized individual investment does not necessarily translate into the beneficiary company performing real investment, insiders are more likely to exploit the tax credit program for tax arbitrage.

We conduct this analysis in the five states where we observe the identities of tax credit beneficiary companies, the names of investors that were awarded tax credits, and the link between these two pieces of information (Ohio, New Jersey, Maryland, New Mexico and Kentucky). There are 628 unique companies in this group, and 3,560 investors. We took three approaches to looking for insiders among tax credit recipient investors. The first is to examine whether the investor reports being employed at the company on LinkedIn. Among investors for whom we observe LinkedIn employment histories, 20 percent identify as employed at the company they invested in during the time period in which they received the tax credit, of which almost half are the CEO (shown in Panel 1 of Table A.4).

The second approach to studying owner-manager investment examines whether investors also appear as executives on SEC Form D filings. Private equity issuances must file Form D in order to be exempt from registering the issue as a security. Essentially all angel and VC investments make use of Form D. We merged 186 of the companies to their SEC Form D filings in the year of the tax credit, and matched executive officers from the Form D to investors.[31] Second, we considered the 61 companies out of the 628 that had at least three investors with the same last name (see Panel 2 of Table A.4). For these investors, we searched websites to identify if they or a family member were an executive (see Panel 3 of Table A.4).

After eliminating duplicate owner-managers across the three methods, our final results are in Table 9. We find that 35 percent of the companies for which we observe the investor-company link have at least one investor who is an executive or family member of an executive, and 33 percent have an investor who is an executive. The share is 24 percent or above in all states but Kentucky, where it is just four percent. Interestingly, while 22 states explicitly permit the investor to be employed at the company, Ohio and Kentucky do not (see Appendix Table 1 column 27). Therefore, it appears that there is considerable skirting of this law in Ohio. Given the difficulty of identifying insider investors, we believe that these calculations likely underestimate the true magnitude of the phenomenon.

The high prevalence of owner-managers benefiting from the tax credit sheds helps explain the absence of an effect, as these owner-managers seem likely to have invested in the absence of the program. Our findings relate to existing work on tax avoidance the interaction between tax policy and entrepreneurship, and suggest that tax policy can create unintended results. Owner-managers may identify as angel investors in order to benefit from angel tax credits. A related phenomenon is Gordon (1998)'s point that one explanation for entrepreneurial entry may be tax avoidance, as individuals with high incomes have an incentive to reclassify income as corporate rather than personal.

[31] A company must list its executive officers and board members in its Form D. We matched our companies to SEC Form Ds available on https://disclosurequest.com, which are those post-2010 when the Form Ds are available in HTML (rather than PDF). Of the 628 unique companies, we were able to match with certainty (i.e. no false positives) 186. We use the Form D filed in the year of the tax credit. There are 407 unique executive officers on these Form Ds, and of them, there are 38 with the same full name as an investor who received a tax credit, and an additional 24 with the same last name as an investor. Of the 186 matched companies, 39 have at least one investor who is an executive or family of an executive. The share of investors implicated is small, as the companies that match tend to have a large number of investors.

5.4 Summing Up

The above mechanisms are not mutually exclusive and, indeed, overlap in the data. Yet it is useful to consider the share of companies that they encompass. Among beneficiary companies, 63 percent of companies had not already raised equity based on the match to external financing data. Of these, the majority are either not in the high growth potential sectors of Biotech and Computer/Info Tech or have an investor who is a company manager. Just 9.5 percent of beneficiary companies have no insider investment, are in the IT/Web/Computer sector (which disproportionately receives VC and generate high-growth, innovative companies), and also did not previously raise external equity.

When we consider all applicants, this rises to 12 percent. This is too small a sample to run our main analysis, but we find that within this narrow slice, beneficiary companies do better than their failed applicant counterparts. Albeit insignificant, the coefficients on having at least 25 employees are large and positive, with magnitudes over 1,000 times the near-zero we find in the whole sample. While very suggestive, this group might be the sort of company that programs might consider targeting in the future. More broadly, the three mechanisms discussed above suggests that the design of the angel tax credit programs may help explain their limited effects.

However, these channels do not explain why constrained companies fail to select in. Note we observe the same null effects in state-years that run out of money as well as those that do not; in the latter case, constrained startups could not have been "left out." Information is one potential explanation; perhaps constrained companies are less likely to be aware of the programs because they are younger, less sophisticated, and have less interaction with the financial system on account of having raised less money. Similarly, the type of angel investor that funds very early stage, high-growth startups may not know about the tax credits. Potentially consistent with this, 80 percent of investors are located in-state (see Table 2 and Appendix Table A.3). The in-state proportions seem much higher than would be the case if the beneficiary companies were targeting a random sample of U.S. angel investors. For example, 90 percent of investors who receive tax credits in New Mexico are in-state, but according to Huang et al. (2017), only 3.8 percent of all U.S. angel investors are in the entire

Southwest region, which encompasses five states.

A second possibility is coordination; taking advantage of the tax credit may require the company to already have established connections with the investor. The programs typically require both parties to register in advance of the deal, often at a particular time of year. The prevalence of owner-managers is consistent with needing to have established the investment in advance. Pre-existing social ties is one mechanism that may help solve coordination frictions. To test for pre-existing social ties, we looked for attendance at the same university. Among the investors where we observe at least one university from which they graduated, we examined whether an executive who isn't related by last name attended the same university. For 22 percent of companies where we observe both investor and executive universities, at least one investor shared a university with an unrelated executive.[32] They are dominated by out-of-state MBA degrees; for example, there are four Wharton instances, two Kellogg, and a variety of other top schools, including Stanford GSB, Columbia GSB, and Duke Fuqua. Of course, there is no obvious benchmark for how often it should be the case that an angel investor attended the same university as an executive.

One sign that the policies may not be targeting the "right" investors is the discrepancy between professional backgrounds in our data and characteristics that Huang et al. (2017) find to be associated with investment success. The majority of angels in their survey have past entrepreneurial experience (i.e., founded a company). They find that these "entrepreneurial" angels invest in more companies, take a more active role in their portfolio companies, and have superior returns. In our data, only six percent of investors benefiting from tax credits identify themselves in their LinkedIn career history as an entrepreneur or co-founder (Table 2).

6 Conclusion

A public subsidy for investors could help compensate for the information frictions that create financial constraints for potentially high-growth startups, frictions thought to be especially

[32]This is 27 out of 122 companies. At the investor level, the rate is of course lower: out of 675 investors in these companies there are 35 cases for which we observe an executive who attended the same university.

severe outside the major entrepreneurship hubs. Angel investor tax credits, relative to direct programs such as grants, have the attractive feature of being relatively market-based tools that do not require the government to identify which companies deserve subsidy. While state-level subsidies could simply reallocate investment from one region to another, the subsidies could also be a means to directly address concerns that there may be insufficient angel investment, especially outside of hub cities.

In this paper, we look for evidence that angel investor tax credits positively affect entrepreneurial activity. At the state level, we find no evidence of positive effects. Similarly, among applicant companies, we find fairly precise zero effects. We document three characteristics of the data that point towards the types of very young, early stage, and risky startups that we would expect to be the most constrained. First, 37 percent of companies have previous outside equity. Second, just 27 percent of beneficiary companies are in the high-growth IT/Web/Computer sector, which disproportionately receives VC and generates high-growth, innovative companies. Third, many beneficiary companies have insider investment, which eliminates the information asymmetry that might cause financial constraints. When we put these three channels together, we find that just 9.5 percent of beneficiary companies have no insider investment, are in the IT/Web/Computer sector, and also did not previously raise external equity. It seems likely that the tax credit program implementation could be improved to align more closely with the stated goal of encouraging high-growth, innovative entrepreneurial activity.

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Table 1: State Tax Credit Program Summary (Details in Appendix)

State	Program	Effective Year	Expiration Year	Share of Investment (Inv) to Claim as TC	Allocated State Funding ($m/yr)	Total Angel Inv in State During Eff. Year ($mill)	State Funding as Share of Total Angel Inv in State	Individuals or Groups Qualify for Tax Credit (TC)	'First Come First' Policy
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Arkansas	Equity Investment Incentive Program	2007	2019	0.333	6.25	0.00	≥ 1	Both	
Arizona	Angel Investment Program	2006	2021	0.3 - 0.35	2.50	4.20	0.60	Both	Y
Colorado	*a.* Innovation Investment Tax Credit	2010	2010	0.15	0.75	44.62	0.02	Both	Y
	b. Advanced Industry Investment Tax Credit	2014	2022	0.25 - 0.3	0.75	143.59	0.01	Both	Y
Connecticut	Angel Investor Tax Credit Program	2010	2019	0.25	3.00	33.04	0.09	Both	Y
Georgia	Qualified Investor Tax Credit	2011	2018	0.35	10.00	28.97	0.35	Individuals	N
Hawaii	High Technology Business Investment Tax Credit	1999	2010	0.1 - 1.0		12.41		Both	
Illinois	Angel Investment Tax Credit Program	2011	2021	0.25	10.00	49.87	0.20	Both	Y
Indiana	Venture Capital Investment Tax Credit Program	2004	2020	0.2 - 0.25	12.50	0.00	≥ 1	Both	N
Iowa	*a.* Innovation Fund Tax Credit	2002	2008	0.2	10.00	0.00	≥ 1	Both	
	b. Innovation Fund Tax Credit	2012	indef.	0.2 - 0.25	2.00	8.33	0.24	Both	Y
Kansas	Angel Investor Tax Credit	2005	2022	0.5	6.00	0.00	≥ 1	Both	Y
Kentucky	Angel Investment Act Tax Credit	2015	indef.	0.4 - 0.5	3.00	9.55	0.31	Individuals	Y
Louisiana	*a.* Angel Investor Tax Credit	2005	2009	0.252	3.60	1.50	2.40	Individuals	Y
	b. Angel Investor Tax Credit	2011	2021	0.252	3.60	6.51	0.55	Individuals	Y
Maine	*a.* Seed Capital Tax Credit Program	1989	2012	0.4 - 0.6	5.00	0.00	≥ 1	Both	Y
	b. Seed Capital Tax Credit Program	2014	indef.	0.4 - 0.6	5.00	3.07	1.63	Both	Y
Maryland	Biotechnology Investment Incentive Tax Credit	2007	indef.	0.5	12.00	75.32	0.16	Both	Y
Michigan	Small Business Investment Tax Credit	2011	2011	0.25	9.00	24.81	0.36	Groups	
Minnesota	Angel Tax Credit	2010	2017	0.25	15.00	33.70	0.45	Individuals	
Nebraska	Angel Investment Tax Credit	2011	2022	0.4	4.00	13.27	0.30	Both	Y
New Jersey	Angel Investor Tax Credit Program	2013	indef.	0.1	25.00	46.17	0.54	Both	Y
New Mexico	Angel Investment Credit	2008	2025	0.25	2.00	7.20	0.28	Both	Y
New York	Qualified Emerging Technology Company Tax Credits	2000	indef.	0.1 - 0.2		279.57		Both	
North Carolin	Qualified Business Tax Credit Program	2008	2013	0.25	7.50	15.82	0.47	Both	N
North Dakota	Seed Capital Investment Tax Credit	2002	indef.	0.45	3.50	0.00	≥ 1	Both	Y
Ohio	*a.* Ohio Technology Investment Tax Credit	1996	indef.	0.25 - 0.3	45.00	0.00	≥ 1	Both	Y
	b. InvestOhio	2011	indef.	0.1 - 0.3	50.00	46.66	1.07	Both	Y
Oklahoma	Credit for Qualified Investment in Qualified Small Business Capital Companies	1998	2011	0.2		0.00		Both	
Rhode Island	Innovation Tax Credit	2007	2016	0.5	0.50	6.18	0.08		
South Carolin	High Growth Small Business Job Creation Act	2013	indef.	0.35	5.00	11.20	0.45	Individuals	
Tennessee	Angel Tax Credit	2017	indef.	0.33 - 0.5	4.00	34.68	0.12	Individuals	Y
Virginia	Qualified Equity and Subordinated Debt Investments Credit	1999	indef.	0.5	5.00	35.00	0.14	Both	N
West Virginia	High-Growth Business Investment Tax Credit	2005	2008	0.5	1.00	0.00	≥ 1	Both	Y
Wisconsin	Qualified New Business Venture Program	2005	indef.	0.5	30.00	1.08	37.96	Both	

Note: This table contains information on U.S. state angel tax credit programs. Additional details are in Appendix Table A.1.

Table 2: Angel Investor Information

Panel 1: Categorical Variables

	N	Fraction		N	Fraction
Number of investor-tax credit pairs	8,218		Profession	3,286	
			Corp. Exec.		0.82
Number of unique investors	5,637		Doctor		0.073
Illinois		0.14	Entrepreneur		0.062
Kentucky		0.05	Lawyer		0.041
Maryland		0.16	Investor		0.007
Minnesota		0.39	Other		0.003
New Jersey		0.09			
New Mexico		0.03	Race	4,446	
Ohio		0.14	White		0.95
			South Asian		0.03
Location is in state	4,694	0.79	East Asian		0.02
			Black		0.007
Male	4,702	0.87	Hispanic		0.002
			Middle Eastern		0.001

Panel 2: Continuous Variables

	N	Mean	Median	S.d.	Min	Max
Investment amount ($thou)	2,810	376	80	3,093	0.348	106,000
Age	2,363	41.9	42	13.1	18	77

Note: This table describes information gathered from LinkedIn about angel investors from four states that publicly release the names of angel investors. Corporate Executive is an investor who lists their current occupation as President, Vice President (SVP and VP), Partner, Principal, Managing Director, or Chief Officer other than CEO. An individuals's approximate age is derived from adding 22 years to the difference between the individual's college graduation year and the median year of investment of the sample, 2013. The number of observations (N) indicates the sample for which the variable is available; for example, we observe the investor location (in LinkedIn data) for 4,694 unique investors.

Table 3: Event-study on Employment

Panel 1: Startups Aged 0-1 Years

	Log (Total)		Log (Manufacturing)		Log (High-Tech)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Tax Credit	-0.013	-0.008	-0.054	-0.032	-0.053	-0.044
	(0.020)	(0.020)	(0.076)	(0.076)	(0.069)	(0.070)
State & Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	1894	1894	1894	1894	1894	1894
R^2	0.996	0.996	0.963	0.964	0.979	0.979

Panel 2: Startups Aged 0-5 Years

	Log (Total)		Log (Manufacturing)		Log (High-Tech)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Tax Credit	-0.001	0.008	-0.004	0.015	0.009	0.031
	(0.014)	(0.013)	(0.066)	(0.066)	(0.043)	(0.041)
State & Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	1894	1894	1894	1894	1894	1894
R^2	0.998	0.998	0.975	0.976	0.992	0.993

Panel 3: Small firms with <20 workers

	Log (Total)		Log (Manufacturing)		Log (High-Tech)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Tax Credit	-0.007	-0.004	0.009	0.006	-0.006	0.002
	(0.006)	(0.006)	(0.010)	(0.012)	(0.016)	(0.016)
State & Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	1894	1894	1894	1894	1894	1894
R^2	0.999	0.999	0.997	0.997	0.998	0.998

Note: This table contains diff-in-diff estimates of the impact of the tax-credit program on employment growth. We combine data on the tax credit programs with state-quarter data from the Census QWI, starting in 2001. We align observations in event-time, such that each state which introduces a tax credit is observed for a six-year window around the event, while those that do not experience any policy-change are set to have event-time equal to zero (i.e., pre-period). As two states introduced the tax credit more than once, the parameter of interest, the Post-Tax Credit indicator, is technically at the state by policy change level. We control for state, calendar time (year-quarter), and Census division by time fixed effects. Specifications in even columns also control for log-population, log-personal income, corporate tax rate, and unemployment. Each panel focuses on a different subpopulation of firms. In Panel 1 (2), startups are defined as firms aged no more than one (five) year(s). In Panel 3, they are defined as firms with less than 20 workers. In each panel, the dependent variable in columns 1-2 is total employment for the relevant category (e.g. startups aged no more than 1 year). In columns 3-4 the dependent variable is employment in manufacturing. In columns 5-6 the dependent variable is employment in high-tech sectors (see text). All are the log of one plus the employment variable. Standard errors are clustered at the state level.

Table 4: Event-study on Investment

	Log (Angel Seed)		Log (Angel all)		Log (VC all)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Tax Credit	-0.046	-0.029	0.012	0.037	-0.035	-0.014
	(0.154)	(0.156)	(0.125)	(0.127)	(0.114)	(0.118)
State & Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	1096	1096	1096	1096	1096	1096
R^2	0.957	0.958	0.968	0.969	0.975	0.975

Note: This table contains diff-in-diff estimates of the impact of the tax-credit program on startup investment. We combine data on the tax credit programs with state-quarter data on investment from commercial databases (see text). We align observations in event-time, such that each state which introduces a tax credit is observed for a six-year window around the event, while those that do not experience any policy-change are set to have event-time equal to zero (i.e., pre-period). As two states introduced the tax credit more than once, the parameter of interest, the Post-Tax Credit indicator, is technically at the state by policy change level. We control for state, calendar time (year-quarter), and Census division by time fixed effects. Specifications in even columns also control for log-population, log-personal income, corporate tax rate, and unemployment. The dependent variable in columns 1-2 is total amount of investment by angels in seed financing. In columns 3-4 the dependent variable is total amount of investment by angels. In columns 5-6 the dependent variable is total amount of VC funding. All are the log of one plus the investment variable. Standard errors are clustered at the state level.

Table 5: Tax Credit Applicant Summary Statistics

Panel 1

Unique Tax Credit Applicants by State and Outcome

	Received TC	Denied TC
AZ	144	145
CO	109	25
CT	100	70
KS	199	63
KY	60	101
MD	87	
MN	338	205
NJ	69	6
NM	72	
OH	374	537
SC	65	136
WI	206	116
Total	1823	1404

Panel 2

	Got Tax Credit	No Tax Credit	T-Test p-value
	Mean	Mean	p-value
Tax Credit (TC) Amount ($ thou)	32	0	0.00
Any Financing Pre-TC	.37	.12	0.00
Amt Financing Pre-TC ($ mill)	3.7	1.9	0.02
Any Financing 2yrs Post-TC	.26	.16	0.00
Amt Financing 2yrs Post-TC ($ mill)	2.9	2	0.19
Startup Exited	.066	.037	0.00
Emp in Credit Yr	6.5	6.2	0.85
Emp 2yrs Post-TC	7.2	6.6	0.79
Emp > p75 in Credit Yr	.21	.2	0.68
Emp > p75 2yrs Post-TC	.25	.16	0.03
Emp > 10 in Credit Yr	.14	.087	0.04
Emp > 10 2yrs Post-TC	.18	.12	0.11
Emp > 25 in Credit Yr	.042	.013	0.04
Emp > 25 2yrs Post-TC	.055	.03	0.25
Biotech	.084	.059	0.01
IT/Web/Computer	.27	.2	0.00
Goods and Services	.12	.15	0.01
Energy Tech	.043	.029	0.04
Financial	.016	.03	0.01
Health	.16	.092	0.00
Manufacturing	.11	.11	0.97
Other	.2	.33	0.00

Note: This table provides the summary statistics of the sample of firms used in the within-program firm level analysis. Panel 1 reports by state the number of firms for which an investor received a tax credit (beneficiary companies, first column) and firms that were certified by the state but for which no investor received a tax credit (failed applicants, second column). Panel 2 reports firm-level information for beneficiary companies and failed applicants as well as the p-value of the difference between these characteristics across the two groups. As discussed in the paper, this information combines data from DB, financial data, and other sources.

Table 6: Within-Program Financing and Exit Outcomes

Panel 1

Dependent Variable:	Raised VC 2 Yrs Post-TC					
	(1)	(2)	(3)	(4)	(5)	(6)
Got Tax Credit	0.099***	0.015	-0.0091	-0.0068	-0.0088	0.039**
	(.022)	(.019)	(.018)	(.017)	(.016)	(.019)
Finance Pre-TC		0.33***	0.18***	0.18***	0.17***	0.20***
		(.032)	(.026)	(.027)	(.028)	(.027)
Got TC*State Prev Fin Rate						-0.16**
						(.073)
State Prev Fin Rate						0.29***
						(.065)
State-Year FE	No	No	No	Yes	Yes	No
Sector-Year FE	No	No	No	No	Yes	No
State FE	No	No	Yes	No	No	No
Sector FE	No	No	Yes	Yes	No	Yes
Year FE	No	No	Yes	No	No	Yes
Observations	3227	3227	3227	3227	3227	3227
R^2	0.014	0.13	0.24	0.27	0.31	0.23

Panel 2

Dependent Variable:	Log amt raised 2yrs Post-TC		Amt raised 2yrs Post-TC	Exit	
	(1)	(2)	(3)	(4)	(5)
Got Tax Credit	1.66***	0.047	0.41	0.029***	-0.0051
	(.31)	(.21)	(.28)	(.0076)	(.0093)
Log amt raised before		0.25***			
		(.03)			
Amt raised before			0.13**		
			(.054)		
Finance Pre-TC					0.086***
					(.015)
State-Year FE	No	Yes	No	No	Yes
Sector-Year FE	No	Yes	Yes	No	Yes
Observations	2835	2835	2835	3227	3227
R^2	0.021	0.32	0.13	0.0040	0.11

Note: This table shows estimates of the relationship between receiving a tax credit and financing outcomes. The dependent variable in Panel 1 is an indicator that denotes whether a startup received VC investment within two years after first applying to have an investor benefit from a tax credit. The dependent variables in Panel 2 are a continuous variable measuring the total amount of financing a startup receives within two years of its first credit year, log of that variable, and whether the startup exited, i.e. is acquired or has an IPO. State Prev Fin Rate is the share of tax credit recipient companies in the state that previously received external financing (see Appendix). In Panel 1, different columns report the results under different combinations of fixed-effects, going from no fixed-effects (column 1) to state-by-year and sector-by-year fixed-effects and control for previous financing in column 5. In Panel 2 we examine alternative outcomes, but report only the least restrictive (odd columns) and most restrictive (even columns) specifications. Standard errors are clustered at state-by-year level.

Table 7: Within-Program Employment Outcomes

Panel 1

Dependent Variable:	Emp. > 25 2yrs Post-TC				
	(1)	(2)	(3)	(4)	(5)
Got Tax Credit	0.011***	-0.00054	-0.00051	-0.00011	-0.00021
	(.0033)	(.0021)	(.0024)	(.0025)	(.0026)
Emp > 25 in Credit Yr		0.66***	0.65***	0.65***	0.65***
		(.1)	(.1)	(.1)	(.11)
Finance Pre-TC		0.012***	0.014***	0.013***	0.015***
		(.0035)	(.0041)	(.0041)	(.0046)
State-Year FE	No	No	No	Yes	Yes
Sector-Year FE	No	No	No	No	Yes
Sector FE	No	No	Yes	Yes	No
Year FE	No	No	Yes	No	No
State FE	No	No	Yes	No	No
Observations	3227	3227	3227	3227	3227
R^2	0.0033	0.46	0.47	0.48	0.50

Panel 2

Dependent Variable:	Emp. > 10 2yrs Post-TC			Emp. > p75 2yrs Post-TC		
	(1)	(2)	(3)	(4)	(5)	(6)
Got Tax Credit	0.034***	-0.0011	0.0023	0.047***	0.0052	0.011
	(.0069)	(.0043)	(.004)	(.0089)	(.0068)	(.0068)
Emp > 10 in Credit Yr		0.54***	0.53***			
		(.069)	(.07)			
Finance Pre-TC		0.038***	0.041***		0.053***	0.053***
		(.0084)	(.0087)		(.0096)	(.01)
Emp > p75 in Credit Yr					0.45***	0.45***
					(.064)	(.065)
State-Year FE	No	No	Yes	No	No	Yes
Sector-Year FE	No	No	Yes	No	No	Yes
Sector FE	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No
State FE	No	Yes	No	No	Yes	No
Observations	3227	3227	3227	3227	3227	3227
R^2	0.0094	0.39	0.46	0.014	0.36	0.41

Note: This table shows estimates of the relationship between receiving a tax credit and employment outcomes. The dependent variable in Panel 1 is an indicator that denotes whether a startup received the 25 employees within two years after first applying to have an investor benefit from a tax credit. The dependent variable in Panel 2 are an indicator equal to one if a startup reached ten employees within two years of its first credit year (columns 1-3) and an indicator equal to one if a startup reached the top quartile of employment within two years of its first credit year (columns 4-6). In every specification, we control for the same measure as the outcome but measured in the year before the tax-credit. In Panel 1, different columns report the results under different combinations of fixed-effects, going from no fixed-effects (column 1) to state-by-year and sector-by-year fixed-effects and control for previous financing in column 5. In Panel 2 we examine alternative outcomes, but reporting only the least restrictive (odd columns) and most restrictive (even columns) specifications. Standard errors are clustered at state-by-year level.

Table 8: Different-State-Matched Employment and Exit Outcomes

Panel 1: Employment

Dependent Variable:	Employment > 10 2yrs Post-TC		Employment > 25 2yrs Post-TC	
	(1)	(2)	(3)	(4)
Got Tax Credit	0.0071	-0.0012	-0.0064	-0.014
	(.017)	(.016)	(.0095)	(.0094)
Sector-Year FE	No	Yes	No	Yes
Controls	No	Yes	No	Yes
Observations	2511	2511	2511	2511
R^2	0.50	0.52	0.44	0.46

Panel 2: High Employment and Exits

Dependent Variable:	Employment > p75 2yrs Post-TC		Startup Exit	
	(1)	(2)	(3)	(4)
Got Tax Credit	0.024	0.019	-0.0054	-0.017
	(.017)	(.015)	(.018)	(.015)
Sector-Year FE	No	Yes	No	Yes
Controls	No	Yes	No	Yes
Observations	2511	2511	4115	4115
R^2	0.41	0.44	0.000031	0.079

Note: This table shows nearest-neighbor matching estimates. The dependent variables are defined within two years following the tax credit year, except for Exits (IPOs and acquisitions), which are ever after. In Panel 1, we consider as outcomes indicators that are equal to one if the employment is above ten workers (columns 1 and 2) or twenty-five workers (columns 3 and 4). In Panel 2, we consider as outcomes indicators that are equal to one if the employment is above the top quartile in the sample (columns 1 and 2) or if the firm experienced a succesful exit (columns 3 and 4). Mirroring the previous analyses, in odd columns we do not control for any fixed-effects, while in even columns we control for sector-by-year and the firm-level control discussed in the paper. Standard errors are clustered at state-by-year level.

Table 9: Angel Investors Serving as Executives or Manager at Company for which they Received Tax Credit

Panel 1: Company-level statistics (unique tax credit beneficiary companies for which observe investor-company link)

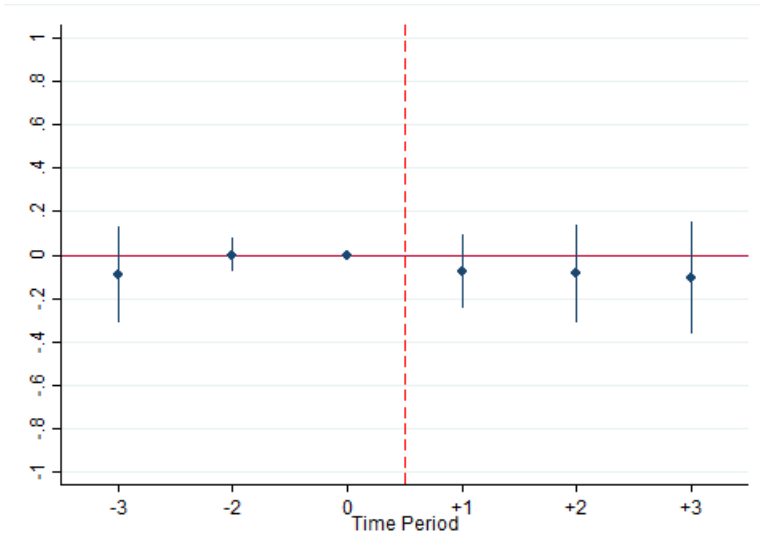
	N	Fraction
$\geq$ 1 investor is executive or has family member who is executive	628	0.35
Among Kentucky companies	77	0.04
Among Maryland companies	81	0.38
Among New Jersey companies	63	0.24
Among New Mexico companies	61	0.26
Among Ohio companies	346	0.44
At least one investor is an executive	628	0.33

Panel 2: Investor-level statistics (unique tax credit recipient investors for which observe investor-company link)

	N	Fraction
Investor is executive or has family who is executive	3,560	0.14
Investor is executive	3,560	0.11

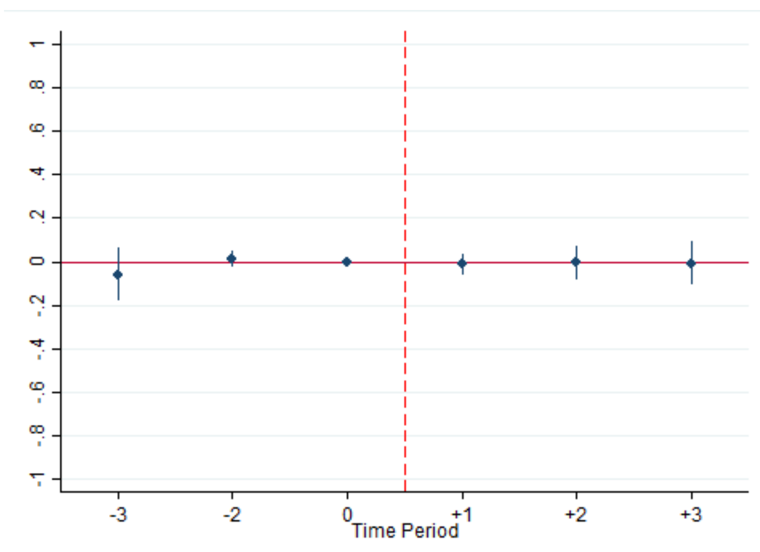
Note: This table describes information from the five states where we observe beneficiary companies linked to the investors who received tax credits for investing in them. Panel 1 reports information on the share of firms among the 628 unique tax credit beneficiary where investor is executive or has family member who is executive. Information on whether an investor is related to an executive is collected from SEC Form D filings, LinkedIn, and web research in cases where at least three investors share the same last name. The investor identifies as employed at the firm that recieved a tax credit and in which he/she invested for 294 unique investors, of which the investor is the CEO/founder. Panel 2 reports the same statistic in aggregate but using the data at investor-level, rather than firm-level.

Figure 1: Angel Investor Tax Credit Program Effect on State Employment at Companies 0-1 Years Old



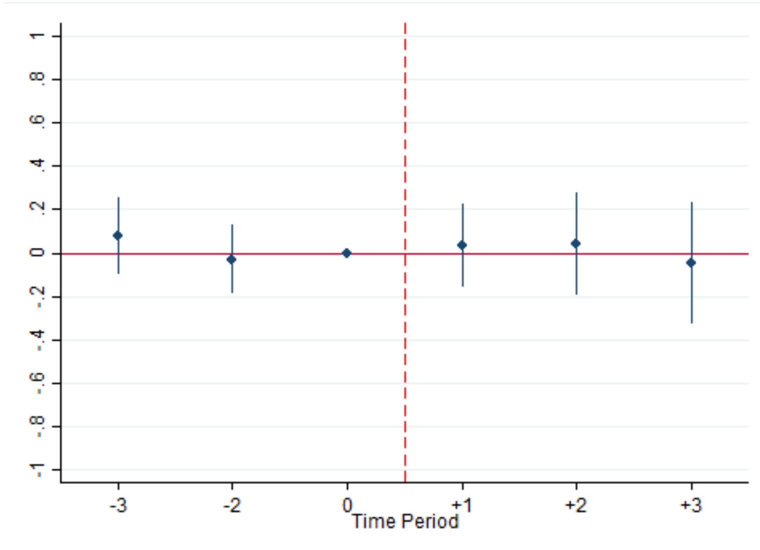
Note: This figure shows the annual effect of introducing an angel tax credit on log total employment at companies no more than one year old. We use a year-by-year version of the difference-in-differences design. The year before policy introduction is normalized to zero. Standard errors are clustered at state-level. 95 percent confidence intervals are shown.

Figure 2: Angel Investor Tax Credit Program Effect on State Employment at High-Tech Companies 0-5 Years Old



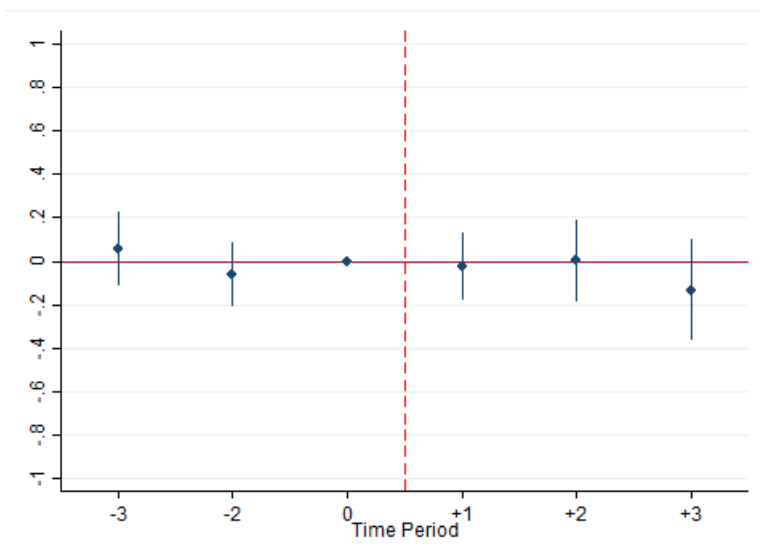
Note: This figure shows the annual effect of introducing an angel tax credit on log total employment at companies no more than five years old that are in high-tech industries. We use a year-by-year version of the difference-in-differences design. The year before policy introduction is normalized to zero. Standard errors are clustered at state-level. 95 percent confidence intervals are shown.

Figure 3: Angel Investor Tax Credit Program Effect on State Angel Investment



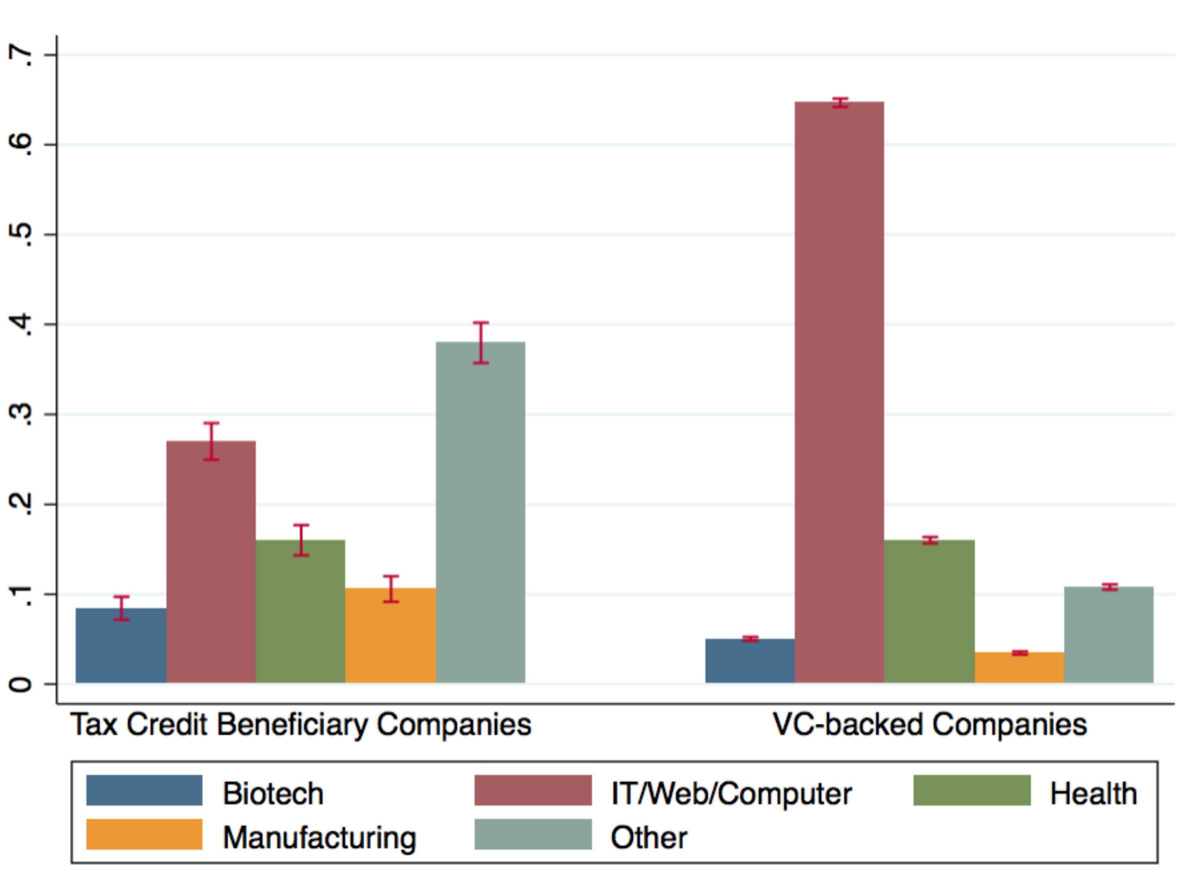
Note: This figure shows the annual effect of introducing an angel tax credit on the log total dollar amount of angel seed investment in the state. We use a year-by-year version of the difference-in-differences design. The year before policy introduction is normalized to zero. Standard errors are clustered at state-level. 95 percent confidence intervals are shown.

Figure 4: Angel Investor Tax Credit Program Effect on State VC Investment



Note: This figure shows the annual effect of introducing an angel tax credit on the log total dollar amount of VC investment in the state. We use a year-by-year version of the difference-in-differences design. The year before policy introduction is normalized to zero. Standard errors are clustered at state-level. 95 percent confidence intervals are shown.

Figure 5: Sector Distribution Comparison



Note: This figure shows the sectoral distribution of venture capital-backed companies and tax credit beneficiary companies. There are 19,229 venture-capital backed companies between 2005 and 2018 and 1,818 tax credit beneficiary companies between 2005 and 2018.

Internet Appendix

Table A.1: State Tax Credit Program Details (Continued from Table 1)

State		TC Can Exceed Total State Income Tax Owed	Tax Credit Can Be Sold or Transferred	TC Can Be Carried Forward	Number of Years of Carry Forward	Max TC Amount Per Business Per Year ($)	Min Inv Amount ($)	Registration Requirement (Req) for Business	Innovation Req for Business	Definition of Innovative
		(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	
AR		Y	Y	Y	9			Y	N	
AZ		Y	N	Y	3	600,000	25,000	Y	N	
CO	*a.*	Y	N	Y	5		25,000	Y	N	
	b.	Y	N	Y	5		10,000	N	N	
CT		N	N	Y	5	500,000	25,000	Y	N	
GA		Y	N	Y	5			Y	N	
HI				Y	Unlimited					
IL		Y	N	Y	5	1,000,000	10,000	Y	Y	Uses proprietary tech.
IN		Y	Y	Y	5			Y	N	
IA	*a.*	Y	N	Y	5			N		
	b.	Y	N	Y	3	500,000		N		
KS		Y	Y	Y	Unlimited			N	Y	Exclusively owned tech, product or service that is new.
KY		Y	Y	Y	15		10,000	Y	N	
LA	*a.*		Y					Y	N	
	b.		Y					Y	N	
ME	*a.*	Y		Y	15	5,000,000		N	N	
	b.	Y		Y	15	5,000,000		N	N	
MD			Y				25,000	Y	N	
MI		Y		Y	5	1,000,000	20,000	Y	Y	Has potential for high growth.
MN				N			10,000	Y	Y	Uses proprietary tech in a preferred industry.
NE				N			25,000	Y	Y	Uses proprietary tech in a high-tech field.
NJ			N	N				N	N	
NM		Y	N	Y	5 years if after 2015; 3 years if before 2015			N	N	
NY		Y		Y	Unlimited			N	Y	Produces emerging technologies or has sufficient R&D activities in NY.
NC		Y	N	Y	5			Y	N	
ND		Y	N	Y	4	225,000		Y	Y	
OH	*a.*	Y		Y	15			Y	N	
	b.	Y		Y	15			Y	N	
OK		Y	N	Y	3 years if after 2006; 10 years if before 2006			N	N	
RI		Y		Y	3			Y	Y	
SC		Y	Y	Y	10			Y	N	
TN		Y	N	Y	5		15,000	Y	Y	Has high-growth potential, SBIR or STTR funding, or tech developed in TN.
VA		Y		Y	15			Y	N	
WV		Y		Y	4	500,000		N	N	
WI		Y	N	Y	15	8,000,000		Y	Y	

State		Size Req for Business	Note	Age Req for Business	Note	Industry Req for Business	Note
		(17)		(18)		(19)	
AR		N		N		Y	Adv materials and manufacturing; agriculture, food, and environmental; biotech/eng, life sciences; IT; transportation
AZ		Y	Assets < \$10m. Assets < \$2m if before 2012	N		N	
CO	*a.*	Y	Annual revenue < \$2m; assets < \$5m	Y	< 5 years old	Y	R&D or use of new tech, products, or processes
	b.	Y	Annual revenue < \$5m	Y	< 5 years old	Y	Manufacturing; aerospace; bioscience; electronics; energy/natural resources/cleantech; IT; infrastructure eng
CT		Y	< 25 full-time employees (FTEs); annual gross revenue < \$1m	Y	In CT < 7 years	Y	Bioscience; adv materials; photonics; IT; clean tech or other emerging tech
GA		Y	< 20 FTEs; annual revenue < \$500k	Y	< 3 years old	Y	Manufacturing; processing; online / digital warehousing / wholesaling; software; IT services; R&D
HI							
IL		Y	< 100 FTEs	Y	In IL < 10 years	Y	Manufacturing; bio/nanotech; communications; agricultural; clean energy creation / storage; pharma; computer software or hardware;
IN		Y	Ave. annual revenues < \$10m	N		Y	Professional motor vehicle racing; R&D; new tech
IA	*a.*	Y	Net worth < \$3m	Y	< 3 years old	Y	Not primarily in retail, real estate, or health care
	b.	Y	Net worth < \$10m	Y	< 6 years old	Y	" "
KS		Y	Annual gross revenues < \$5m	Y	< 5 years	N	
KY		Y	< 100 FTEs; net worth < \$10m; income < \$3m	N		Y	Bioscience; environmental and energy tech; health and human dev; IT; materials science and adv manufacturing
LA	*a.*	Y	< 50 FTEs; annual gross sales < \$10m or net worth < \$2m	N		N	
	b.	Y	" "	N		N	
ME	*a.*	Y	Annual gross sales < \$3m	N		Y	Manufacturing; adv tech; natural resources; visual media
	b.	Y	Annual gross sales < \$5m	N		Y	" "
MD		Y	< 50 FTEs	Y	< 10 years old	Y	Biotech
MI		Y	< 100 FTEs; pre-investment valuation < \$10m	Y	< 5 years old; < 10 years if business uses MI university	Y	Adv materials; alt energy; defense and homeland security; IT; med tech; next gen manufacturing
MN		Y	< 25 FTEs	Y	< 10 years old; < 20 if med tech or pharma	N	High-tech; agriculture; tourism; forestry; mining; manufacturing; transportation
NE		Y	< 25 FTEs	N		N	
NJ		Y	< 225 FTEs	N		Y	Adv computing; adv materials; biotech; electronics; IT; life sciences; med tech; communications; renewable energy
NM		Y	< 100 FTEs; annual gross revenues < \$5m	N		Y	Manufacturing and high-tech
NY		Y	Annual sales < \$10m	N		Y	Adv materials; engineering, production, and defense; electronics; IT; biotech; remanufacturing
NC		Y	Annual gross revenue < \$5m	N		Y	Manufacturing; processing; warehousing; wholesaling; R&D; services
ND		N		N		N	
OH	*a.*	Y	Annual gross revenue < \$2.5m or net book value < \$2.5m	N		Y	R&D; biotech; IT; R&D-derived tech
	b.	Y	" "	N		Y	" "
OK		Y	Net worth < \$1m	N			
RI		Y	Annual gross revenues < \$1m	N		Y	IT; digital media; healthcare; life science; marine trades; defense; financial, professional and educational services; retail and design; industrial products
SC		Y	< 25 FTEs; gross revenue < \$2m	Y	< 5 years old	Y	Manufacturing, processing, warehousing, wholesaling; software; IT; R&D
TN		Y	< 50 FTEs; gross revenue < \$3m	Y	< 5 years old	N	
VA		Y	Annual gross revenue < \$3m	N		Y	Computing; adv materials; manufacturing; agriculture; biotech; electronics; energy; environment; IT; med tech; nanotech
WV		Y	Annual gross receipts < \$20m; payroll < \$2.5m	N		N	
WI		Y	< 100 FTEs	Y	In WI < 10 years	Y	Manufacturing; biotech; med tech; software / hardware; semiconductors; nanotech; communications; agriculture; clean energy

State		Reporting Req for Investor's Firm	In-State Location Req for Business	Note	Total Previous Inv Req for Business	Note	Max TC Amount Per Investor Per Year ($)	Max TC Amount Per Investor Per Business Per Year ($)	Holding or Waiting Req for TC Claim	Note	SEC Accreditation Req for Investor	Investor Can Be Employed by Business	Investor Can Reside Out-of-State
		(20)	(21)		(22)		(23)	(24)	(25)		(26)	(27)	(28)
AR		N	N		N				N		N	Y	Y
AZ		N	Y	Business and > 2 full-time employees (FTEs)	Y	< $2m in total inv	250,000		Y	1 year	N	Y	Y
CO	*a.*	N	Y	Principal business, > 2 FTEs, and > 50% of assets	N		20,000		N		N	Y	
	b.	N	Y	HQ and > 50% of FTEs	Y	< $10m in inv, debt, equity	50,000		N		N		
CT		N	Y	> 75% of FTEs	Y	< $2m in angel financing	250,000		N		Y	Y	Y
GA		N	Y	HQ	Y	< $1m in equity or debt	50,000		Y	2 years	Y	Y	Y
HI							700,000		Y	5 years			
IL		Y	Y	Principal business and > 50% of FTEs	Y	< $10m in PE, < $4m TC inv		500,000	Y	3 years	N	Y	Y
IN		N	Y	HQ, > 50% of FTEs, and > 75% of assets	N		1,000,000				N	Y	Y
IA	*a.*	N	Y	Principal business	N		100,000	50,000	Y	3 years	N	Y	Y
	b.	N	Y	HQ and > 50% FTEs	N		100,000	50,000	Y	3 years if before 2014,	N	Y	Y
KS		Y	Y	> 60% operations or > 80% production	N		250,000	50,000	N		Y	N	Y
KY		Y	Y	> 50% assets, operations, and FTEs	Y	< $1m in TC angel inv	200,000				Y	N	Y
LA	*a.*	N	Y	Principal business and > 50% FTEs	N		362,880	181,440	Y	3 years	Y	Y	Y
	b.	N	Y	Principal business and > 50% FTEs	N		362,880	181,440	Y	3 years	Y	Y	Y
ME	*a.*	Y	Y	Physically reside in ME	N			500,000			N	Y	
	b.	Y	Y	Physically reside in ME	N			500,000			N	Y	
MD		N	Y	HQ and base of operations	N		250,000		Y	2 years	N	Y	Y
MI		Y	Y	HQ and > 50% of FTEs	N		250,000	250,000	Y	3 years	N		
MN		Y	Y	HQ and > 50% FTEs, payroll, and contracts	Y	< $4m in PE	125,000		Y	3 years	N	Y	N
NE		Y	Y	HQ	N		300,000		Y	3 years	N	Y	N
NJ		N	Y	Business and > 75% of FTEs	N			500,000			N	Y	Y
NM		N	Y	Principal business	N			62,500			Y	Y	
NY		N	Y	Physically resides or has R&D activities in NY	N		150,000		N		N	Y	Y
NC		N	N		N			50,000	Y	1 year	N	N	N
ND		N	Y	Principal business, > 50% of businesses/sales and FTEs	N		112,500				N	Y	
OH	*a.*	N	Y	Principal business, > 50% of gross assets and FTEs	N		62,500				N	N	
	b.	N	Y	Principal business, > 50% of gross assets and FTEs	N		62,500				N	N	
OK		Y	Y	Principal business							N		
RI								100,000				Y	
SC		N	Y	HQ	N		100,000		Y	2 years	Y	Y	Y
TN		Y	Y	Product derived from R&D in TN. > 60% of FTEs	N		50,000				Y		Y
VA		N	Y	> 50% gross receipts and > 80% expenses	Y	< $3m in equity or debt	50,000		Y	3 years	N	N	
WV		N	Y	HQ	N		50,000		Y	5 years	N		
WI		N	Y	HQ, and > 50% of FTEs	Y	< $10m in PE			Y	3 years	Y		

Table A.2: Comparison of Pre- and Post-Match Covariates by Tax Credit Status

Panel 1
Pre-Match

	Got Tax Credit			No Tax Credit			T-Test	
	Mean	SD	Obs	Mean	SD	Obs	t-value	p-value
Year Founded	2009.6	4.652	619	2008.6	6.549	20403	-3.797	0.000147
Total Financing	10.17	27.77	619	14.43	158.7	20403	0.668	0.504
Average Emp	6.221	9.838	619	23.07	563.2	20403	0.744	0.457
Average Sales	720732.7	3111565.6	619	4554826.4	241016016.1	20403	0.396	0.692
Exit Rate	0.107	0.309	619	0.153	0.360	20403	3.144	0.00167

Panel 2
Post-Match: Different State, Narrow Sectors

	Got Tax Credit			No Tax Credit			T-Test	
	Mean	SD	Obs	Mean	SD	Obs	t-value	p-value
Year Founded	2009.5	4.137	517	2009.3	3.803	3129	-1.282	0.200
Total Financing	10.15	27.25	517	8.106	23.28	3129	-1.035	0.301
Average Emp	6.450	10.55	517	7.811	88.61	3129	0.386	0.700
Average Sales	777256.0	3390226.5	517	663930.9	3015808.0	3129	-0.661	0.508
Exit Rate	0.110	0.314	517	0.127	0.333	3129	1.175	0.240

Note: This table compares covariates across treatment and control, both before (panel 1) and after the matching process (panel 2) used as robustness. In each panel, we examine firms' founding year, total financing, sales, and employment, and exit-rate. The pre-match universe of potential controls includes all companies in the financing data that received angel or seed investment.

Table A.3: Share of Tax Credit Recipients with Previous External Financing by State and Share Investors In-State

	Share tax credit beneficiary companies with previous external financing	Share investors in-state (conditional on observing investors)
	(1)	(2)
Ohio	0.06	0.95
Kansas	0.33	
Arizona	0.34	
Minnesota	0.37	0.86
South Carolina	0.40	
Maryland	0.41	0.63
Connecticut	0.46	
Wisconsin	0.53	
Kentucky	0.62	0.80
New Jersey	0.62	0.23
New Mexico	0.68	0.90
Colorado	0.70	
Illinois		0.91

Note: This table provides state-by-state information on two variables. In column (1), the table reports the share of companies whose investors received a tax credit that had previous external financing. In column (2), we report the share of investors that we can identify as in-state investor. Missing information means we do not have the data to compute the statistic.

Table A.4: Detailed Matching Statistics on Angel Investors Serving as Executives or Manager at Company for which they Received Tax Credit

Panel 1: LinkedIn Matching Statistics (where N is sample conditional on observing investor-company link and matching to LinkedIn)

	N	Fraction
Company-level		
≥ 1 investor employed at or CEO	514	0.35
Investor-level		
Employed at company during relevant time period	2,060	0.20
CEO	2,060	0.08

Panel 2: SEC Form D Matching Statistics (where N is sample conditional on observing investor-company link and matching to Form D)

	N	Fraction
Company-level		
≥ 1 investor executive or family of executive	186	0.21
Investor-level		
Executive	1,416	0.03
Family of executive officer	1,416	0.02

Panel 3: Multiple Last Name Matching Statistics (where N is sample conditional on observing investor-company link and having ≥ 3 investors with same last name)

	N	Fraction
Company-level		
≥ 1 investor executive or shares executive last name	61	0.61
Investor-level		
Executive	285	0.35
Shares last name of executive	285	0.24

Note: This table describes information from the five states where we observe beneficiary companies linked to the investors who received tax credits for investing in them. In panel 1, we report information on whether an investor is an employee of the firm, either as a CEO or not. In particular, we first report the share of firms in which at least one investor is either a CEO or an employee and then the share of investors that are either CEO or non-CEO employee. These variables are constructed using Linkedin information. In panel 2, we report information on whether an investor is an executive or family member of an executive. In particular, we first report the share of firms in which at least one investor is an executive or family of an executive and then the share of investors that are either an executive or family of an executive. Information on the identity of executives are collected from SEC form D. We define an investor as a family member of an executive if she has the same surname of an executive. In panel 3, we report information on whether several investors belong to the same family. In particular, we first identify the share of firms in which there are at least three investors with the same surname. Second, we report the share of investors that has the same surname of at least two other investors in the same firm.

Table A.5: Aggregate State-Quarter Summary Statistics

Panel 1
States with Tax Credit Programs

	Mean	SD	Min	Med	Max	Obs
High-Tech 0-1 yr.	3734.35	3030.2	141	2362.5	19492	644
IT 0-1 yr.	3297.38	2621.4	136	2057.0	12332	644
Life Sciences 0-1 yr.	436.97	1142.8	0	202.5	10140	644
High-Tech 0-5 yr.	12297.19	9001.8	808	10194.0	39012	644
IT 0-5 yr.	10980.27	8286.2	751	7469.0	33397	644
Life Sciences 0-5 yr.	1316.92	1757.1	36	756.5	10498	644

Panel 2
States without Tax Credit Programs

	Mean	SD	Min	Med	Max	Obs
High-Tech 0-1 yr.	7692.31	14703.8	133	2245.0	113014	1501
IT 0-1 yr.	6960.75	12907.0	133	2106.0	87803	1501
Life Sciences 0-1 yr.	731.56	2124.3	0	147.0	28599	1501
High-Tech 0-5 yr.	25133.40	45600.4	505	7658.0	263536	1501
IT 0-5 yr.	22767.80	40426.2	502	7024.0	238373	1501
Life Sciences 0-5 yr.	2365.60	5666.8	3	573.0	42698	1501

Note: This table reports summary statistics on aggregate start-up activity by state using the data from QWI. Data is reported by quarter-state and state, using the same sample that is employed from the aggregate analysis. For each variable, we report several moments, as reported in the first row of the table. The first panel, we report the summary statistic for the set of states that introduced a tax credit at some point in the sample-period. In the same panel, we report the summary statistic for the set of states that did not introduced a tax credit.