Investor Tax Credits and Entrepreneurship: Evidence from U.S. States[*]

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Abstract

Angel investor tax credits are commonly used around the world to spur entrepreneurship. Exploiting the staggered implementation of these tax credits in 31 U.S. states, we find that while they increase angel investment, marginal investments flow to relatively low-growth firms. Tax credits induce entry by non-professional, inexperienced investors, and are often received by firm insiders. Consistent with these findings, we show that angel tax credits have no significant effect on state-level entrepreneurial activity or on beneficiary firm outcomes relative to failed applicants. Overall, the results raise concerns about whether investor tax credits achieve their stated goal of promoting high-growth entrepreneurship.

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1. Introduction

Fostering entrepreneurship is a central policy objective for governments around the world. Consequently, many policy initiatives aim to increase high-growth entrepreneurship through direct grants, loan guarantees, prize competitions, and tax subsidies, among other means. This paper studies a popular policy tool that has been adopted by more than 12 countries around the world and by the majority of U.S. states: angel investor tax credits.[1] These programs offer personal income tax credits equal to a certain percentage of the investment, regardless of the investment outcome. While this tax policy has attracted much attention and debate, we know little about its effects on investors and startups.[2]

Tax subsidies targeting angel investors have several attractive features. First, there is no need for the government to "pick winners," which requires policymakers to be informed about the underlying technologies and also might lead to regulatory capture (Lerner (2009)). Tax credits retain market incentives, leaving investors with skin in the game. Second, the administrative burden of tax subsidies is relatively low. Third, as a targeted subsidy, angel investor tax credits are a more precise tool than lowering capital gains taxes broadly (Poterba (1989)). However, stimulating local high-growth entrepreneurship requires that the intended investors – those with experience and skill to allocate capital – receive the tax credits and increase their investments in response to the policy. Therefore, while the flexibility of tax credit programs is attractive, there is no guarantee that the subsidy will go to the type of activities envisioned by policymakers.

To assess the effect of angel investor tax credits, we exploit their staggered introductions and terminations from 1988 to 2018 across 31 states in the U.S. Importantly for our empirical analysis, we find that state-level economic, political, fiscal, and entrepreneurial factors do not predict the implementation of angel investor tax credits, which suggests that the timing of a program in a particular state appears to be orthogonal to relevant local economic conditions. Based on available data for programs in our sample, subsidized

[1] Angels are wealthy individuals who invest in early-stage startups in exchange for equity or convertible debt. Countries with angel tax credits include Canada, England, France, Germany, Ireland, Portugal, Spain, Sweden, China, Japan, Brazil, Australia, and 31 states in the U.S.

[2] See, for example, "Should Angel Investors Get Tax Credits to Invest in Small Businesses?," *Wall Street Journal*, 3/9/2012; "The Problem with Tax Credits for Angel Investors," *Bloomberg*, 8/20/2010; "Angel Investment Tax Credit Pricey but Has Defenders," *Minnesota Star Tribune*, 10/31/2015.

investors received $8.1 billion in tax credits, which is large relative to state funding for entrepreneurship in states with these programs. Furthermore, these programs are also characterized by a high take-up rate, at 88%. Given an average tax credit percentage of 33%, these tax credits support up to $24.5 billion of angel investment over our sample period.[3]

To study the impact of angel tax credits, we use data on angel investments and investors compiled from Crunchbase, VentureXpert, VentureSource, Form D filings, and AngelList. We augment these with data on sales and employment of angel-backed firms from the National Establishment Time-Series (NETS) database. For a subset of states, we received data directly from state governments on startup certification applications, firms for which an investor received a tax credit, and investor identities. In our baseline analysis, we use a difference-in-differences framework to identify the effect of tax credits on angel investments.[4]

We begin by examining the impact of angel tax credits on angel investments. We find that these tax subsidies increase the number of angel investments by approximately 18%. This effect is amplified when programs are less restrictive and when the supply of alternative startup capital is more limited. Additionally, we show that angel tax credits increase the average investment size by 14% to 25% and the number of angel investors by about 31%.

Furthermore, we find that, after the introduction of angel tax credits, angel-backed startups have significantly lower pre-investment sales, employment, and labor productivity. They also have lower ex-ante growth and fewer serial entrepreneurs on the founding team. We show that this shift occurs throughout the distribution. Marginal angel investments flow primarily to firms with ex-ante low-growth characteristics relative to the average angel deal in the state, though there is no impact on the volume of high-growth startup deals. While the decline in the marginal quality may be expected in response to a positive funding shock, the large effect across different firms raises concerns about the ability of the tax credit to reach high-growth startups.

[3]As a comparison, Crunchbase estimates that global angel and seed investment in 2018 is around $15 billion (https://news.crunchbase.com/news/q4-2018-closes-out-a-record-year-for-the-global-vc-market).

[4] Alternatively, we estimate a generalized difference-in-differences model using the tax credit percentage, which is the maximum tax credit available as a percentage of an angel's investment, as a continuous treatment variable.

To explore this issue, we consider investor characteristics. The ability of angel tax credit programs to stimulate high-growth entrepreneurship depends partially on whether they attract professional, experienced angel investors, who have access to high-quality deals and the ability to screen deals. We evaluate this in two ways. We first examine characteristics of the investors who have used the tax credits, using data from the state tax credit programs. We find that take-up is primarily by investors who are younger, more local, and less experienced than the average angel investor. Such non-professional investors may have lower screening ability and reduced access to deals. They may also invest for non-pecuniary reasons (Huang et al. (2017)) or to exploit tax credits to minimize their tax burdens. In particular, insiders of beneficiary firms may invest for private benefits of control (Morck, Shleifer, and Vishny (1988) and Bena and Xu (2017)) and are well-positioned to engage in tax arbitrage. We find that at least 35% of beneficiary companies have at least one investor who is also a company executive or a family member of an executive, which is large relative to the 8% of angel-backed firms on AngelList with at least one insider investor.

While these results are informative about who uses the credits, they do not tell us which types of investors drive the increase in angel activity documented above. To address this, we conduct a second analysis using state-level data on angel investor characteristics. Following the introduction of angel tax credits, we observe a surge of in-state, new, and inexperienced investors. However, there is limited entry of professional, arms-length angels. This suggests that non-professional investors respond to these tax incentives, while professional investors do not.

Last, we test whether angel tax credits achieve their objectives stated in legislation, which typically include increasing employment, startup entry, and innovation. We find that these policies have no effect on a plethora of entrepreneurial activity metrics, including young-firm employment, job creation, startup entry, successful exits, and patenting. Across many specifications, subsamples, and measures, we consistently show that the angel tax credits have an economically small and statistically insignificant effect on local entrepreneurship. These results may not be surprising given that the increase in angel activity is mostly driven by non-professional investors.

We also examine the effect of angel tax credits at the firm-level by comparing startups backed by subsidized investors ("beneficiary companies") with firms certified for its investors to receive a tax credit but whose investors never received a tax credit ("failed applicants"). Failed applicants are a useful comparison group because they are in the same state and indicated interest in the tax credit. However, they are likely to be lower quality, suggesting that any bias might be positive. We continue to find very small and insignificant effects of receiving subsidized investment on subsequent financing, employment, and exit. This suggests that the scale of these programs is not responsible for the null effect.

These null effects are informative. They are not only statistically insignificant, but also small in magnitude. Although our measures may not capture all possible effects of the policy, they demonstrate that tax credits do not substantially impact common measures of entrepreneurial activity representing program objectives. Moreover, Abadie (2019) shows that insignificant results are actually more informative than significant ones when there is a prior on finding a significant effect and conditional on having sufficient power. Our analysis fits this framework well. First, many studies of other innovation tax credits find large positive effects, so a natural prior is to expect a positive effect.[5] Indeed, the programs' popularity suggests that policymakers have such a prior and believe angel tax credits can stimulate local entrepreneurship. Second, we show that our analyses have sufficiently high power. Therefore, our robustly null results provide useful new information about the debate on angel tax credits.

Taken together, our results suggest that U.S. state angel tax credits fail to reach the investor-startup pairs that would generate the impact intended by policymakers. Consistent with this idea, marginal investments flow to low-growth firms and we find no evidence of a significant increase in entrepreneurial activity in the affected states. These results suggest that implementation matters greatly in determining whether policy instruments have their desired impacts. That is, there may be a tradeoff between program flexibility and effective targeting. Angel tax credits may not reach investors with a comparative advantage in allocating capital. During the fast-paced deal process, professional angels in hub cities likely face coordination, information, and transaction costs to using angel tax credits in the startup's state. The tax credits seem to attract individuals with lower barriers to accessing

[5] This literature includes Hall (1993), McCutchen (1993), Mamuneas and Nadiri (1996), Hall and Van Reenen (2000), Bloom, Griffith, and Van Reenen (2002), Klassen et al. (2004), Wilson (2009), Clausen (2009), Agrawal, Rosell and Simcoe (2014), Dechezleprêtre et al. (2016), and Balsmeier, Kurakina and Fleming (2018).

the programs, helping to explain why non-professional investors – who tend to be more local and connected to firms – respond more than professional investors. This is consistent with evidence from public economics that informational and transaction costs to accessing government programs can deter precisely the individuals that the programs wish to target (Chetty and Finkelstein (2020), Bhargava and Manoli (2015), and Deshpande and Li (2019)).

The importance of targeting the right set of investors is also relevant to understanding the impact of other types of entrepreneurship programs. For instance, consider the case of matching funds, which are similar to tax credits in that they also subsidize investors at the time of investment. An example of a highly successful program is Yozma, the Israeli venture capital matching fund introduced in 1992, which targeted expert foreign investors (Lerner (2020)). In contrast, China's apparently similar program, the Government Guidance Fund Initiative, has not had the same success, since much of its matching capital came from local governments and state-owned companies rather than high-quality venture capital firms. Consistent with the contrast between the Israeli and Chinese programs, our results demonstrate that targeting investors who can identify and monitor high-growth startups is an important element of a government program focused on subsidizing capital for high-growth entrepreneurship.

Broadly, this paper contributes to the growing literature on early-stage financing, especially angel investment (e.g. Kerr, Lerner and Schoar (2011), Hellman and Thiele (2015), and Lerner et al. (2018)). González-Uribe and Paravisini (2019) evaluate the combined effects of U.K. investor tax credits *and* capital gains tax credits targeting new, external investors on firm decisions. Lindsey and Stein (2020) find that a decrease in the supply of angel investors after the Dodd-Frank Act leads to a decline in firm entry and a contraction in employment.[6] Additional work studies different sources of early-stage investment, such as bank debt and crowdfunding (Hellman, Lindsey, and Puri (2007), Robb and Robinson (2012), González-Uribe and Mann (2017), Hochberg, Serrano, and Ziedonis

[6] Our results do not contradict these papers. In González-Uribe and Paravisini (2019), capital gain tax credits are state-contingent and give investors strong incentives to screen and monitor. They also ban all types of insider investment. In Lindsey and Stein (2020), marginal investors are wealth constrained, but not necessarily lower ability (they were experienced before losing accreditation status). In our context, marginal investors tend to be non-professional investors with lower ability. This explains why a positive angel capital shock generates a null effect in our paper but a positive effect in Lindsey and Stein (2020).

(2018), Davis, Morse, and Wang (2019), and Xu (2019)). Finally, a recent strand of the literature examines how early-stage investors make decisions (Bernstein, Korteweg and Laws (2017), Ewens and Townsend (2019) and Gornall and Strebulaev (2019)).

We also contribute to the broad literature on government investment incentives, which overwhelmingly finds positive effects. Zwick and Mahon (2017) show that tax incentives increase investment, particularly for small firms, and Curtis and Decker (2018) show that lower corporate taxes spur new business formation. R&D grant programs have a positive effect on high-tech startups (Lach (2002), Bronzini and Iachini (2014), and Howell (2017)). Accelerators and new venture competitions – both of which often benefit from public funds – are also useful for startups (McKenzie (2017), González-Uribe and Leatherbee (2017), Fehder and Hochberg (2019), and Howell (2019)). The above policies are diverse, yet they have a key feature that distinguishes them from angel investor tax credits: Rather than targeting investors or financial intermediaries, they target firms performing real investment directly.[7] Despite being attractive to policymakers, the flexibility of tax incentives could also limit its impact.

2. Angel Investor Tax Credits

2.1 Background on U.S. State Angel Investor Tax Credit Programs

Over the last three decades, 31 states in the U.S. have introduced and passed legislation to provide accredited angel investors with tax credits.[8] Based on data available, Figure 1 shows the annual allocated expenditure on angel tax credits from 1989 to 2019, which totals $8.1 billion.[9] Take-up is high, at 88 percent of allocated funding by state legislatures. Based on an average tax credit percentage of 33%, these tax credits support up to $24.5 billion of angel investments, which is large relative to the total angel volume in these states. As a comparison, Crunchbase estimates that angel and seed investment *globally* in 2018 is around

[7] In contrast, the literature on government-backed venture capital, where the investor rather than the firm is subsidized, is more mixed (Brander, Egan, and Hellmann (2010), Lerner (2010), Brander, Du, and Hellmann (2015), González-Uribe and Paravisini (2019), and Denes (2019)).
[8] In addition to these 31 states, Massachusetts and Delaware have also introduced these programs but failed to launch the programs or attract qualified firms as of the time of this paper.
[9] New York and Oklahoma do not provide data on funds received by subsidized investors.

$15 billion. Furthermore, while the programs are typically small relative to overall state budgets, they often represent a significant portion of funding allocated to supporting entrepreneurship or small businesses.[10]

Panel A of Figure 2 provides a map of states with angel tax credit programs. The blue shading indicates the tax credit percentage, with darker shades representing larger tax credits. The figure highlights that angel tax credits are prevalent across the U.S. The extent of these programs is particularly notable since they do not occur in the seven states with no income tax, which are shaded in grey.[11] Panel B of Figure 2 shows the introduction and termination of these programs. In 1988, Maine introduced the Seed Capital Tax Credit Program, one of the earliest angel tax credit programs that continues today. A steady progression of states started programs during the following three decades. Colorado, Maryland, Minnesota, North Dakota and Ohio passed more than one version of an angel tax credit. Though the pace of adoption increased recently, the geography is dispersed and the program duration varies from just one year to three decades.

Tax credits are available to accredited investors and their pass-through entities.[12] State-level angel tax credits reduce the state income tax of an investor. For example, suppose that an investor earns $250,000 in a particular year and invests $20,000 in a local startup. If the state tax rate is 5% on all income, then the investor pays annual state taxes of $12,500. Assuming that the state introduced an angel tax credit of 35%, the investor can reduce her state taxes by $7,000, which is a decline of 56% relative to her annual state taxes.[13] Unlike capital gains tax credits that require positive returns, angel tax credits are not contingent on the startup's outcome. Therefore, angel tax credits are a fixed subsidy to investors that is provided after the investment event.

[10] For example, funding in Ohio, Minnesota, and Wisconsin are respectively 19%, 58%, and 86% of annual state funding for high-tech jobs or small businesses, most of which takes the form of grants.

[11] While there is no personal income tax for Tennessee and New Hampshire, these states tax investment income.

[12] We refer to accredited angel investors as angels throughout the paper. An accredited investor is defined as a person who earned income of more than $200,000 ($300,000 with a spouse) or has a net worth over $1 million. Since July 2010, net worth excludes home equity (Lindsey and Stein (2020)). The tax implications might differ for accredited investors compared to pass-through entities. Angel investor tax credits are more likely provided to individuals because most programs include investment caps.

[13] 35% is the maximum tax credit percentage available to an investor. The tax credit available to a particular investor will depend on her state tax liability. For ease of discussion, we refer to this as tax credit percentage.

Policymakers state that they implement angel tax credits to increase local economic activity, particularly employment of high-skill workers. As one example, the stated goal of Maine's angel tax credit program is "to spur venture capital investment in Maine startups and ultimately create more jobs in the state." In Wisconsin, "the Qualified New Business Venture (QNBV) Program helps companies create high-paying, high-skill jobs throughout Wisconsin." The three goals of the Louisiana program are: "To encourage third parties to invest in early stage wealth-creating businesses in the state; to expand the economy of the state by enlarging its base of wealth-creating businesses; and to enlarge the number of quality jobs available."[14] Since most programs cite spurring new investment and job creation as their goals, the analysis in subsequent sections focuses on financing outcomes and employment.

Table 1 provides summary statistics on the angel tax credit programs. *Tax credit percentage* is the share of an investment that can be deducted from an investor's tax liability. The mean (median) tax credit percentage is 34% (33%). The majority of programs set the maximum tax credit between 20% and 40%, with just three programs below 20% and only one program above 60%.[15] Programs often include eligibility criteria for both beneficiary companies and investors. These restrictions can include age caps (31% of programs), employment caps (39%), revenue caps (47%), assets caps (22%), and minimum investment holding period (50%). While many programs do not allow participation by owners and their families (64%), most states permit full-time employees, executives, and officers to receive tax credits. Lastly, tax credits are generally non-refundable (72% of programs) and non-transferrable (72%). Though these tax credits reduce a taxpayer's income liability for the current year, most programs allow excess credits to be carried forward to future taxable years (89%). Most programs target the high-tech sector, which guides our empirical design. Appendix Table A1 provides details for all programs.

2.2 Why are Angel Tax Credit Programs Enacted?

Angel tax credit programs have often been touted as "relatively simple and cost-effective for states" (Kousky and Tuomi (2015)) and proponents argue that they promote job creation,

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[14] See https://www.pressherald.com/2019/01/02/startup-investors-camp-out-for-maine-tax-credit, Wisconsin Economic Development Corporation 2013 Qualified New Business Venture Program Report; http://www.legis.la.gov/Legis/Law.aspx?d=321880;

[15] From 2001 to 2009, Hawaii offered an angel tax credit of 100%, which essentially guaranteed returns for investors. This tax credit was later revised to 80%.

innovation, and economic growth.[16] In light of this, states may introduce angel tax credit programs in times of local economic stagnation, which could pose a threat to our identification strategy.

We examine this concern by estimating a predictive regression to determine whether economic, political, fiscal, and entrepreneurial factors explain the introduction of angel tax credit program. The outcome, *ATC*, is an indicator variable equaling one if a state introduces an angel tax credit program in a given year. We also use *Tax credit percentage*, which is the maximum tax credit percentage available in a state-year with an angel tax credit program and is set to zero if there is no program in place in a state-year. We include year fixed effects and omit the years after a program starts. Appendix B defines the state-level variables included in each specification.

Table 2 provides the estimates for the predictive regression. In column 1, we find that lagged state economic, political and fiscal measures do not significantly predict the introduction of angel tax credit programs, except for the state income tax indicator. Column 3 incorporates entrepreneurship variables, which include establishment entry and exit rates, net job creation rate and venture capital volume. These variables do not have significant predictive power and are also economically small. When we include state fixed effects (even columns), we find that the maximum state personal income tax rate negatively predicts *ATC*, suggesting that there might be complementarities for the role of tax cuts and tax credit programs in stimulating a state's economy. We obtain similar estimates when we use *Tax credit percentage* as an outcome (columns 5 to 8). Overall, state economic, political, fiscal, and entrepreneurial conditions do not seem to drive the passage of angel tax credit programs.

The lack of predictability is consistent with the presence of considerable frictions in the passage of these programs. Some states discussed introducing these programs, but never proposed a law (e.g., Idaho and Montana). Other states proposed bills, but they did not pass the legislature (e.g., Mississippi and Pennsylvania). Even if a state legislature passed a program, several states failed to implement the program due to lack of funding or resistance after its passage (e.g., Delaware, Massachusetts, Michigan, and Missouri).[17]

[16] Tuomi and Boxer (2015) conduct case studies of two angel tax credit programs in the U.S. (Maryland and Wisconsin) and find suggestive evidence that these programs generate benefits that outweigh the costs.

[17] For example, the Missouri House of Representatives passed legislation in 2014, but it did not advance because of a controversial amendment barring investment in companies that do stem cell research (Moxley (2014)).

3. Data

3.1 Angel Deals, Investors, and State-level Real Outcomes

Angel investments are notoriously difficult to observe in the U.S. There is no comprehensive data set on angel investments, and much of what is known about the size of the angel market relies on estimates from surveys (Shane (2009) and Lindsey and Stein (2020)). To overcome this challenge, we combine data from Crunchbase, Thomson Reuters VentureXpert, and Dow Jones VentureSource, which we collectively refer to as "CVV," and Form D filings available through the U.S. Securities and Exchange Commission (SEC).

Crunchbase tracks startup financings using crowdsourcing and news aggregation. VentureXpert and VentureSource are commercial databases for investments in startups and mainly capture firms that eventually received venture capital financing.[18] Appendix C provides our detailed classification criteria for angel investments. We collect additional angel investment data from Form D filings. Form D is a notice of an exempt offering of securities under Regulation D and allow startups to raise capital from accredited investors without registering their securities (Ewens and Farre-Mensa (2019)).[19] Investment details, such as investment amount, security type, and issuer's industry, are available for electronic filings starting in March 2008. We drop financial issuers and pooled investment funds.[20]

We combine angel investments from the above data sources and disambiguate the data to eliminate duplicate coverage of the same investments in multiple sources.[21] This process generates 199,144 angel investments from 1985 to 2017. While not all angel investments trigger a Form D filing or appear in the databases described above, our dataset represents one of the most comprehensive set of angel deals available.

[18] We restrict to the following round type or investor type: "angel," "angel group," "angel fund," "individual," "micro," "pre-seed," "seed," "convertible note," "equity crowdfunding," or "accelerator." Our results are robust to restricting to investments explicitly classified as angel investments.

[19] Offerings under Regulation D are typically through Rule 506, which preempts state securities law. Before March 2008, Form D filings were paper-based and we use a Freedom of Information Act (FOIA) request to obtain these non-electronic Form D records from 1992 to 2008.

[20] We include only the first three issuances by each firm to more precisely identify angel investments. The results are similar if we include only the first issuance or the first two issuances by each firm. To capture unique offerings and information available at the time of offering, we drop amendments and only keep original filings.

[21] We use the following order of VentureXpert, VentureSource, Crunchbase and Form D filings. We find similar results using different orderings to disambiguate our data.

We match these angel investments to the National Establishment Time-Series (NETS) database, based on firm name, address, and founding year. This allows us to observe the characteristics of 129,568 angel-backed firms over time. We focus on the following ex-ante characteristics in the year before angel investment: sales, employment, sales growth, employment growth, and sales-to-employment ratio. For firms in the CVV sample, we also observe entrepreneurs' prior founder experience at the time of investment, which we use as another measure of startup growth potential (Hsu (2007) and Lafontaine and Shaw (2016)).[22]

We collect data from AngelList to study the effect of angel tax credits on investor composition. While AngelList is largely self-reported, it is the most comprehensive data available about the identities and locations of investors for angel investments. The drawbacks of AngelList are that the coverage is concentrated in more recent years, and that it does not contain information on investment amount or the exact investment date.

Lastly, we employ data on state-level real outcomes from the U.S. Census Bureau's Business Dynamics Statistics (BDS), Quarterly Workforce Indicators (QWI), and County Business Patterns (CBP). Our main measures are job creation and destruction by young firms and establishment entry and exit rates. We also examine other dimensions of state-level activity, such as innovation (based on patent applications from USPTO), entry of high-growth firms (based on Startup Cartography data from Fazio, Guzman, and Stern (2019)), number of successful startup exits, and others. Since tax credit programs primarily target the high-tech sector (information technology, biotech, and renewable energies), our analyses generally focus on angel investments in these sectors. The sample for the baseline specification is collapsed to a state-year panel of angel investment volume and average deal characteristics in the high-tech sector. Additional details on the data, variables, and sample periods for this analysis are in Section 6.1.

Table 3 contains summary statistics for the state-year level data. Appendix A provides detailed definitions of all variables. In our main sample from 1993 to 2016, approximately 25% of state-years have an active angel tax credit program. The average angel-backed firm is 5.4 years old at the time of investment, has about $200,000 in sales,

[22] The NETS-matched sample period 1993 to 2016. We start the sample in 1993 because Form D data is incomplete in 1992. Additionally, we require up to two years of pre-investment data from NETS to measure deal quality. Given that NETS covers 1990 to 2014, our sample ends in 2016. The CVV sample period is 1985 to 2016. We start this subsample in 1985 because the coverage of CVV is relatively poor before 1985 and the first angel tax credit program began in 1988.

seven employees, a sales growth rate of 72%, an employment growth rate of 45%, and generates nearly $27,000 in sales per employee in the year before investment. On average, 5% of the founders on a founding-team are serial entrepreneurs.

3.2 Applicant Company Data

We obtain data on startups receiving subsidized investment ("beneficiary companies") for 12 states from public records or privately from state officials, including seven states with investor-level data. For ten of these states, we also observe companies that were certified to receive subsidized investment, but for which no investor actually was awarded a tax credit. We refer to these firms as "failed applicants." The sample period for these data is 2005 to 2018. The data are comprehensive for a given program-year, though we do not always observe every year for a given program. Panel A of Appendix Table A2 shows the number of unique companies by state. In total, there are 1,823 beneficiary companies and 1,404 failed applicants. We merge unique tax credit recipients to CVV and NETS, by name and location. We match 1,227 firms to the financing data and 808 startups to the firm-level data.

4. Angel Investments and Firm Type

4.1. Identification Strategy

Our empirical approach is a difference-in-differences design, exploiting the staggered introduction and expiration of 37 angel tax credit programs in 31 states from 1988 to 2018. Specifically, we estimate the following specification:

$$Angel\ investments_{st}\ or\ Real\ outcomes_{st} = \alpha_s + \alpha_t + \beta \cdot ATC_{st} + \gamma' \cdot X_{s,t-1} + \varepsilon_{st}, \quad (1)$$

where ATC_{st} is an indicator equaling one if state s has an angel tax credit program in year t. $X_{s,t-1}$ is a vector of state-year controls.[23] We find similar results without including these controls. The specification includes state (α_s) and time (α_t) fixed effects. Standard errors are clustered by state (Bertrand, Duflo, and Mullainathan (2004)). The coefficient of interest

[23] In particular, we include lagged Gross State Product (GSP) growth, natural log of income per capital, natural log of population, indicators for whether a state is controlled by Republicans or Democrats, ratio of revenue to GSP, ratio of expenditure to GSP, ratio of debt to GSP, an indicator for whether a state has personal income tax, and the maximum state personal income tax rate. Our results are similar without controls.

is β, which captures the marginal effect of angel tax credits on the angel investments and real outcomes.

We extend our baseline analysis along two dimensions. First, we estimate a generalized difference-in-differences model that exploits variation in the size of tax credit incentives across programs. Specifically, we replace ATC_{st} in equation (1) with a continuous treatment variable, *Tax credit percentage*$_{st}$, which equals the maximum tax credit percentage available in a state-year with an angel tax credit program, and zero otherwise. Second, we estimate the following dynamic difference-in-differences specification:

$$Angel\ investments_{st}\ or\ Real\ outcomes_{st} = \alpha_s + \alpha_t + \delta \cdot ATC_{s,\leq t-4} + \beta' \cdot \sum_{n=-3}^{3} ATC_{s,t+n} + \theta \cdot ATC_{s,\geq t+4} + \gamma' \cdot X_{s,t-1} + \varepsilon_{st}, \tag{2}$$

where $ATC_{s,\ t+n}$ are indicator variables for each year in a three year window around the tax credit introduction. Additionally, we define $ATC_{s,\ \leq t+4}$ as an indicator variable equaling four or more years before an angel tax credit program starts, and similarly construct $ATC_{s,\ \geq t+4}$. The year before the start of an angel tax credit program is normalized to zero.[24]

4.2. Tax Credits and Angel Investments

Panel A of Table 4 reports the difference-in-differences estimates using equation (1) for the effect of angel tax credits on the number of angel investments. In column 1, we find that angel tax credits significantly increase angel investments by 18.4%.[25] This indicates that these tax incentives led to an economically significant increase in angel activity along the extensive margin. We also examine the impact of the size of the tax credits on the quantity of angel capital invested by constructing a continuous treatment variable, *Tax credit percentage*. In column 2, we find that a 10-percentage-point increase in the tax credit available to investors significantly increases the number of angel-backed firms by 5.7%.

A key identifying assumption for our empirical design is that, if angel tax credits were not implemented, there would be parallel trends in states with these programs. Using equation (2), we estimate a dynamic difference-in-differences specification. In Panel A of Figure 4, we find no pre-treatment differences in angel investment volume before the

[24] Section 4.4 discusses additional identification tests, including a triple difference (DDD) approach that compares the high- and low-tech sectors.
[25] When the outcome is a natural logarithm, we report the exponentiated coefficient minus one.

introduction of angel tax credits. Notably, the effect only appears in the year following the implementation of these programs and persists for at least the four following years. This finding supports the parallel trends assumption.

We also cross-validate these findings using AngelList data. These data allow us to observe investors' identities, yet they are more concentrated in recent years. In Table A3, we find that angel tax credits significantly increase the number of angel investments, the number of invested firms, and the number of unique angel investors on AngelList by 27.6% to 32.3%. In addition to validating an increase in angel activity, these results also suggest that this increase is not solely driven by the same investors investing in more firms, but rather that there is entry of angel investors.

Next, we examine the importance of program design in the effect of angel tax credits on angel investments. The variable *Program flexibility* measures the presence and strictness of the 16 restrictions in Table 1.[26] If the increase in investment is driven by angel tax credits, we expect more flexible programs to have a larger effect on investment. In column 1 of Panel B in Table 4, we find this to be the case: A one-standard-deviation increase in program flexibility leads to an additional 12.1% increase in the quantity of angel investments. When we use tax credit percentage as the treatment in column 3, we find similar and significant results. These results highlight the importance of the program design.

We further explore whether the supply of local capital plays a role in the impact of angel tax credits on the volume of angel investments. To capture the supply of venture capital relative to young firms, we construct a state-year level measure of venture capital supply, *VC supply*, which is the aggregate venture capital investment amount (excluding angel and seed rounds identified in our main sample) scaled by the total number of young firms (of age 0 to 5) in a state-year. We standardize *VC supply* by subtracting its mean and dividing by its standard deviation. Columns 2 and 4 show that angel tax credits have a weaker effect on angel investment volume in states with an ample supply of venture capital. This is consistent with angel financing and venture capital being substitutes (Hellmann, Schure and Vo

[26] For each non-binary restriction, we rank programs from least to most strict and assign the highest rank to programs without this restriction. These rank values are normalized to the unit interval. We also construct indicator variables for programs that do not exclude insider investors and for each of the non-refundable, non-transferable, and no carry forward restrictions. To form the *Program flexibility* index, we sum these 16 variables and then standardize the index by subtracting its mean and dividing by its standard deviation prior to interacting it with our treatment variables.

(2017)), and suggests that angel tax credit programs are particularly effective in states with a lower supply of venture capital and where firms may face more limited options in raising early-stage capital.

While angel tax credits increase investment, it is not clear that they will also increase the amount of capital invested in a particular startup. First, projects may not be scalable. Second, entrepreneurs might be very concerned with dilution, and therefore may want to minimize capital raised in each round (Myers and Majluf (1984)). Lastly, due to the benefits of diversification, investors may prefer to invest in more firms rather than increasing the amount per investment. We can observe the amount invested in an angel round in the Form D data starting in 2009 and in the CVV data. Panel C of Table 4 examines the effect of angel tax credits on average investment amount using these two subsamples. In columns 1 and 3, we find that angel tax credits increase the average investment amount by 13.8% to 25.0%. Columns 2 and 4 show that a 10-percentage-point increase in the credit percentage increases investment amounts by 3.7% to 4.8%. Therefore, there are positive effects in both the intensive and extensive margins.

Combining the estimates in Tables 3 and 4, our results suggest that a 10-percentage-point tax credit increases total angel investment by 9.4% to 10.5%. To interpret this magnitude, we benchmark it against the scenario in which tax credit subsidies do not crowd out investors' out-of-pocket investment. For example, if investors would have invested \$100 million in the absence of a credit, a 10-percentage-point credit could increase investment to \$111 million, with investors still paying \$100 million (\$111 million × (1-10%)). A 10-percentage-point tax credit thus generates an 11% increase in investment (or, equivalently, a multiplier of 1.11) in a no-crowding-out scenario. Our estimate of 9.4% to 10.5% is slightly lower than this benchmark, suggesting a small amount of crowding out.

Taken together, we find that angel investors respond to tax credit incentives by both investing in more startups and investing larger amounts. These results provide the first evidence that angel tax credits significantly affect the deployment of capital to startup firms.

4.3 Tax Credits and Angel-Backed Firms

Given the increase in investment by angels, it is important to understand how tax credits affect the type of firms receiving angel financing. On the one hand, these tax subsidies could increase the quantity of high-growth firms being financed if there are frictions in the angel market that are relaxed by the policy. The tax credit program may also induce the local angel community to become more professional, leading to higher quality investments. On the other hand, an increase in the supply of financing should reduce the quality of the marginal investment, leading to lower average growth characteristics after the policy. Such a decrease might be exacerbated if new investors are worse than pre-existing investors at selecting potentially high-growth firms.

Table 7 estimates the changes in ex-ante characteristics of high-tech angel-backed firms at the state-year level using equation (1). In column 1 we find that startups have an 18.7-percentage-point lower pre-investment sales growth in states with angel tax credits, which is large relative to an average pre-investment sales growth of 72%. Column 2 shows that the average pre-investment sales for angel-backed firms are 41.6% lower when a state implements an angel tax credit. We find similar effects when examining ex-ante employment and employment growth: pre-investment employment growth is 12.6 percentage points lower and employment 12.5% lower after a state introduces angel tax credits. In column 5, we construct a measure of labor productivity by calculating the natural logarithm of sales divided by employment. We find that the pre-investment startup productivity is 33.8% lower during angel tax credit programs.

One important predictor of startup success is founders' prior entrepreneurship experience. Hsu (2007) and Lafontaine and Shaw (2016) show that serial entrepreneurs are associated with better startup performance. We use detailed biographic information from CVV on firms' founders to measure their prior entrepreneurship experience using the fraction of serial entrepreneurs on a startup's founding team. In column 6, we find that, after a state implements angel tax credits, the firms receiving angel investments have 1.3 percentage points lower fraction of serial entrepreneurs on their founding teams, which is a 26% decline relative to the sample mean. Overall, the results indicate that after the introduction of tax credit programs, angel-backed firms have lower ex-ante growth potential.[27]

It is possible that these average declines in ex-ante growth characteristics reflect a positive impact on investor risk tolerance or interest in experimentation, which are important

[27] We find similar results using the *Tax credit percentage* as the treatment variable.

for innovation (Manso 2011, Kerr, Nanda and Rhodes-Kropf 2014). To assess this, we compare the distributions of angel-backed firms' ex-ante growth characteristics in state-years with an angel tax credit program to state-years without a program. Figure A1 in the appendix shows that consistent with our regression estimates, the distribution of angel-backed firms shifts to the left – towards lower growth characteristics – in state-years with angel tax credit programs. Importantly, this shift occurs across the entire distribution. There are no substantial differences in the dispersion of the distributions, nor are there significant differences in the tails. These findings suggest that our results are not driven by investors' increasing tolerance for risk or greater willingness to experiment with unproven firms after receiving subsidies.[28]

To examine where the marginal angel investments flow, we employ the same specification used in Panel A of Table 5, but split angel investments by ex-ante characteristics at the median. Across all columns in Panel B of Table 5, we find that angel tax credit programs have insignificant effects on the amount of capital allocated to high-growth firms, but the programs significantly increase the capital invested in low-growth firms.

Overall, we show that tax credits are used to invest in firms with relatively low-growth characteristics. This result has two important implications. First, the decline in high-growth investments supports our empirical design. Given the increase in angel activity documented before, a residual threat to our identification strategy is the concern that states introduce tax credits when the local entrepreneurial ecosystem is about to experience a boom. Since we find that investment increases but investment into high-growth startups declines, our results appear to be more consistent with an increase in the supply of angel financing, rather than a shift in demand. Second, along with the distributional shift described above, the result suggests that the increase in angel activity is not driven by the discovery of startups with high-growth potential.

[28] We find similar results when we examine ex-post exit outcomes. As shown in Figure A2, firms receiving angel financing during tax credit programs have worse exit outcomes: they are less likely to achieve successful exits through IPO or M&A, and conditioning on exit, have lower exit pricing.

4.4 Robustness

We examine the robustness of our results on the effect of angel tax credits on angel investments and the growth characteristics of angel-backed firms. Since angel tax credit programs primarily target the high-tech sector, we use the non-high-tech sector as a placebo group and estimate a triple-difference (DDD) model. There are two benefits of DDD. First, the non-high-tech sector serves as a counterfactual as to what would have happened in the high-tech sector in the absence of angel tax credits. Second, the DDD specification allows us to additionally include state-year fixed effects to eliminate any remaining time-varying state-level confounders and compare the impact of angel tax credits across sectors within the same state-year. Specifically, we estimate the following DDD model at the state-year-sector level:

$$Volume_{sti} \text{ or } Quality_{sti} = \alpha_{si} + \alpha_{it} + \alpha_{st} + \beta \cdot ATC_{st} \cdot High\text{-}tech_i + \varepsilon_{sti}, \quad (3)$$

where $High\text{-}tech_i$ is an indicator for sector i being high-tech, which we define as information technology, biotech, and renewable energy based on program requirements. α_{si} represents state-sector fixed effects, α_{it} sector-year fixed effects, and α_{st} state-year fixed effects, which absorb ATC_{st} and the state-year controls $X_{s,t-1}$. Standard errors are clustered by state.

In Panel A of Table A4, we examine the effect of angel investor tax credit programs on the quantity of angel investments, while Panel B studies the effect on angel-backed firms. We find that in the high-tech sector relative to the non-high-tech sector, angel tax credits significantly increase the number of angel investments but lead to lower growth characteristics of angel-backed firms. The magnitudes are similar to those estimated in Tables 4 and 5 using the difference-in-differences specification.[29]

We also evaluate the robustness of our results to several different sample restrictions. First, we limit our sample to 2001 to 2016, when our data have better coverage of angel investments. In Panel A of Table A5, we find that the results are quite similar for effects on both the quantity and ex-ante characteristics of angel investments. Second, Panel B of Table A5 drops sales and employment estimated by NETS, and reports that the estimates are quantitatively similar. Third, we separately estimate our results for the CVV sample (Panel

[29] There is no impact of angel tax credits on the quantity or quality of angel investments in the non-high-tech sector, which is consistent with the eligibility criteria of most programs. Further, the null results for the non-high-tech sector suggest that our findings are not driven by unobserved state economic shocks or by unobserved trends in local entrepreneurship.

C) and the Form D sample (Panel D), and find strikingly similar results across estimates.[30] Fourth, Panel E shows that our main findings are robust to dropping angel investments from VentureXpert and VentureSource, which tend to capture angel-backed firms that eventually received institutional capital. Fifth, Panel F shows that our results remain highly similar if we drop California and Massachusetts from our sample. Taken together, these findings provide extensive robustness of the results in this section and address potential concerns about the sample.

5. Investor Characteristics

Examining what types of investors take up angel tax credits sheds light on how these programs affect the local entrepreneurial ecosystem. Program success depends on inducing investors to make new investments in startups with the potential of having a large impact on the local economy. Therefore, the ability of subsidized investors to allocate funds effectively is key in generating benefits for the economy. Not surprisingly, a common goal of these programs is to attract professional angel investors that would not otherwise invest in firms in the state.[31]

It is an empirical question which type of investors respond to this policy. We first examine which investors actually participated in the program (Section 5.1). Within this context, we also discuss some of the potential concerns related to the presence of non-professional investors that are subsidized by angel tax credits. We then quantify the relative importance of different types of investors in explaining the increase in angel activity (Section 5.2).

5.1. Which Investors Receive Tax Credits?

We first describe the individuals who use angel tax credits. For seven states, we obtain data on angel investor identities and connect them with LinkedIn for investors' demographics.

[30] This addresses a concern that the Form D data might capture investments by other types of investors.

[31] For instance, this article advertises the success of the program in Minnesota based on its ability to attract out-of-state investors, which would have not otherwise looked into Minnesota firms (https://www.americaninno.com/minne/inno-insights-minne/minnesotas-angel-tax-credit-is-back-heres-what-you-need-to-know).

Table 6 reports the statistics for the 5,637 subsidized individual investors.[32] We find that 87% of the subsidized investors are male and 95% are white, which is consistent with the findings in Ewens and Townsend (2019) that the vast majority of angel investors are white males.[33] The average angel investor is 42 years old, lower than the average age of 58 in Huang et al. (2017).

We also find evidence supporting the idea that subsidized investors are often not professional investors. First, only 6.2% of the subsidized investors have prior entrepreneur or co-founder experience, and just 0.7% self-identify as professional investors. In their survey, Huang et al. (2017) find that 55% of angels have past entrepreneurial experience. These entrepreneurial angels invest in more companies, take a more active role in their portfolio companies, and have superior returns. In our data, the majority of subsidized investors are corporate executives (82%), with the next largest groups being doctors (7.3%) and lawyers (4%). Second, a disproportionate share (79%) of subsidized investors are located in the same state as the tax credit program, which is much higher than if startups were targeted randomly by angels (Huang et al. (2017)).

Together, these statistics paint a portrait of angel investors who receive tax credits: they are, on average, younger, more local, and less entrepreneurial than the typical angel investor. In other words, investors taking up the programs appear to be less professional than the average angel.

Take-up of tax credits by non-professional investors may limit the effect of these programs in spurring entrepreneurship. First, non-professional investors tend to be inexperienced, and therefore have lower ability to screen deals or less access to high-quality deals. As a result, the investments by non-professional investors may fail to target firms that have high-growth potential. This is consistent with our earlier finding that the increase in angel activity is completely driven by investment in low-growth firms (Section 4.3).

Second, non-professional investors may invest for non-pecuniary reasons (Huang et al. (2017)) or exploit tax credits to minimize their taxes. If subsidized investors do not target high-growth firms to maximize financial returns, then it is unlikely that the tax credits will

[32] This excludes investors that provide capital through a fund.

[33] We coded the ethnicity or race using pictures. 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).

have a substantial impact on the local economy. To examine these motives, we focus on insider investors of beneficiary firms, who may have non-pecuniary reasons for investing or have private benefits of control (Morck, Shleifer, and Vishny (1988) and Bena and Xu (2017)). Insiders may also be in a unique position to exploit tax credits for tax arbitrage. Note that the tax credit program imposes no restrictions on how the beneficiary firm uses the investment; the firm could, for example, pay out the investment as dividends or wages to executives. Some investments by insiders might be relabeled as angel investments to obtain the tax credits.

We examine insider investors using data from states where we observe the identities of beneficiary companies and the names of investors that were awarded tax credits.[34] These data include 628 unique companies and 3,560 investors. We identify an investor as an insider if the person is an executive on a Form D filing, listed as an employee on LinkedIn, or shares a last name with an executive. Appendix D provides additional details for identifying insiders.

We document that a substantial share of investors receiving tax credits are insiders. In Panel B of Table 6, we find that 35% of the firms have at least one investor who is an executive or family member of an executive, and 33% have an investor who is an executive. The share is 24% or higher in all states except Kentucky, where it is just 4%. As a benchmark, only 8% of startups in AngelList have at least one investor who is also employed at the company in which they are investing. In Panel C of Table 6, we summarize insiders at the investor level and report that 14% of subsidized investors are the executives of the invested company or their family members.[35] The corresponding benchmark in AngelList is only 2%.

[34] We observe these data for Ohio, New Jersey, Maryland, New Mexico and Kentucky. These five states are reasonably representative of states that employ angel tax credits, including some high-tech clusters (New Jersey and Maryland), as well as rural areas (Kentucky and New Mexico), and the Rust Belt (Ohio).

[35] Interestingly, many states explicitly permit the investor to be employed at the company (see Appendix Table A1). Ohio, New Jersey, Kentucky and Maryland do not exclude executives, but do exclude owners with above a certain threshold of pre-investment ownership stake, ranging from 5% for Ohio to 80% for New Jersey. New Mexico excludes executives but has no limits for owners, families, or employees.

5.2. Which Investors Respond to Tax Credits?

The previous section suggests that non-professional investors represent a substantial share of tax credit recipients. The presence of non-professionals could limit the policy's impact because this type of investors may have lower ability to select high-growth firms or worse deal access, in addition to potentially using tax credits for non-pecuniary reasons or for tax planning purposes. While the analysis of recipients is important because it allows us to focus on the group of investors that actually benefited from the tax credit, it is also limited because it does not allow us to quantify the relative importance of each type of investors in explaining the increase in angel investment.

Therefore, we study the impact of angel tax credits on the composition of investors making angel investments using AngelList data.[36] In Panel A of Table 7, we estimate equation (1) at the state-year level, where each dependent variable is the log number of investors in the particular category. We find that angel tax credits increase in-state angel investors by 31.9% in column 1, while there is no significant change in out-of-state investors in column 2. Column 3 shows that tax subsidies lead to an increase of 30.0% in investors with experience of one year or less, though there is no significant effect on more experienced investors. We observe a similar pattern for investors that had a portfolio company with a successful exit (columns 5 and 6) and with past entrepreneurial experience (columns 7 and 8). Given that most professional angels have prior entrepreneurial experience and are active in making investments (Huang et al. (2017)), these results are consistent with an increase in non-professional investors.

In Panel B, we also conduct the analysis at the investor level. For these specifications, the dependent variable is an indicator equaling one if the characteristic in the column header describes an investor. Each regression is weighted by the inverse of the number of deals in a state.[37] In column 1, we find that angel tax credits increase the likelihood of an in-state investor by 8.7 percentage points. We also show that the probability of new investors increases by 5.8 percentage points in column 2. Additionally, investors during angel tax credit programs are more likely to have no exit (column 3) and no entrepreneurial experience

[36] We find similar results if we restrict the sample to start in 2010 to mitigate a potential concern about backfilled data.

[37] This provides each state with an equal weight and accounts for the overrepresentation of hub states (California, New York, and Massachusetts), which comprise 79% of the sample.

(column 4). In sum, the increase in angel investments in Section 4.2 seems to be driven primarily by local, inexperienced angel investors, whereas professional, arms-length angels do not respond to tax incentives. These results also help explain why marginal investments flow to lower-growth firms as documented in Section 4.3. As we show in Table A6, non-professional investors tend to invest in startups that have worse eventual exit outcomes.

There are at least four reasons why investment by professional angels might not increase as a result of angel tax credit programs. First, professional investors might use tax subsidies without the subsidies altering their investment decisions. This could, for example, reflect a limited supply of local worthy startups. Second, professional investors might not apply for tax credit if it is administratively burdensome or they use the Alternative Minimum Tax. Third, professional investors might find it costly to coordinate access to the tax credit with the startups, who must also submit information to the state to be certified. If these investors focus on providing capital to promising startups in a short period of time, it might take too long to pursue angel tax credits. Finally, since professional investors aim to invest in firms that provide substantial returns, the marginal value of the tax credit could be second-order relative to the ex-ante administrative costs.

6. The Impact of Angel Tax Credits on the Real Economy

6.1. State Economic Outcomes

States introduce angel tax credit programs primarily to stimulate the local economy and entrepreneurial ecosystem. To examine the impact of these programs, we consider several standard measures of startup activity and economic outcomes. First, we use the Quarterly Workforce Indicators (QWI) to measure the total employment in a state and year across all industries, in addition to the high-tech sector. Second, we use the Census' Business Dynamics Statistics (BDS) to explore the effect of the policy on job destruction and job creation rates for all firms and also for young firms. Third, we examine the policy's effect on entry and exit rates of young establishments using BDS, in addition to establishment counts of small firms (those with less than 20 workers) for manufacturing and high-tech from Census' County Business Patterns (CBP).[38] Lastly, we evaluate the likelihood of a successful exit through an IPO or acquisition, the entry of potentially high-growth firms (Fazio, Guzman, and Stern (2019)), and patent application counts to capture the right-tail of entrepreneurial activity. In total, our analysis uses 13 state-year variables.[39] To interpret the result as a percentage increase, we log-transform all outcomes.[40]

We present the results in Figure 3. For each variable, we report the coefficient and the 95% confidence interval, which are estimated using equation (1). Panel A reports the findings without controls, while Panel B includes state-level controls. Across the broad array of outcomes, we consistently find that the impact of the policy is insignificant, and the coefficient magnitudes are economically small. For instance, employment in young firms in manufacturing and high-tech increases by 0.6%, while job creation in young firms increases by 0.9%. We also estimate dynamic difference-in-differences specifications for five main outcomes using equation (2) and report the coefficients in Panels B to F of Figure 4. Across all outcomes, we observe no pre-trends and find that the estimates remain statistically insignificant and economically negligible following the introduction of angel tax credits.[41]

Overall, these results suggest that angel tax credits do not significantly impact state-level economic activity or the local entrepreneurial ecosystem. Although the lack of a significant effect does not necessarily imply that the policy had no effect, the null results are informative for two reasons. First, our findings are economically small, which is in stark contrast to the estimates for the other types of tax credits. One useful benchmark is the R&D tax credit that many states and the federal government offer to R&D-performing firms. Many studies find large positive effects of these R&D tax credits (see Introduction for references), but two examples are useful to highlight. Balsmeier, Kurakina and Fleming (2018) find that California's R&D tax credit increased patents, citations, and the stock market value of patents by 5% to 12%. Dechezleprêtre et al. (2016) show that an R&D tax credit for small

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[38] Since there is no information on establishment counts for young firms by industry in the CBP, we split by size. We find the same effect on establishment across all industries.
[39] These variables are described in the table in Appendix B. For each variable, we use the largest sample available at the time of the paper between 1993 and 2017. The exact sample used for each variable is reported always in Appendix B.
[40] The log transformation also facilitates our subsequent power analysis (Appendix E). In Appendix Table A.4, we show that our results are similar without log-transforming the rate variables.
[41] The same results hold if we drop California and Massachusetts (Table A.3)

firms in the UK increased patenting by 60%. In both cases, the R&D credit value relative to payable taxes is smaller than the average angel tax credit percentage in our data.[42]

The second the null results are important is that as shown in Abadie (2019), null effects are especially informative when the prior is that a policy will be effective, regardless of how tight the confidence intervals are around zero. Since policymakers implement angel tax credit programs to stimulate the local economy and tax credits appear to have a large positive effect in other settings, angel tax credits fit this framework. Furthermore, if the power of the test is sufficiently high (above 0.5), a null effect is actually more informative than a significant effect (Abadie (2019)). We calculate the power of our analysis across all outcome variables based on Burlig, Preonas, and Woerman (2020). Under the assumption that the effect is relatively small (3%), we find that the power – i.e. the probability of rejecting the null across all outcomes, when the policy impacted at least one of them – is always substantially higher than 0.5. Appendix E provides details about our power analysis.

6.2. Firm-Level Effects

One potential concern about the null aggregate finding is that state angel tax credit programs might not be large enough to generate significant impacts on aggregate outcomes. However, as highlighted in Section 2.1, these tax subsidies are in fact large relative to state-level support for entrepreneurial activity, suggesting that their potential effects should be detectable. That said, if the null aggregate effects reflect program size, we expect to observe an effect at the firm level. In this section, we examine the impact of angel tax credits on beneficiary firms.

We evaluate the effect of angel tax credits on startups by comparing firms financed by subsidized investors ("beneficiary companies") to other companies that were certified but failed to have an investor receive a tax credit ("failed applicants"). Failed applicants represent a useful comparison group because they are in the same state and indicated interest in the tax credit. However, failed applicants are likely to be relatively lower quality because they either failed to raise angel financing or applied after the state ran out of funding for the

[42] Other interventions, such as grants, also appear to have large effects. Howell and Brown (2019) find that small business grants, which are about five times the average tax credit amount, increase employment by 27%.

tax credits.[43] It is reasonable to assume that if there is bias in comparing these groups, it should be in the direction of beneficiary companies performing better.[44]

We estimate the following equation:

$$Y_{i,t+k} = \alpha_{gt} + \alpha_{st} + \beta \cdot TC_{st} + \theta Y_{i,t-1} + \varepsilon_{st}, \tag{4}$$

where the dependent variable $Y_{i,t+k}$ is the outcome for startup i in year $t+k$, for k = 1, 2, 3. Year t is the year that the startup either received its first tax credit or unsuccessfully applied for a tax credit for the first time. TC_{st} is an indicator for whether startup i received a tax credit or was denied a tax credit. $Y_{i,t-1}$ is the outcome variable in the previous year. The specification includes sector-year (α_{gt}) and state-year (α_{st}) fixed effects. Standard errors are clustered by state-year.[45]

Table 8 shows the relationship between receiving a tax credit and subsequent venture capital financing, which is a common proxy in the literature for early stage startup success. The outcome variable in column 1 is an indicator equaling one if a firm raises venture capital funding within two years following the tax credit application year. We find that receiving subsidized angel investment has no impact on subsequently raising venture capital. We also find no effects on the amount of investment (unreported). In column 2, we show that angel tax credits do not impact the probability of a successful exit based on an IPO or acquisition. In columns 3 to 5, we examine several measures of firm-level employment. We continue to find that subsidized investment does increase the probability of having at least 25 employees in the second year after the tax credit (column 3), at least 10 employees (column 4) or employment greater than the 75th percentile among certified companies (column 5). In Appendix Table A7, we show similar results using a matching estimator comparing beneficiary companies to similar control firms in nearby states without tax credit programs.

Overall, beneficiary companies do not raise more money or grow more than certified companies for which no investor received a tax credit. This is to be expected if the investments either reflect tax arbitrage on the part of insiders, or if they are simply poor quality, zero NPV investments. More generally, these findings are consistent with the null

[43] In some states, there is no time limit on when a qualified business can receive an investment that can claim a tax credit, while in other states it is limited to one year (Appendix Table A1).
[44] Panel B of Table A2 provides summary statistics on beneficiary firms and failed applicants.
[45] We cluster by state-year because there are limited clusters by state. The results are quite similar with other approaches, including robust standard errors.

effect of angel tax credits on local economic activity and suggests that the scale of these programs is not responsible for the null effect.

7. Conclusion

There is substantial government interest in supporting startups, with investor incentives being a particularly appealing option. As a result, states across the U.S. have implemented tax credits for angel investors. Yet despite debate, there has been no systematic evidence on the effectiveness of these policies. Understanding angel tax credits is particularly important for both academics and policymakers, as more regions propose implementing such tax credits and the global angel market is rapidly expanding (OECD (2011)). For example, Senator Christopher Murphy recently proposed legislation to establish a federal angel investor tax credit in the U.S.[46]

This paper offers the first analysis of U.S. angel tax credits and presents three main results. First, we find that angel tax credits significantly increase state-level angel investors' activity. This increase is connected to a decline in the ex-ante growth characteristics of the marginal start-up funded by angels. Second, we show that the increase is mostly explained by a surge in inexperienced, young, and new investors, with no impact on professional angel activity. This has important implications for understanding how angel tax credits affect local entrepreneurship, since non-professional investors may have a lower ability to screen deals and less access to high-quality firms. Furthermore, non-professional investors may be driven by non-pecuniary or tax arbitrage motives. Consistent with this concern, we find that a substantial share of subsidized investors are firm insiders. Third, in line with the response by non-professional investors, we find no evidence that these policies had any impact on the local entrepreneurial ecosystem.

These findings suggest that policymakers should be cautious in using tax credits to stimulate entrepreneurial activity. Angel tax credits, relative to direct programs such as grants, have the attractive feature of being more market-based tools that do not require the government to identify which companies deserve subsidy. However, this flexibility presents

[46] See https://www.congress.gov/bill/114th-congress/senate-bill/973.

problems of its own, since the intended investors may not be sensitive to the policy. This point has broad implications for designing policies to foster entrepreneurship.

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Figure 1. Total Expenditure on Angel Investor Tax Credit Programs

This figure shows the total annual expenditure on state angel investor tax credits (i.e. take-up). All states in Table A1 are included except Oklahoma and New York, for which no data are available. The total across all years is $8.1 billion. On average, take-up is 88 percent of allocated funding.

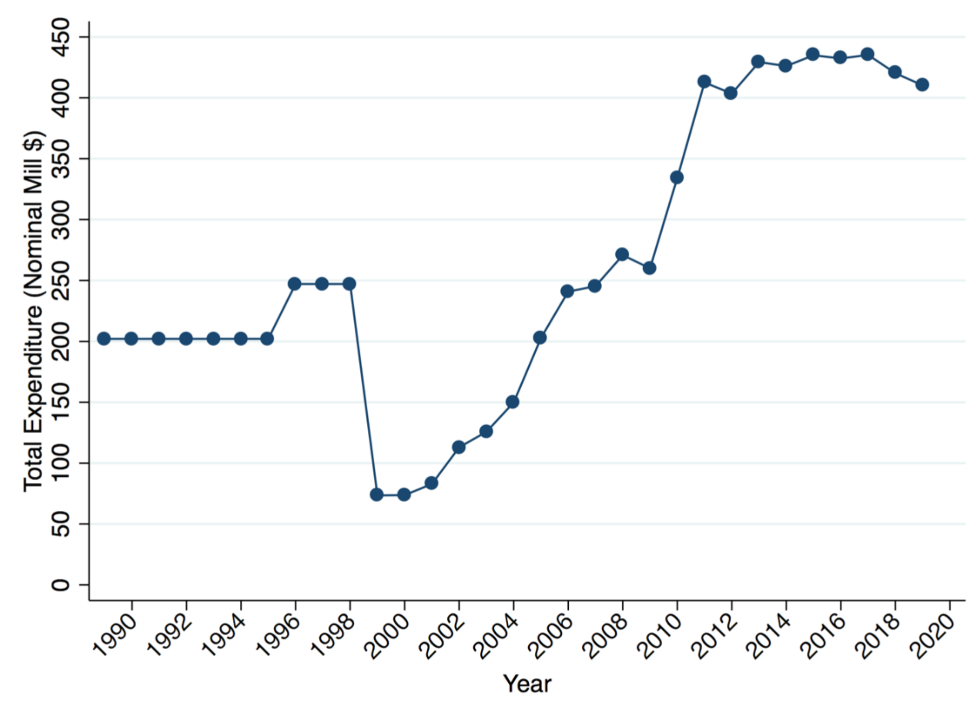
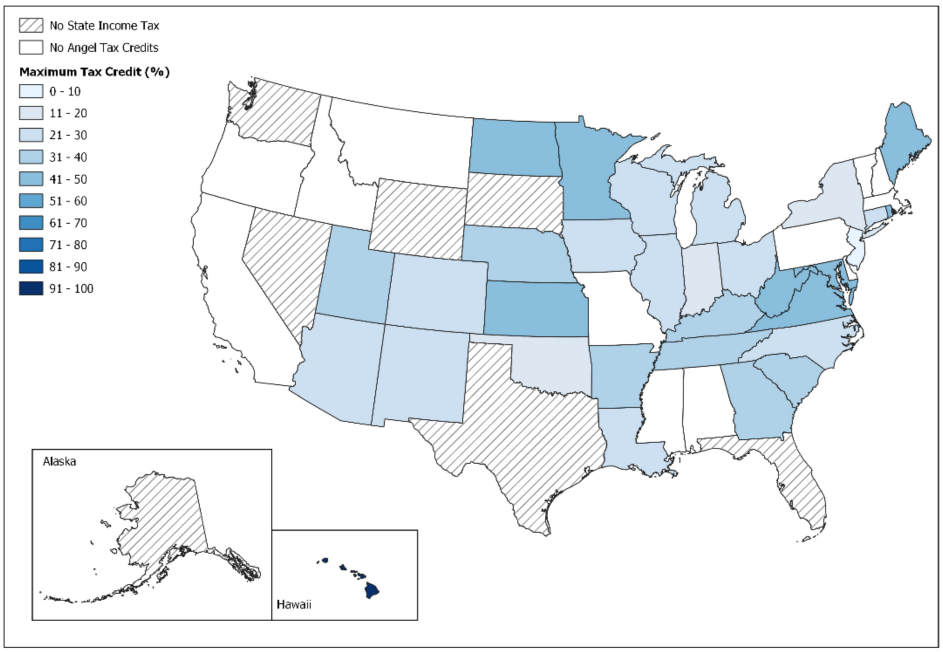


Figure 2. State Angel Tax Credit Programs

Panel A provides a map of states that have adopted angel tax credit programs from 1988 to 2018. The blue shading indicates the tax credit percentage, with darker shades representing larger tax credits. The slanted lines denote states with no state income tax. Panel B shows the introduction and termination of each program in our sample, starting with the earliest program and ending with the most recent one.

Panel A. States with Angel Tax Credit Programs



Panel B. Timing of State Angel Tax Credit Programs

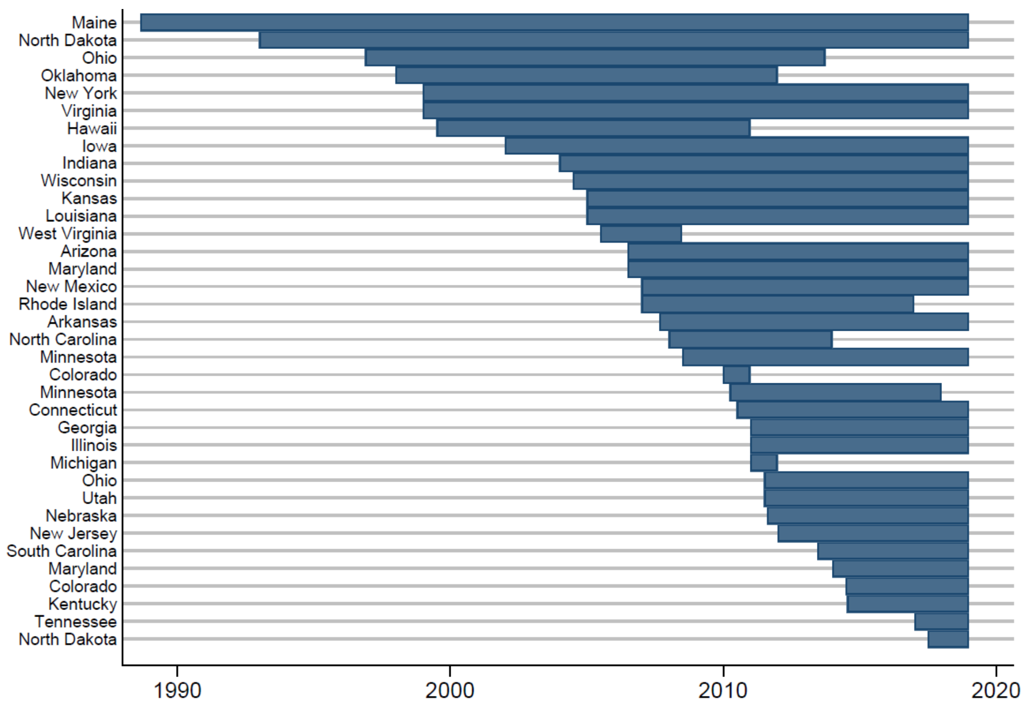
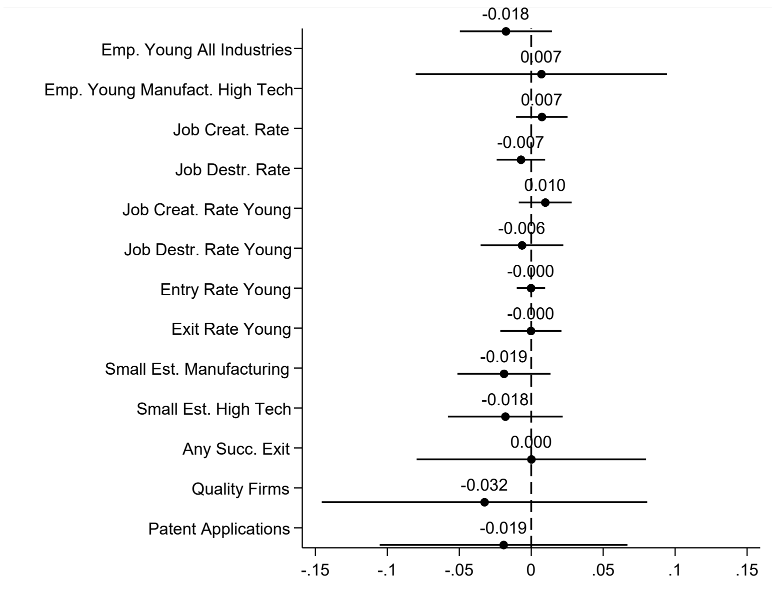


Figure 3. Aggregate Effects and Confidence Intervals

Panel A reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using baseline specification (1) with no controls. Panel B reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using baseline specification (1) with all controls. All outcome variables are defined in Appendix B.

Panel A. Effects of Angel Tax Credits, without Controls



Panel B. Effects of Angel Tax Credits, with Controls

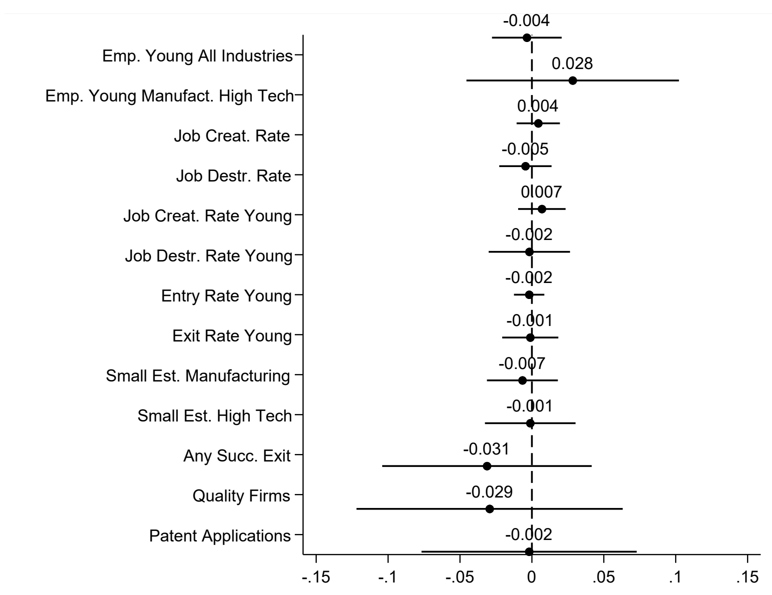
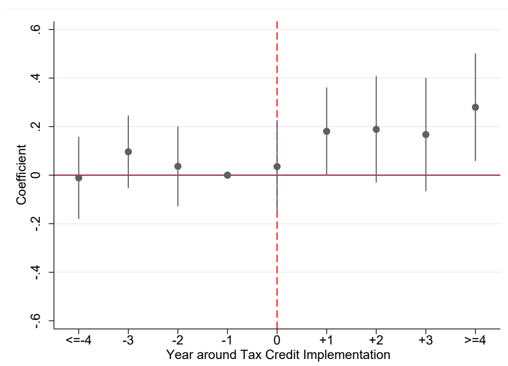


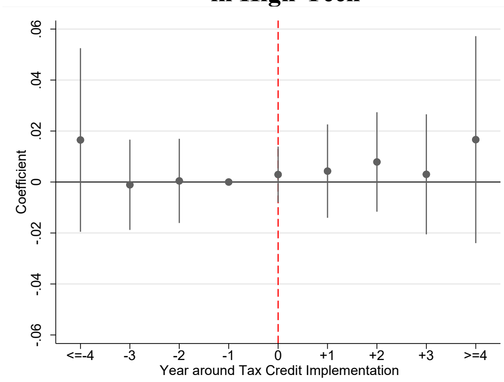
Figure 4. Dynamic Effects of Angel Tax Credit Introduction on Real Outcomes

This figure shows the dynamic effect of a state introducing angel tax credits using equation (2). The sample is the same as used for figure 3. The year before policy introduction is normalized to zero. Panel A shows the number of angel investments; Panel B examines the number of small establishments (with employment of 0 to 19) in high-tech sectors; Panel C shows total employment in young firms (0-5 years); Panel D shows job creation rate among young firms (0-5 years); Panel E looks at the number of patent applications; and Panel F examines the probability of having at least one successful exit (IPO or high-price M&A) by angel-backed firms receiving investment in a state-year. Each outcome variable is log (plus one) transformed, except for Panel F. The data is described in the paper. Standard errors are clustered at state-level. 95% confidence intervals are shown.

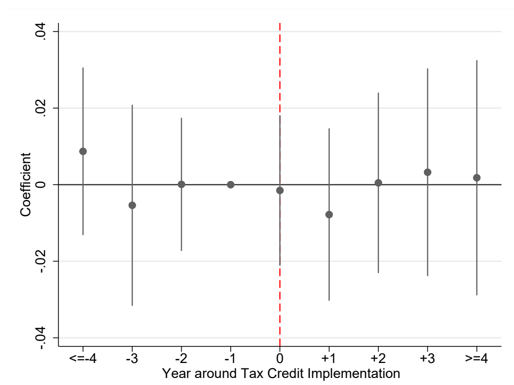
Panel A. Number of Angel Investments



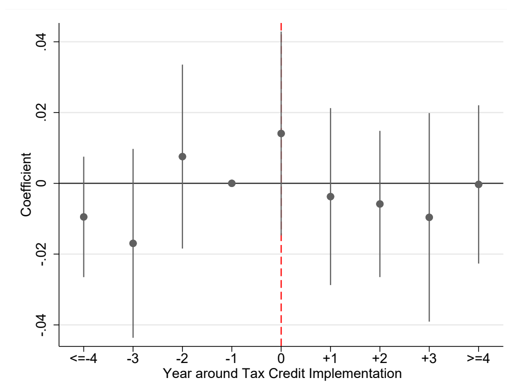
Panel B. Number of Small Establishments in High-Tech



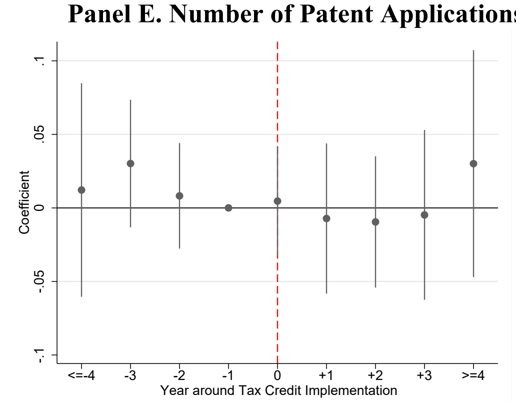
Panel C. Aggregate Employment in Young Firms



Panel D. Job Creation Rate in Young Firms



Panel E. Number of Patent Applications



Panel F. Probability of Successful Exit

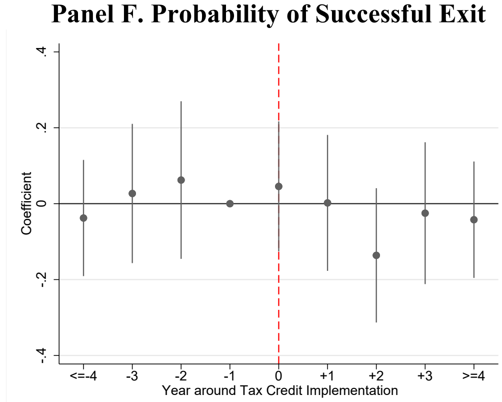


Table 1. Summary Statistics on Angel Tax Credit Programs

Table 1 presents the program parameters for the 36 angel tax credit programs in our sample. Column 1 reports the percentage of programs that have a particular restriction in place. Columns 2 and 3 report the mean and median values of the restriction.

	% with restriction	Mean	Median
Tax credit percentage		34%	33%
		Company restrictions	
Age cap	31%	7.1	6.0
Employment cap	39%	64.6	50.0
Revenue cap ($ million)	47%	5.4	5.0
Asset cap ($ million)	22%	11.5	7.5
Prior total external financing cap ($ million)	19%	5.7	4.0
		Investment and investor restrictions	
Minimum investment per investor ($)	36%	19,231	25,000
Minimum holding period	50%	3.2	3.0
Ownership cap before investment	64%	35%	30%
Exclude owners and their families	61%		
Exclude full-time employees	22%		
Exclude executives and officers	33%		
		Tax credit restrictions	
State tax credit allocation per year ($ million)	86%	9.0	5.0
Maximum tax credit per company per year ($ million)	42%	0.81	0.60
Maximum tax credit per investor per year ($ million)	78%	0.21	0.11
Non-refundable	72%		
No carry forward	11%		
Non-transferrable	72%		

Table 2. Predictive Regressions

This table examines whether a state's economic, political, fiscal, or entrepreneurial conditions predict the adoption of angel tax credit programs for the sample period 1985 to 2018. The dependent variable is an indicator equal to one (*ATC*) if a state has adopted an angel tax credit programs in that year (columns 1 to 4) or a continuous variable (*Tax credit percentage*) equal to the maximum tax credit percentage available in state-years with an angel tax credit program and zero otherwise (columns 5 to 8). State-years after a state adopts a program are excluded from the sample. All independent variables are lagged by one year relative to the dependent variable and are defined in detail in Appendix A. Each column includes year fixed effects, while the even-numbered columns also include state fixed effects. Standard errors are reported in parentheses and clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	ATC				Tax credit percentage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GSP growth	-0.051	0.056	-0.042	0.047	0.002	0.024	0.013	0.033
	(0.112)	(0.135)	(0.135)	(0.145)	(0.039)	(0.045)	(0.046)	(0.048)
Ln(Income per capita)	-0.003	0.013	-0.002	0.011	-0.000	-0.004	-0.002	-0.004
	(0.027)	(0.066)	(0.027)	(0.066)	(0.010)	(0.022)	(0.011)	(0.022)
Ln(Population)	0.000	-0.118	0.002	-0.126*	-0.001	-0.041	-0.001	-0.045
	(0.005)	(0.072)	(0.008)	(0.075)	(0.002)	(0.026)	(0.003)	(0.028)
Unemployment rate	-0.002	0.005	-0.001	0.006	-0.001	0.001	-0.001	0.001
	(0.003)	(0.005)	(0.003)	(0.005)	(0.001)	(0.002)	(0.001)	(0.002)
Democratic control	0.002	-0.008	0.001	-0.008	-0.001	-0.006	-0.001	-0.006
	(0.010)	(0.013)	(0.010)	(0.013)	(0.003)	(0.005)	(0.003)	(0.005)
Republican control	-0.009	-0.016	-0.009	-0.015	-0.003	-0.005	-0.003	-0.005
	(0.009)	(0.014)	(0.010)	(0.014)	(0.003)	(0.005)	(0.003)	(0.005)
Revenue/GSP	-0.133	-0.171	-0.129	-0.188	-0.049	-0.060	-0.040	-0.060
	(0.222)	(0.275)	(0.227)	(0.273)	(0.086)	(0.104)	(0.088)	(0.105)
Expenditure/GSP	0.131	-0.355	0.085	-0.273	0.064	-0.164	0.055	-0.140
	(0.276)	(0.440)	(0.281)	(0.461)	(0.098)	(0.151)	(0.099)	(0.158)
Debt/GSP	-0.023	0.480	-0.010	0.460	-0.028	0.132	-0.035	0.126
	(0.099)	(0.299)	(0.101)	(0.319)	(0.032)	(0.101)	(0.033)	(0.108)
Has income tax	0.032**	0.032	0.027	0.036	0.011**	0.006	0.009*	0.008
	(0.016)	(0.035)	(0.016)	(0.035)	(0.005)	(0.012)	(0.005)	(0.012)
Max income tax rate	-0.001	-0.016**	-0.001	-0.015**	-0.000	-0.005**	-0.000	-0.005*
	(0.003)	(0.007)	(0.003)	(0.007)	(0.001)	(0.002)	(0.001)	(0.003)
Capital gains tax	0.000	0.003	0.001	0.003	-0.000	0.001	-0.000	0.001
	(0.003)	(0.005)	(0.003)	(0.005)	(0.001)	(0.002)	(0.001)	(0.002)
Neighbor ATC	0.015	0.012	0.015	0.011	0.004	0.004	0.005	0.004
	(0.013)	(0.015)	(0.013)	(0.015)	(0.005)	(0.005)	(0.004)	(0.005)
Establishment entry rate			-0.016	0.329			0.019	0.112
			(0.227)	(0.345)			(0.079)	(0.112)
Establishment exit rate			-0.247	-0.292			-0.112	-0.083
			(0.224)	(0.385)			(0.083)	(0.144)
Net job creation rate			-0.034	-0.066			-0.062	-0.080
			(0.242)	(0.273)			(0.086)	(0.098)
Venture capital volume			-0.001	0.004			0.000	0.002
			(0.004)	(0.005)			(0.001)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1343	1343	1343	1343	1343	1343	1343	1343
Adjusted R^2	0.022	0.038	0.02	0.036	0.017	0.04	0.015	0.039

Table 3. State-Year Level Summary Statistics

This table reports summary statistics for the samples used in our analyses. All angel investment-related variables are state-year averages based on angel investments in the high-tech sector (IT, biotech, and renewable energies). All variables are defined in detail in Appendix A.

Variable	N	Mean	Std. dev.	p5	p50	p95
	Treatment variables					
ATC	1,200	0.25	0.43	0.00	0.00	1.00
Tax credit percentage	1,200	0.09	0.18	0.00	0.00	0.50
	Angel volume					
Ln(number of angel investments)	1,200	2.38	1.40	0.00	2.30	4.64
Ln(average investment amount) in CVV	1,251	16.29	1.20	14.29	16.28	18.39
Ln(average investment amount) in Form D	400	14.01	0.58	13.04	14.05	14.79
	Ex-ante characteristics of angel-backed firms					
Age at investment	1,200	5.40	2.67	1.78	5.00	10.25
Pre-investment ln(sales)	1,200	12.22	3.63	0.00	13.15	14.79
Pre-investment ln(employment)	1,200	2.06	0.87	0.00	2.09	3.30
Pre-investment sales growth	1,200	0.72	0.94	-1.00	0.67	2.12
Pre-investment employment growth	1,200	0.45	0.66	-1.00	0.45	1.35
Pre-investment ln(sales/employment)	1,200	10.20	2.97	0.00	11.09	11.70
Fraction of serial entrepreneurs on team	1,199	0.05	0.09	0.00	0.00	0.17
	State-year level controls and outcomes					
GSP growth	1,343	1.05	0.04	1.00	1.05	1.11
Ln(Income per capita)	1,343	10.12	0.41	9.46	10.12	10.78
Ln(Population)	1,343	15.03	1.04	13.33	15.16	16.73
Unemployment rate	1,343	5.75	1.90	3.14	5.41	9.38
Democratic control	1,343	0.24	0.43	0.00	0.00	1.00
Republican control	1,343	0.20	0.40	0.00	0.00	1.00
Revenue/GSP	1,343	0.13	0.04	0.09	0.12	0.19
Expenditure/GSP	1,343	0.12	0.03	0.08	0.11	0.18
Debt/GSP	1,343	0.07	0.04	0.02	0.06	0.15
Has income tax	1,343	0.77	0.42	0.00	1.00	1.00
Max income tax rate	1,343	4.90	3.30	0.00	5.51	9.86
Capital gain tax rate	1,343	4.40	3.07	0.00	4.77	9.00
Neighbor ATC	1,343	0.21	0.41	0.00	0.00	1.00
Venture capital volume	1,343	3.95	2.41	0.00	4.10	7.72
Ln(Emp. Young All Industries)	970	12.09	1.03	12.41	12.20	13.96
Ln(Emp. Young Manufact. High Tech)	970	9.76	1.28	7.64	9.90	11.72
Ln(Job destr. Rate)	1,200	2.58	0.16	2.31	2.59	2.85
Ln(Job creat. Rate)	1,200	2.70	0.16	2.42	2.70	2.98
Ln(Job destr. Rate Young)	1,100	3.08	0.12	2.89	3.08	3.28
Ln(Job creat. Rate Young)	1,100	3.73	0.10	3.56	3.75	3.87
Ln(Entry rate young)	1,100	3.76	0.04	3.74	3.76	3.79
Ln(Exit rate young)	1,100	2.71	0.10	2.57	2.71	2.87
Ln(Small est. manufacturing)	900	7.92	0.100	6.14	7.90	9.50
Ln(Small est. high Tech)	900	8.42	1.09	6.77	8.42	10.25
Any succ. exit	1,300	0.61	0.49	0	1	1
Ln(Quality firms)	1,166	1.95	1.15	0.25	1.93	4.13
Ln(patent applications)	1,250	7.00	1.49	4.89	7.12	9.22
	Investors on AngelList					
Ln(number of investors)	735	2.09	1.97	0.00	1.61	5.74
Ln(number of in-state investors)	735	1.44	1.72	0.00	0.69	4.80
Ln(number of out-of-state investors)	735	1.78	1.80	0.00	1.39	5.21
Ln(number of new investors)	735	1.70	1.75	0.00	1.39	5.02
Ln(number of experienced investors)	735	1.55	1.78	0.00	1.10	5.14
Ln(number of investors with no exits)	735	1.73	1.76	0.00	1.39	5.04
Ln(number of investors with exits)	735	1.50	1.79	0.00	0.69	5.07
Ln(number of investors with no founder exp.)	735	1.98	1.92	0.00	1.61	5.58
Ln(number of investors with founder exp.)	735	0.99	1.39	0.00	0.00	4.00

Table 4. Angel Tax Credits and Angel Investments

Panel A reports the difference-in-differences estimates for the effect of angel tax credits on the quantity of angel investments in the high-tech sector. The sample period is 1993 to 2016. The dependent variable is the natural logarithm of the total number of angel investments in a state-year. *ATC* is an indicator equaling one if a state has an angel tax credit program in that year. *Tax credit percentage* is a continuous variable equal to the maximum tax credit parentage available in a state-year with an angel tax credit program. Panel B reports the heterogeneous effect of angel tax credit programs. *Program flexibility* is an index ranging from 0 to 16 that measures the presence and strictness of the 16 program restrictions in Table 1. Higher values of the index represent more flexible programs. *VC supply* is state-year-level aggregate VC investment amount (excluding angel and seed rounds identified in our main sample) scaled by the total number of young firms (of age 0 to 5) in that state-year from BDS. Both *Program flexibility* and *VC supply* are standardized by subtracting the sample mean and dividing by the standard deviation. Panel C reports the difference-in-difference effect of angel tax credits on the average investment amount of angel investments in the high-tech sector. The dependent variable is the natural logarithm of the average size of angel rounds in a state-year. Control variables are defined in equation (1). Each observation is a state-year. All specifications include state and year fixed effects. Standard errors are reported in parentheses and clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A. Angel Tax Credits and Angel Investment Volume

	Ln(Number of angel investments)	
	(1)	(2)
ATC	0.169**	
	(0.080)	
Tax credit percentage		0.552***
		(0.179)
Controls	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,200	1,200
Adjusted R^2	0.925	0.926

Panel B. Heterogeneity

	Ln(Number of angel investments)			
	(1)	(2)	(3)	(4)
ATC	0.156**	0.161**		
	(0.071)	(0.070)		
ATC × Program flexibility	0.114*			
	(0.065)			
ATC × VC supply		0.148***		
		(0.054)		
Tax credit percentage			0.415***	0.393**
			(0.147)	(0.155)
Tax credit percentage × Program flexibility			0.329***	
			(0.100)	
Tax credit percentage × VC supply				0.254***
				(0.068)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200
Adjusted R^2	0.926	0.926	0.927	0.927

Panel C. Angel Tax Credits and Angel Investment Size

	Ln(Average investment amount)			
	(1)	(2)	(3)	(4)
ATC	0.129*		0.223**	
	(0.077)		(0.103)	
Tax credit percentage		0.361**		0.465**
		(0.150)		(0.217)
Sample	Form D		CVV	
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	400	400	1,251	1,251
Adjusted R^2	0.215	0.215	0.217	0.216

Table 5. Ex-ante Characteristics of Angel-Backed Companies

Panel A reports the difference-in-differences estimates for the effect of angel tax credits on the ex-ante characteristics of angel-backed startups in the high-tech sector. *ATC* is an indicator equaling one if a state has an angel tax credit program in that year. The baseline specification (1) uses the NETS-matched sample from 1993 to 2016. The dependent variables are the average natural logarithm of sales, sales growth, natural logarithm of employment, employment growth, natural logarithm of sales-to-employment ratio (productivity), and the fraction of serial entrepreneurs on founding team in the year before angel investment. Panel B reports the difference-in-differences estimates for the effect of angel tax credits on the quantity of angel investments in the high-tech sector split by pre-investment startup characteristics. Each observation is a state-year. Control variables are defined in equation (1). All specifications include state and year fixed effects. Standard errors are reported in parentheses and clustered by state. ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Panel A. Pre-investment Size, Growth, Productivity, and Entrepreneur Experience

	Sales growth	Ln(Sales)	Employment growth	Ln(Employment)	Ln(Productivity)	Fraction of serial entrepreneurs
	(1)	(2)	(3)	(4)	(5)	(6)
ATC	-0.187*	-0.538**	-0.126*	-0.133**	-0.413**	-0.013*
	(0.103)	(0.238)	(0.064)	(0.066)	(0.188)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200	1,200	1,199
Adjusted R^2	0.365	0.787	0.442	0.548	0.802	0.152

Panel B. Angel Volume by Ex-Ante Growth Characteristics

	High sales and sales growth	Low sales or sales growth	High emp. and emp. growth	Low emp. or emp. growth	High sales/emp.	Low sales/emp.	High fraction of serial entrepreneurs	Low fraction of serial entrepreneurs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATC	0.021	0.227***	0.054	0.189**	0.080	0.209***	0.084	0.176*
	(0.086)	(0.079)	(0.089)	(0.078)	(0.077)	(0.076)	(0.115)	(0.093)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200	1,200	1,200	1,600	1,600
Adjusted R^2	0.853	0.897	0.841	0.901	0.873	0.872	0.741	0.879

Table 6. Characteristics of Investors Receiving Tax Credits

This table provides characteristics of investors that receive angel tax credits. Panel A describes information gathered from LinkedIn about angel investors from seven states that publicly release the names of angel investors. Corporate Executive is an investor who lists their current occupation as President, Vice President, Partner, Principal, Managing Director, or Chief Officer other than CEO. An individual'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. Panels B and C report summary statistics for insider investors, defined as angel investors that also serve executives or managers at the firm for which they receive angel tax credits. The unit of observation for Panel B is a unique tax credit beneficiary company for which we observe investor-company link and for Panel C is a unique investor for which we observe investor-company link.

Panel A. Investor Location and Demographics

	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
	N	Mean			
Age	2,363	41.9			

Panel B. Insiders at the Company Level

	N	Fraction
≥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 C. Insiders at the Investor Level

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

Table 7. Which Investors Respond to Angel Tax Credits?

This table examines changes in investor composition during angel tax credit programs. Panel A reports the difference-in-differences estimates for the effects of angel tax credits on the entry of investors based on AngelList data. *ATC* is an indicator equaling one if a state has an angel tax credit program in that year. The dependent variable is the natural logarithm of the number of investors in each category (in-state, out-of-state, new, not new, had no prior exit, had exit, no prior founder experience, had founder experience) that invested in a state-year. Each observation is a state-year. Control variables are defined in equation (1). Panel B reports the difference-in-differences estimates for the effects of angel tax credits on investor composition on AngelList. Each observation is an investor-startup pair (i.e., investment) and is weighted by one over the number of observation in each state. The dependent variables are dummies indicating that an investor was in-state, new, had no prior exit, had no prior founder experience, or was an insider at the time of investment. All specifications include CBSA and year fixed effects. The sample period is 2003 to 2017 in both panels. Standard errors are reported in parentheses and clustered by state. ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Panel A. Investor Entry at the State-Year Level

	In-state	Out-of-state	New	Not new	Had no exit	Had exit	No founder experience	Has founder experience
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATC	0.277**	0.189	0.262**	0.154	0.273**	0.156	0.256**	0.119
	(0.131)	(0.146)	(0.128)	(0.161)	(0.133)	(0.146)	(0.128)	(0.177)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	735	735	735	735	735	735	735	735
Adjusted R^2	0.862	0.841	0.845	0.843	0.849	0.836	0.863	0.791

Panel B. Investor Characteristics at the Investment Level

	In-state	New	Had no exit	No founder experience
	(1)	(2)	(3)	(4)
ATC	0.087***	0.058**	0.085***	0.066**
	(0.031)	(0.025)	(0.027)	(0.031)
Controls	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	90,702	90,702	90,702	90,702
Adjusted R^2	0.220	0.109	0.187	0.112

Table 8. Firm-Level Effects

This table reports effect of receiving a tax credit and firm-level outcomes. The dependent variable in column 1 is an indicator that denotes whether a startup receives VC financing within two years after receiving a tax credit. The dependent variable in column 2 is an indicator equal to one if a startup reaches a successful exit. The dependent variable in columns 3 (4) (5) are indicators equal to one if a startup received 10 (25) (75^{th} percentile) employees within two years after first applying to have an investor benefit from a tax credit. In every specification, we control for the same measure as the outcome but measured in the year before the tax credit. All specifications include state-year and sector-year fixed effects. Standard errors are clustered at the state-year level.

	Raised VC 2 Yrs Post-TC (1)	Exit (2)	Emp. > 10 2yrs Post-TC (3)	Emp. > 25 2yrs Post-TC (4)	Emp. > p75 2yrs Post-TC (5)
Got Tax Credit	-0.0088	-0.0051	0.0023	-0.00021	0.011
	(0.0160)	(0.0093)	(0.004)	(0.0026)	(0.007)
Emp > 10 in Credit Yr			0.53***		
			(0.070)		
Emp > 25 in Credit Yr					
				0.65***	
Emp > p75 in Credit Yr				(0.11)	0.45***
					(0.065)
Finance Pre-TC	0.17***	0.086***	0.041***	0.015***	0.053***
	(0.028)	(0.015)	(0.009)	(0.0046)	(0.010)
State-Year FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3227	3227	3227	3227	3227
Adjusted R^2	0.31	0.11	0.46	0.50	0.41

Appendix Figures and Tables

Figure A1. Distributions of Ex-Ante Growth Characteristics: State-Years with vs. without ATC

This figure compares the distributions of ex-ante characteristics of angel-backed firms in state-years with an angel tax credit program to state-years without a program, restricting to states that eventually had an angel tax credit program. All characteristics are measured in the year before angel investment. The solid lines (dotted lines) represent the estimated kernel density for firms that received angel investments in state-years with (without) an angel tax credit program.

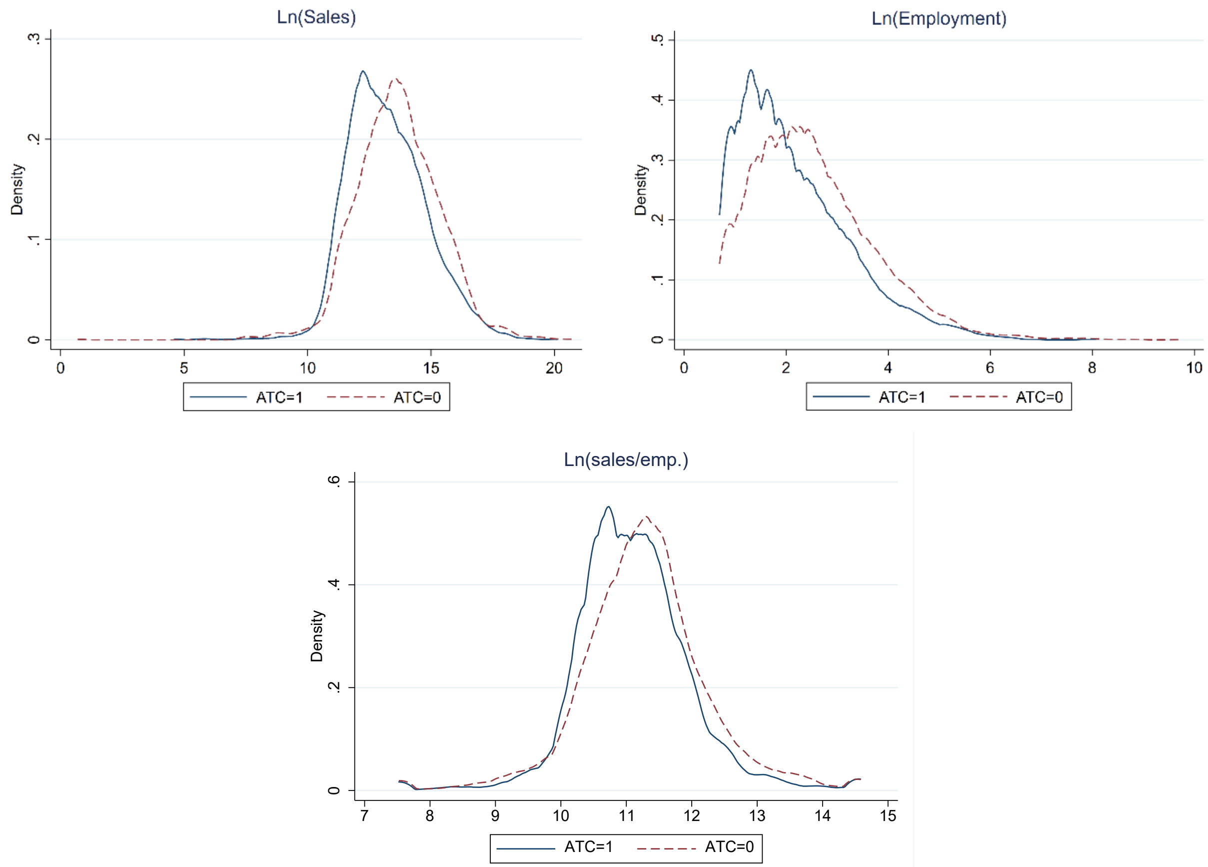
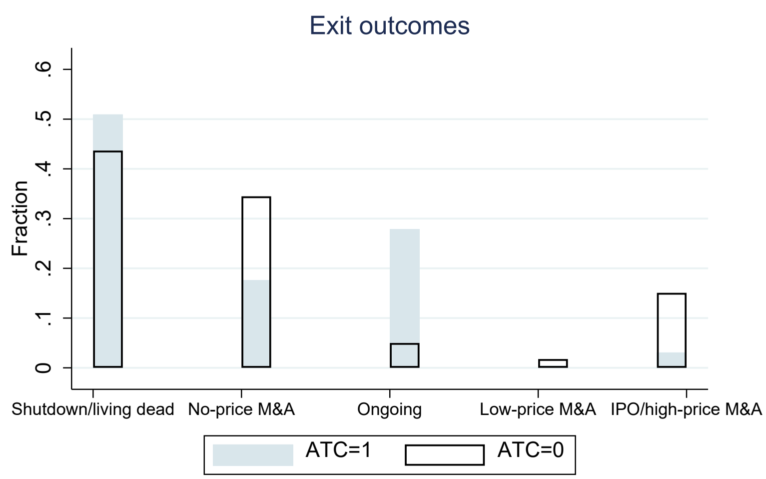


Figure A2. Distributions of Ex-Post Exit Outcome: State-Years with vs. without ATC

This figure compares the histograms of exit outcomes by angel-backed firms in state-years with an angel tax credit program to state-years without a program, restricting to states that eventually had an angel tax credit program. In the top panel, the blue bars (empty bars) represent the fraction of angel-backed firms achieving each exit outcome by the end of 2018 and who received angel investments in state-years with (without) an angel tax credit program from 1985 to 2016. The bottom panel compares the distribution of the logarithm of exit multiple for angel-backed firms that have achieved M&A or IPO by the end of 2018 and who received angel investments in state-years with (without) an angel tax credit program from 1985 to 2016. Exit multiple is defined as total enterprise value at exit divided by total invested capital. Data come from CVV, SDC Platinum, and Kenney-Patton IPO Database.



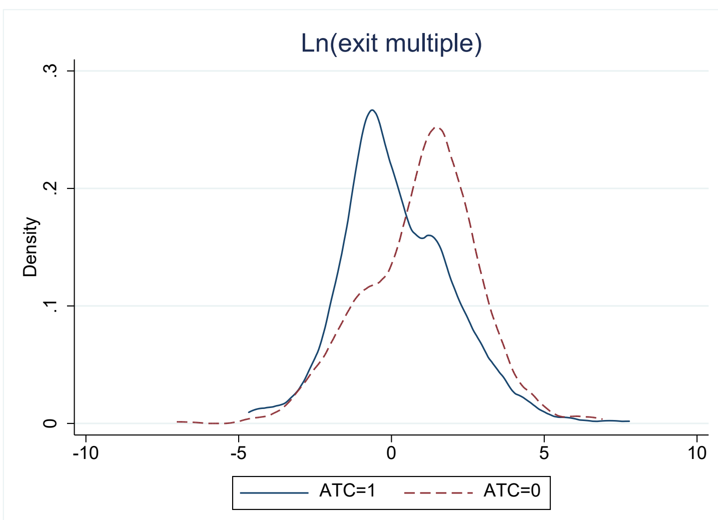
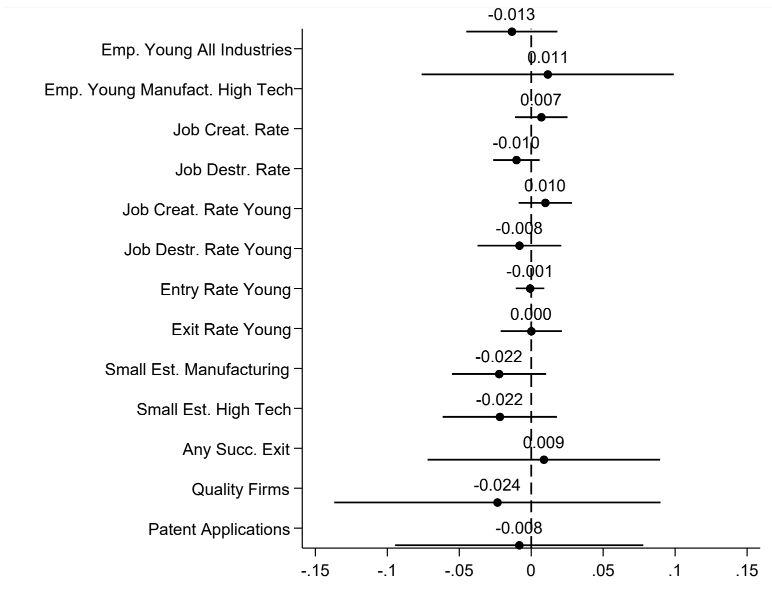


Figure A3. Aggregate Effects and Confidence Intervals: Robustness 1

This Figure replicates the result in Figure 3, dropping now states of California and Massachusetts. Panel A reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using baseline specification (1) with no controls. Panel B reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using baseline specification (1) with all controls.

Panel A. Effects of Angel Tax Credits, without Controls



Panel B. Effects of Angel Tax Credits, with Controls

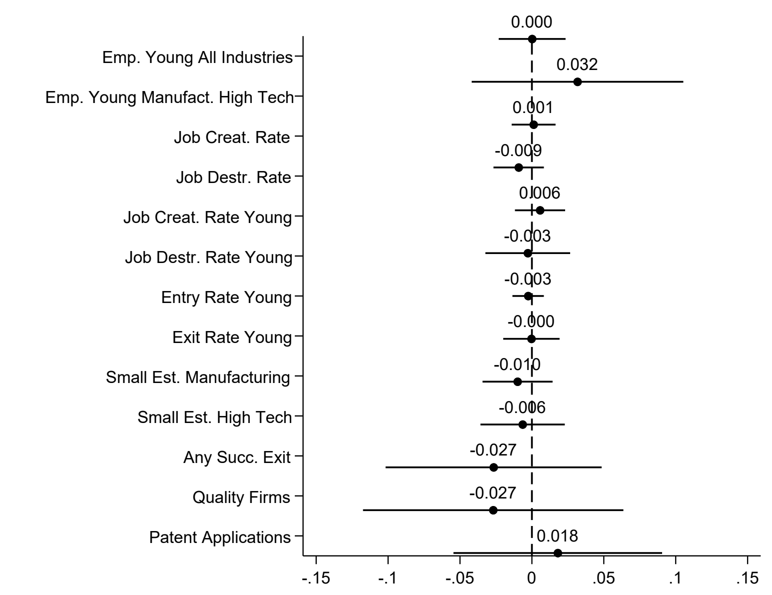
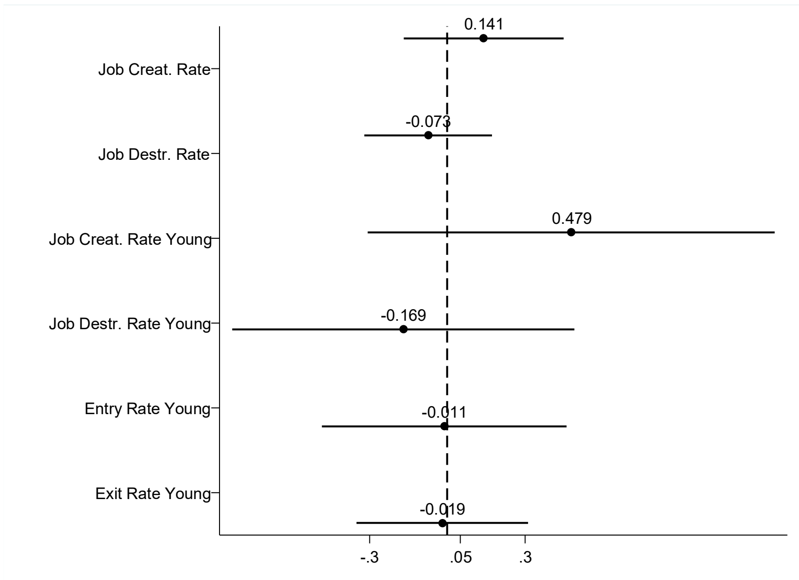


Figure A4. Aggregate Effects and Confidence Intervals: Robustness 2

This Figure provides a robustness to the result in Figure 3. In particular, we consider the outcomes that are rates and show the results without log-transformation the outcome variables. Panel A reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using baseline specification (1) with no controls. Panel B reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using baseline specification (1) with all controls.

Panel A. Effects of Angel Tax Credits, without Controls



Panel B. Effects of Angel Tax Credits, with Controls

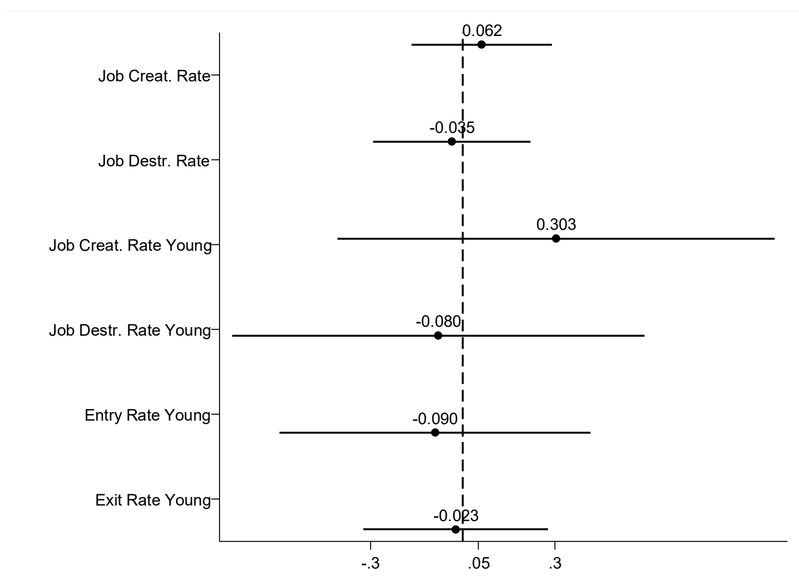


Table A1. Tax Credit Program Details

This table lists the angel tax credit programs in the U.S. from 1988 to 2018. For each program, it provides the state, program name, effective period and tax credit percentage. It also details program-level company, investment, investor and tax credit restrictions. We include the latest value for any restrictions that vary over a program's life. Additionally, we do not list state programs for direct investment or co-investment, in addition to support for investments in funds or universities.

State	Program	Effective Year	Expiration Year	Individuals or Groups Qualify for Tax Credit (TC)	Max tax credit percentage
Arkansas	Equity Investment Incentive Program	2007	2019	Both	0.333
Arizona	Angel Investment Program	2006	2021	Both	0.3 - 0.35
Colorado	*a.* Innovation Investment Tax Credit	2010	2010	Both	0.15
	b. Advanced Industry Investment Tax Credit	2014	2022	Both	0.25 - 0.3
Connecticut	Angel Investor Tax Credit Program	2010	2019	Both	0.25
Delaware	Angel Investor Tax Credit	2018	2022	Both	0.25
Georgia	Angel Investment Tax Credit	2011	2018	Individuals	0.35
Hawaii	High Technology Business Investment Tax Credit	1999	2010	Both	0.1 - 1.0
Illinois	Angel Investment Credit Program	2011	2021	Both	0.25
Indiana	Venture Capital Investment Tax Credit Program	2004	2020	Both	0.2 - 0.25
Iowa	*a.* Innovation Fund Tax Credit	2002	2008	Both	0.2
	b. Innovation Fund Tax Credit	2012	indef.	Both	0.2 - 0.25
Kansas	Angel Investor Tax Credit	2005	2021	Both	0.5
Kentucky	Angel Investment Act Tax Credit	2015	indef.	Individuals	0.4 - 0.5
Louisiana	*a.* Angel Investor Tax Credit	2005	2009	Individuals	0.25
	b. Angel Investor Tax Credit	2011	2021	Individuals	0.25
Maine	*a.* Seed Capital Tax Credit Program	1989	2013	Both	0.3-0.6
	b. Seed Capital Tax Credit Program	2014	indef.	Both	0.5-0.6
Maryland	Biotechnology Investment Incentive Tax Credit	2007	indef.	Both	0.5
Maryland	Cybersecurity Investment Tax Credit	2014	2023	Both	0.33-0.5
Massachusetts	Angel Investor Tax Credit	2017		Individuals	0.2-0.3
Michigan	Small Business Investment Tax Credit	2011	2011	Groups	0.25
Minnesota	Angel Tax Credit	2010	2017	Both	0.25
Minnesota	Seed Capital investment Credit	2019		Both	0.45
Nebraska	Angel Investment Tax Credit	2011	2022	Both	0.35-0.4
New Jersey	Angel Investor Tax Credit Program	2013	indef.	Both	0.1
New Mexico	Angel Investment Credit	2007	2025	Individuals	0.25
New York	Qualified Emerging Technology Company Tax Credits	2000	indef.	Both	0.1 - 0.2
North Carolina	Qualified Business Tax Credit Program	2008	2013	Both	0.25
North Dakota	Seed Capital Investment Tax Credit	1993	indef.	Both	0.45
North Dakota	Angel Fund Investment Credit	2007	2017	Both	0.45
North Dakota	Angel Investor Investment Credit	2017		Both	0.35
Ohio	*a.* Ohio Technology Investment Tax Credit	1996	2013	Both	0.25 - 0.3
	b. InvestOhio	2011	indef.	Both	0.1

Oklahoma	Credit for Qualified Investment in Qualified Small Business Capital Companies	1998	2011	Both	0.2
Rhode Island	Innovation Tax Credit	2007	2016	Both	0.5
South Carolina	High Growth Small Business Job Creation Act	2013	2019	Individuals	0.35
Tennessee	Angel Tax Credit	2017	indef.	Individuals	0.33 - 0.5
Utah	Life Science and Technology Tax Credits	2011		Both	0.35
Virginia	Qualified Equity and Subordinated Debt Investments Credit	1999	indef.	Individuals	0.5
West Virginia	High-Growth Business Investment Tax Credit	2005	2008	Both	0.5
Wisconsin	Qualified New Business Venture Program	2005	indef.	Both	0.25

State	**Program**	**Size Req for Business**	**Asset cap (mil)**	**Revenue cap (mil)**	**Employment cap**	**Age Cap**
Arkansas	Equity Investment Incentive Program	N				
Arizona	Angel Investment Program	Y	Assets < $10m. Assets < $2m if before 2012			
Colorado	*a.* Innovation Investment Tax Credit	Y	Assets < $5m	$2m		< 5 years old
	b. Advanced Industry Investment Tax Credit	Y		$5m		< 5 years old
Connecticut	Angel Investor Tax Credit Program	Y		$1m	25	In CT < 7 years
Delaware	Angel Investor Tax Credit	Y			25	<10 years <20 years if medical devices or pharma
Georgia	Angel Investment Tax Credit	Y		$500k	20	< 3 years old
Hawaii	High Technology Business Investment Tax Credit					
Illinois	Angel Investment Credit Program	Y			100	In IL < 10 years
Indiana	Venture Capital Investment Tax Credit Program	Y		$10m		
Iowa	*a.* Innovation Fund Tax Credit	Y	Net worth <3m before 2005, <10m after 2005			< 3 years old
	b. Innovation Fund Tax Credit	Y	Net worth < $10m			< 6 years old
Kansas	Angel Investor Tax Credit	Y		$5m		< 5 years
Kentucky	Angel Investment Act Tax Credit	Y	Net worth < $10m		100	
Louisiana	*a.* Angel Investor Tax Credit	Y	Net worth < $2m	$10m	50	
	b. Angel Investor Tax Credit	Y				
Maine	*a.* Seed Capital Tax Credit Program	Y		$3m		
	b. Seed Capital Tax Credit Program	Y		$5m		
Maryland	Biotechnology Investment Incentive Tax Credit	Y			50	< 10 years old
Maryland	Cybersecurity Investment Tax Credit	Y			50	
Massachusetts	Angel Investor Tax Credit	Y		$500,000	20	
Michigan	Small Business Investment Tax Credit	Y	Pre-investment valuation < $10m		100	< 5 years old; < 10 years if business uses MI university research
Minnesota	Angel Tax Credit	Y			25	< 10 years old; < 20 if med tech or pharma
Minnesota	Seed Capital investment Credit	Y				
Nebraska	Angel Investment Tax Credit	Y			25	
New Jersey	Angel Investor Tax Credit Program	Y			225	
New Mexico	Angel Investment Credit	Y		$5m	100	

State	Program	Size Req for Business	Asset cap (mil)	Revenue cap (mil)	Employment cap	Age Cap
New York	Qualified Emerging Technology Company Tax Credits	Y		$10m		
North Carolina	Qualified Business Tax Credit Program	Y		$5m		
North Dakota	Seed Capital Investment Tax Credit	N				
North Dakota	Angel Fund Investment Credit	Y		$10m		
North Dakota	Angel Investor Investment Credit	Y		$10m		
Ohio	*a.* Ohio Technology Investment Tax Credit	Y	Net book value < $2.5m	$2.5m		
	b. InvestOhio	Y	Assets < $50m	$10m		
Oklahoma	Credit for Qualified Investment in Qualified Small Business Capital Companies	Y	Net worth < $1m			
Rhode Island	Innovation Tax Credit	Y		$1m		
South Carolina	High Growth Small Business Job Creation Act	Y				< 5 years old
Tennessee	Angel Tax Credit	Y		$3m	25	< 5 years old
Utah	Life Science and Technology Tax Credits	Y				
Virginia	Qualified Equity and Subordinated Debt Investments Credit	Y		$3m		
West Virginia	High-Growth Business Investment Tax Credit	Y		$20m		
Wisconsin	Qualified New Business Venture Program	Y			100	In WI < 10 years

State	Program	Min. investment per investor	Min. holding period	Ownership cap before investment	Exclude existing owners and their families	Exclude full-time employees	Exclude executives and officers	SEC Accreditation Req for Investor	Investor Can Reside Out-of-State
Arkansas	Equity Investment Incentive Program							N	Y
Arizona	Angel Investment Program	25,000	1 year	30%	Y			N	Y
Colorado	*a.* Innovation Investment Tax Credit	25,000		30%	Y			N	
	b. Advanced Industry Investment Tax Credit	10,000		30%	Y			N	
Connecticut	Angel Investor Tax Credit Program	25,000		50%	Y			Y	Y
Delaware	Angel Investor Tax Credit	10,000	3 years	20%	Y		Y	N	
Georgia	Angel Investment Tax Credit		2 years					Y	Y
Hawaii	High Technology Business Investment Tax Credit		5 years						
Illinois	Angel Investment Credit Program	10,000	3 years	50%	Y			N	Y
Indiana	Venture Capital Investment Tax Credit Program			50%	Y			N	Y
Iowa	*a.* Innovation Fund Tax Credit		3 years	70%	Y			N	Y
	b. Innovation Fund Tax Credit		3 years if before 2014, none if after	70%	Y			N	Y
Kansas	Angel Investor Tax Credit					Y	Y	Y	Y
Kentucky	Angel Investment Act Tax Credit	10,000		20%	Y	Y		Y	Y
Louisiana	*a.* Angel Investor Tax Credit		3 years	50%	Y		Y	Y	Y
	b. Angel Investor Tax Credit		3 years	50%	Y		Y	Y	Y
Maine	*a.* Seed Capital Tax Credit Program		4 years	50%	Y		Y	N	
	b. Seed Capital Tax Credit Program		4 years	50%	Y		Y	N	
Maryland	Biotechnology Investment Incentive Tax Credit	25,000	2 years	25%	Y			N	Y
Maryland	Cybersecurity Investment Tax Credit	25,000	2 years	25%	Y			N	Y
Massachusetts	Angel Investor Tax Credit			50%	Y	Y	Y	Y	Y
Michigan	Small Business Investment Tax Credit	20,000	3 years		Y		Y	N	
Minnesota	Angel Tax Credit	10,000	3 years	20%	Y		Y	N	N
Minnesota	Seed Capital investment Credit			50%	Y			N	
Nebraska	Angel Investment Tax Credit	25,000	3 years	50%	Y		Y	N	N
New Jersey	Angel Investor Tax Credit Program			80%	Y			N	Y
New Mexico	Angel Investment Credit					Y	Y	Y	
New York	Qualified Emerging Technology Company Tax Credits		4	10%	Y			N	Y
North Carolina	Qualified Business Tax Credit Program		1 year	10%	Y	Y	Y	N	N
North Dakota	Seed Capital Investment Tax Credit		3 years	50%	Y			N	
North Dakota	Angel Fund Investment Credit		3 years						
North Dakota	Angel Investor Investment Credit		3 years					N	
Ohio	*a.* Ohio Technology Investment Tax Credit		3 years	5%	Y	Y		N	
	b. InvestOhio		2-5 years					N	
Oklahoma	Credit for Qualified Investment in Qualified Small Business Capital Companies							N	
Rhode Island	Innovation Tax Credit								
South Carolina	High Growth Small Business Job Creation Act		2 years					Y	Y

State	Program	Min. investment per investor	Min. holding period	Ownership cap before investment	Exclude existing owners and their families	Exclude full-time employees	Exclude executives and officers	SEC Accreditation Req for Investor	Investor Can Reside Out-of-State
Tennessee	Angel Tax Credit	15,000						Y	Y
Utah	Life Science and Technology Tax Credits	25,000	3 years	30%	Y			N	
Virginia	Qualified Equity and Subordinated Debt Investments Credit		3 years		Y	Y	Y	N	
West Virginia	High-Growth Business Investment Tax Credit		5 years	5%	Y		Y	N	
Wisconsin	Qualified New Business Venture Program		3 years	20%	Y			Y	

State	Program	Industry Req for Business	Reporting Req for Investor's Firm	In-State Location Req for Business	Previous external financing cap (mil)	Registration Req for Business	Innovation Req for Business
Arkansas	Equity Investment Incentive Program	Y	N	N		Y	N
Arizona	Angel Investment Program	N	N	Y	< $2m in total inv	Y	N
Colorado	*a.* Innovation Investment Tax Credit	Y	N	Y		Y	N
	b. Advanced Industry Investment Tax Credit	Y	N	Y	< $10m in inv, debt, equity	N	N
Connecticut	Angel Investor Tax Credit Program	Y	N	Y	< $2m in angel financing	Y	N
Delaware	Angel Investor Tax Credit	Y	Y	Y	< $4m	Y	Y
Georgia	Angel Investment Tax Credit	Y	N	Y	< $1m in equity or debt inv	Y	N
Hawaii	High Technology Business Investment Tax Credit						
Illinois	Angel Investment Credit Program	Y	Y	Y	< $10m in PE, < $4m TC inv	Y	Y
Indiana	Venture Capital Investment Tax Credit Program	Y	N	Y		Y	N
Iowa	*a.* Innovation Fund Tax Credit	Y	N	Y		N	
	b. Innovation Fund Tax Credit	Y	N	Y		N	
Kansas	Angel Investor Tax Credit	N	Y	Y		N	Y
Kentucky	Angel Investment Act Tax Credit	Y	Y	Y	< $1m in TC angel inv	Y	N
Louisiana	*a.* Angel Investor Tax Credit	N	N	Y		Y	N
	b. Angel Investor Tax Credit	N	N	Y		Y	N
Maine	*a.* Seed Capital Tax Credit Program	Y	Y	Y		N	N
	b. Seed Capital Tax Credit Program	Y	Y	Y		N	N
Maryland	Biotechnology Investment Incentive Tax Credit	Y	N	Y		Y	N
Maryland	Cybersecurity Investment Tax Credit	Y	N	Y		Y	Y
Massachusetts	Angel Investor Tax Credit	N	N	Y			N
Michigan	Small Business Investment Tax Credit	Y	Y	Y		Y	Y
Minnesota	Angel Tax Credit	N	Y	Y	< $4m in PE	Y	Y
Minnesota	Seed Capital investment Credit	N	Y	Y		Y	Y
Nebraska	Angel Investment Tax Credit	N	Y	Y		Y	Y
New Jersey	Angel Investor Tax Credit Program	Y	N	Y		N	N
New Mexico	Angel Investment Credit	Y	N	Y		N	N
New York	Qualified Emerging Technology Company Tax Credits	Y	N	Y		N	Y
North Carolina	Qualified Business Tax Credit Program	Y	N	N		Y	N
North Dakota	Seed Capital Investment Tax Credit	N	N	Y		Y	Y
North Dakota	Angel Fund Investment Credit	N	N	N		N	N
North Dakota	Angel Investor Investment Credit	Y	N	Y		N	N
Ohio	*a.* Ohio Technology Investment Tax Credit	Y	N	Y		Y	N

State	Program	Industry Req for Business	Reporting Req for Investor's Firm	In-State Location Req for Business	Previous external financing cap (mil)	Registration Req for Business	Innovation Req for Business
	b. InvestOhio	N	N	Y		Y	N
Oklahoma	Credit for Qualified Investment in Qualified Small Business Capital Companies		Y	Y		N	N
Rhode Island	Innovation Tax Credit	Y				Y	Y
South Carolina	High Growth Small Business Job Creation Act	Y	N	Y		Y	N
Tennessee	Angel Tax Credit	N	Y	Y		Y	Y
Utah	Life Science and Technology Tax Credits	Y	N	Y		N	N
Virginia	Qualified Equity and Subordinated Debt Investments Credit	Y	N	Y	< $3m in equity or debt inv	Y	N
West Virginia	High-Growth Business Investment Tax Credit	N	N	Y		N	N
Wisconsin	Qualified New Business Venture Program	Y	N	Y	< $10m in PE	Y	Y

State	Program	Aggregate tax credit cap (mil)	Max tax credit per company	Max tax credit per investor	Max TC Amount Per Investor Per Business Per Year ($)	'First Come First Served' Policy	Refundable	Transferrable	Carry Over	Number of Years of Carry Forward	Total Angel Inv in State During Eff. Year ($mill)	State Funding as Share of Total Angel Inv in State
Arkansas	Equity Investment Incentive Program	6.25					N	Y	Y	9	0.00	≥ 1
Arizona	Angel Investment Program	2.50	600,000	250,000		Y	N	N	Y	3	4.20	0.60
Colorado	*a.* Innovation Investment Tax Credit	0.75		20,000		Y	N	N	Y	5	44.62	0.02
	b. Advanced Industry Investment Tax Credit	0.75		50,000		Y	N	N	Y	5	143.59	0.01
Connecticut	Angel Investor Tax Credit Program	3.00	500,000	250,000		Y	N	N	Y	5	33.04	0.09
Delaware	Angel Investor Tax Credit	5.00	500,000	125,000			Y	N	N			
Georgia	Angel Investment Tax Credit	5-10		50,000		N	N	N	Y	5	28.97	0.35
Hawaii	High Technology Business Investment Tax Credit			700,000			Y	Y	Y	Unlimited	12.41	
Illinois	Angel Investment Credit Program	10.00	1,000,000		500,000	Y	N	N	Y	5	49.87	0.20
Indiana	Venture Capital Investment Tax Credit Program	12.50		1,000,000		N	N	Y after 2012, N before 2012	Y	5	0.00	≥ 1
Iowa	*a.* Innovation Fund Tax Credit	3-4		100,000	50,000		Y	Y	Y	5	0.00	≥ 1
	b. Innovation Fund Tax Credit	2.00	500,000	100,000	50,000	Y	Y	Y	Y	3	8.33	0.24
Kansas	Angel Investor Tax Credit	6.00		250,000	50,000	Y	N	Y	Y	Unlimited	0.00	≥ 1
Kentucky	Angel Investment Act Tax Credit	3.00		200,000		Y	N	Y	Y	15	9.55	0.31
Louisiana	*a.* Angel Investor Tax Credit	3.60		362,880	181,440	Y		Y			1.50	≥ 1
	b. Angel Investor Tax Credit	3.60		362,880	181,440	Y		Y			6.51	0.55
Maine	*a.* Seed Capital Tax Credit Program	Lifetime cap $30 million	5,000,000		500,000	Y	Y	N	Y	15	0.00	≥ 1
	b. Seed Capital Tax Credit Program	5.00	5,000,000		500,000	Y	Y	N	Y	15	3.07	≥ 1
Maryland	Biotechnology Investment Incentive Tax Credit	6-12		250,000		Y	Y	N			75.32	0.16
Maryland	Cybersecurity Investment Tax Credit	2.0-4.0	250,000 to 500,000			Y	Y	N	N			
Massachusetts	Angel Investor Tax Credit	25		50,000			N		Y	3		
Michigan	Small Business Investment Tax Credit	9.00	1,000,000	250,000	250,000		N		Y	5	24.81	0.36
Minnesota	Angel Tax Credit	15.00		125,000			Y	N	Y		33.70	0.45
Minnesota	Seed Capital investment Credit			112,500			N	N	Y	4		
Nebraska	Angel Investment Tax Credit	3-4		300,000		Y	Y	N	N		13.27	0.30

State	Program	Aggregate tax credit cap (mil)	Max tax credit per company	Max tax credit per investor	Max TC Amount Per Investor Per Business Per Year ($)	'First Come First Served' Policy	Refundable	Transferrable	Carry Over	Number of Years of Carry Forward	Total Angel Inv in State During Eff. Year ($mill)	State Funding as Share of Total Angel Inv in State
New Jersey	Angel Investor Tax Credit Program	25.00			500,000	Y	Y	N	Y for corporate, N for individuals		46.17	0.54
New Mexico	Angel Investment Credit	2.00			62,500	Y	N	N	Y	5 years if after 2015; 3 years if before 2015	7.20	0.28
New York	Qualified Emerging Technology Company Tax Credits			150,000			Y		Y	Unlimited	279.57	
North Carolina	Qualified Business Tax Credit Program	7.50			50,000	N		N	Y	5	15.82	0.47
North Dakota	Seed Capital Investment Tax Credit	3.50	225,000	112,500		Y	N	N	Y	4	0.00	≥ 1
North Dakota	Angel Fund Investment Credit			45,000			N	N	Y	7		
North Dakota	Angel Investor Investment Credit			45,000			N	N	Y	5		
Ohio	*a.* Ohio Technology Investment Tax Credit	45.00		62,500		Y	N	N	Y	15	0.00	≥ 1
	b. InvestOhio	50.00		500,000		Y	N	N	Y	7	46.66	≥ 1
Oklahoma	Credit for Qualified Investment in Qualified Small Business Capital Companies						N	N	Y	3 years if after 2006; 10 years if before 2006	0.00	
Rhode Island	Innovation Tax Credit	0.50			100,000		N	N	Y	3	6.18	0.08
South Carolina	High Growth Small Business Job Creation Act	5.00		100,000			N	Y	Y	10	11.20	0.45
Tennessee	Angel Tax Credit	4.00		50,000		Y	N	N	Y	5	34.68	0.12
Utah	Life Science and Technology Tax Credits						N		N			
Virginia	Qualified Equity and Subordinated Debt Investments Credit	5.00		50,000		N	N	N	Y	15	35.00	0.14
West Virginia	High-Growth Business Investment Tax Credit	1.00	500,000	50,000		Y	N	N	Y	4	0.00	≥ 1
Wisconsin	Qualified New Business Venture Program	30.00	2,000,000				N	Y for early stage, seed investment credit, N for angel investor tax credit	Y	15	1.08	≥ 1

Table A2. Tax Credit Applicant Summary Statistics

This table contains summary statistics about companies that applied to be eligible for an investor tax credit, some of which did have an investor receiving a credit ("beneficiary companies") and some of which did not ("failed applicants"). Panel A shows these two groups by state. Panel B compares characteristics. "Pre-TC" means before the application year.

Panel A. Unique Tax Credit Applicants by State

	Received Tax Credit	No Tax Credit
AZ	144	145
CO	109	25
CT	100	70
KS	199	63
KY	60	101
MD	87	0
MN	338	205
NJ	69	6
NM	72	0
OH	374	537
SC	65	136
WI	206	116
Total	1,823	1,404

Panel B. Summary Statistics

	Received Tax Credit	No Tax Credit	T-Test P-Value
Tax Credit (TC) Amount ($ thou)	32.00	0.00	0.00
Any Financing Pre-TC	0.37	0.12	0.00
Amt Financing Pre-TC ($ mill)	3.70	1.90	0.02
Any Financing 2yrs Post-TC	0.26	0.16	0.00
Amt Financing 2yrs Post-TC ($ mill)	2.90	2.00	0.19
Startup Exited	0.07	0.04	0.00
Emp in Credit Yr	6.50	6.20	0.85
Emp 2yrs Post-TC	7.20	6.60	0.79
Emp > p75 in Credit Yr	0.21	0.20	0.68
Emp > p75 2yrs Post-TC	0.25	0.16	0.03
Emp > 10 in Credit Yr	0.14	0.09	0.04
Emp > 10 2yrs Post-TC	0.18	0.12	0.11
Emp > 25 in Credit Yr	0.04	0.01	0.04
Emp > 25 2yrs Post-TC	0.06	0.03	0.25

Table A3. Effect of ATC on Angel Activities on AngelList

This table reports the difference-in-differences estimates for the effect of angel tax credits on the amount of angel activities based on AngelList data. The sample period is 2003 to 2017. The dependent variables are the natural logarithm of the number of angel investments, the number of unique invested companies, and the number of unique investors in a state-year, respectively. Investments, companies, and investors are assigned to state-years based on the invested companies' locations. *ATC* is an indicator equaling one if a state has an angel tax credit program in that year. *Tax credit percentage* is a continuous variable equal to the maximum tax credit parentage available in a state-year with an angel tax credit program. Control variables are defined in equation (1). Each observation is a state-year. All specifications include state and year fixed effects. Standard errors are reported in parentheses and clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	No. of Investments		No. of Companies		No. of Investors	
ATC	0.280**		0.244**		0.272**	
	(0.140)		(0.113)		(0.130)	
Tax credit percentage		0.902***		0.715***		0.852***
		(0.268)		(0.228)		(0.239)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	735	735	735	735	735	735
Adjusted R^2	0.867	0.869	0.893	0.894	0.866	0.867

Table A4. Triple-Difference

This table provides the estimates from a triple-difference (DDD) specification as described in equations (2) and (3). *ATC* is an indicator equaling one if a state has an angel investor tax credit program in that year. *High-tech* is an indicator variable equaling one if the startup is in the high-tech sector (IT, biotech, and renewable energies). The dependent variable in Panel A is the natural logarithm of the number of angel investments. In Panel B, we estimate the triple-difference model where the dependent variable is a startup characteristic at the time of investment. The sample consists of state-year averages for the high-tech sector and state-year averages for the non-high-tech sector. Each observation is a state-sector-year. Control variables are defined in equation (1). Standard errors are reported in parentheses and clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A. Volume

	Ln(Number of angel investments)	
	(1)	(2)
ATC	-0.014	
	(0.049)	
ATC × High-tech	0.184***	0.184***
	(0.060)	(0.060)
Controls	Yes	No
State × High-tech FE	Yes	Yes
Year × High-tech FE	Yes	Yes
State × Year fixed effects	No	Yes
Observations	2,400	2,400
Adjusted R^2	0.926	0.937

Panel B. Ex-ante Angel-Backed Startup Characteristics

	Ln(Sales)		Ln(Employment)		Sales growth		Employment growth		Ln(Productivity)		Fraction of serial entrepreneurs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ATC	-0.006		0.022		0.016		-0.002		-0.039		0.004	
	(0.130)		(0.039)		(0.039)		(0.030)		(0.105)		(0.010)	
ATC × High-tech	-0.581**	-0.581**	-0.170**	-0.170**	-0.199*	-0.199*	-0.128*	-0.128*	-0.409**	-0.409**	-0.021*	-0.019*
	(0.236)	(0.235)	(0.076)	(0.076)	(0.113)	(0.113)	(0.074)	(0.073)	(0.180)	(0.180)	(0.011)	(0.010)
Controls	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
State × High-tech FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × High-tech FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,400	2,400	2,400	2,400	2,400	2,400	2,400	2,400	2,400	2,400	2,380	2,380
Adjusted R^2	0.831	0.828	0.574	0.587	0.4	0.375	0.484	0.465	0.848	0.841	0.179	0.132

Table A5. Robustness Tests

Panel A repeats the main analysis in Panel A of Table 4 and Table 5, restricting to the sample period of 2001 to 2016. Panel B repeats our main analysis, dropping estimated sales and employment values in NETS. Panel C (Panel D) repeats our main analysis, restricting to angel investments from the CVV sample (Form D sample) only. Panel E repeats the main analysis, dropping angel investments from VentureXpert and VentureSource and keeping only those in Crunchbase and Form D. Panel F repeats our main analysis excluding California and Massachusetts. *Tax credit percentage* is a continuous variable equal to the maximum tax credit percentage available in a state-year with an angel tax credit program. The dependent variables are the average natural logarithm of sales, sales growth, natural logarithm of employment, employment growth, and natural logarithm of sales-to-employment ratio (productivity) in the year before angel investment. Each observation is a state-year. Control variables are defined in equation (1). All specifications include state and year fixed effects. Standard errors are reported in parentheses and clustered by state. ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Panel A. Post-2000 Sample

	Ln(Number of angel investments)	Ln(Sales)	Ln(Employment)	Sales growth	Employment growth	Ln(Productivity)	Fraction of serial entrepreneurs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ATC	0.158**	-0.634**	-0.149***	-0.267***	-0.213***	-0.487**	-0.016*
	(0.076)	(0.257)	(0.049)	(0.078)	(0.057)	(0.221)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	800	800	800	800	800	800	672
Adjusted R^2	0.927	0.814	0.645	0.523	0.561	0.822	0.148

Panel B: Dropping Estimated Values in NETS

	Ln(Sales)		Sales growth		Ln(Employment)		Employment growth		Ln(Productivity)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ATC	-0.444		-0.259*		-0.202**		-0.125*		-0.353*	
	(0.467)		(0.134)		(0.094)		(0.075)		(0.193)	
Tax credit percentage		-0.330		-0.423		-0.517***		-0.225*		-1.072**
		(1.132)		(0.264)		(0.183)		(0.128)		(0.411)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200	1,200	1,200	1,200	1,200	1,200	1,200
Adjusted R^2	0.296	0.296	0.168	0.166	0.551	0.551	0.426	0.425	0.727	0.727

Panel C. CVV Sample

	Ln(Number of angel investments) (1)	Ln(Sales) (2)	Ln(Employment) (3)	Sales growth (4)	Employment growth (5)	Ln(Productivity) (6)
ATC	0.141**	-0.408*	-0.201**	-0.157*	-0.132**	-0.451**
	(0.070)	(0.245)	(0.079)	(0.094)	(0.066)	(0.205)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200	1,200	1,200
Adjusted R^2	0.889	0.632	0.380	0.239	0.294	0.640

Panel D: Form D Sample

	Ln(Number of angel investments) (1)	Ln(Sales) (2)	Ln(Employment) (3)	Sales growth (4)	Employment growth (5)	Ln(Productivity) (6)
ATC	0.181**	-0.643**	-0.138**	-0.179*	-0.116*	-0.510**
	(0.072)	(0.296)	(0.069)	(0.103)	(0.065)	(0.249)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200	1,200	1,200
Adjusted R^2	0.904	0.730	0.454	0.268	0.344	0.749

Panel E: Dropping VentureXpert and VentureSource Deals

	Ln(Number of angel investments) (1)	Ln(Sales) (2)	Ln(Employment) (3)	Sales growth (4)	Employment growth (5)	Ln(Productivity) (6)
ATC	0.170**	-0.562**	-0.131*	-0.186*	-0.127*	-0.441*
	(0.083)	(0.271)	(0.069)	(0.095)	(0.065)	(0.220)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200	1,200	1,200
Adjusted R^2	0.908	0.744	0.479	0.285	0.350	0.762

Panel F. Dropping California and Massachusetts

	Ln(Number of angel investments)	Ln(Sales)	Ln(Employment)	Sales growth	Employment growth	Ln(Productivity)	Fraction of serial entrepreneurs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ATC	0.169**	-0.556**	-0.140**	-0.190*	-0.133*	-0.426**	-0.014*
	(0.083)	(0.246)	(0.068)	(0.104)	(0.066)	(0.195)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,152	1,152	1,152	1,152	1,152	1,152	1,135
Adjusted R^2	0.905	0.778	0.534	0.353	0.429	0.794	0.145

Table A6. Investor Characteristics and Startup Exit Outcomes

This table reports the relationship between investor characteristics the exit outcomes of the invested startups based on AngelList data. In columns 1 to 4, the dependent variable is a dummy equal to one if the startup achieved exit through IPO or M&A. In columns 5 to 8, the dependent variable is a dummy equal to one if the startup achieved exit through IPO. Independent variables are defined the same as in Panel B of Table 7. The sample period is 2003 to 2017. All specifications include company state-year fixed effects and investor state-year fixed effects. Standard errors are reported in parentheses and clustered by state. ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Exit though IPO or M&A				Exit though IPO			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-state	-0.014***				-0.009***			
	(0.004)				(0.002)			
Had no exit		-0.285***				-0.030***		
		(0.020)				(0.007)		
New			-0.031***				-0.003***	
			(0.003)				(0.001)	
No founder exp.				-0.002				-0.002***
				(0.002)				(0.000)
Company state-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor state-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,942	76,942	76,942	76,942	76,942	76,942	76,942	76,942
Adjusted R^2	0.113	0.232	0.115	0.113	0.096	0.106	0.095	0.095

Table A7. Different-State-Matched Employment and Exit Outcomes

This table shows nearest-neighbor matching estimates. Instead of comparing beneficiary firms to failed applicants, we compare them to control firms in nearby states without tax credit programs. We match each beneficiary 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. 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. The dependent variables are defined within two years following the tax credit year, except for Exit (IPOs and acquisitions), which are ever after. As in Table 8, we consider as outcomes indicators that are equal to one if the employment is above ten workers, twenty-five workers, the top quartile in the sample, or if the firm experienced a successful exit. We control for sector-by-year and the firm-level control discussed in the paper. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Emp. > 10 2yrs Post-TC	Emp. > 25 2yrs Post-TC	Emp. > p75 2yrs Post-TC	Exit
	(1)	(2)	(3)	(4)
Got Tax Credit	-0.0012	-0.014	0.019	-0.017
	(0.016)	(0.0094)	(0.015)	(0.015)
Sector-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	2511	2511	2511	4115
Adjusted R^2	0.52	0.46	0.44	0.079

Appendix B. Variable Definitions

Variable Name	Definition
ATC	Indicator variable equaling one if a state has am angel investor tax credit programs in that year.
Tax credit percentage	Continuous variable equal to the maximum tax credit available (percent) in a particular state-year when there is an angel investor tax program and set to zero if there is no program in place in a state-year.
Number of angel investments	Total number of financing rounds that include angel investors in a state-year. Source: CVV and Form D.
Average investment amount	Average amount raised in an angel-participated round in a state-year. Note that this is not specific to an investor. Source: CVV and Form D.
Pre-investment sales	Firm sales in the year prior to receiving angel investment. Source: NETS.
Pre-investment employment	Number of employees in the year prior to receiving angel investment. Source: NETS.
Pre-investment sales growth	The percentage change in firm sales from year t-2 to t-1. Source: NETS.
Pre-investment employment growth	The percentage change in firm employment from year t-2 to t-1. Source: NETS.
Pre-investment sales/employment	Ratio of firm sales to employment in the year prior to receiving angel investment. Source: NETS.
Fraction of serial entrepreneurs	Fraction of founding team members that have prior entrepreneurship experience at the time of angel investment. Source: CVV.
Exit	Indicator variable equaling one if a startup has an IPO or high-valued M&A, defined as the sale price being at least 1.25 times the total invested capital. Source: CVV.
Exit multiple	Enterprise value at exit divided by the total cumulative amount of invested capital. Source: CVV.
GSP growth	Gross State Product (GSP) at the state-year level. Source: BEA.
Income per capita	Income per capita at the state-year level. Source: BEA.
Population	Population at the state-year level. Source: BEA.
Unemployment rate	State unemployment rate in a given year. Source: BEA.
Democratic control	Indicator variable for whether a state (both the legislative and executive branch) is controlled by Democrats. Source: NCSL.
Republication control	Indicator variable for whether a state (both the legislative and executive branch) is controlled by Republicans. Source: NCSL.
Revenue/GSP	Ratio of revenue to Gross State Product at the state-year level. Source: Annual Survey of State and Local Government Finances.
Expenditure/GSP	Ratio of expenditure to Gross State Product at the state-year level. Source: Annual Survey of State and Local Government Finances.
Debt/GSP	Ratio of debt to Gross State Product at the state-year level. Source: Annual Survey of State and Local Government Finances.
Has income tax	Indicator variable equal to one if a state has personal income tax in a given year. Source: NBER.
Max income tax rate	Maximum state personal income tax rate. Source: NBER.
Capital gains tax rate	State long-term capital gains tax rate. Source: NBER.
Neighbor ATC	Indicator variable equaling one if a state has a least one neighboring state with an active angel tax credit program.
Venture capital volume	Natural logarithm of aggregate VC investment amount (in millions) in a state-year. Source: VentureXpert
Program flexibility	An index ranging from 0 to 16 and is constructed based on the restrictions in Table 1. For each non-binary restriction, we rank programs from least to most strict and assign the highest rank to programs without this restriction. These rank values are then normalized to the unit interval by dividing all values by the maximum value. We also construct indicator variables for programs that do not exclude insider investors and for each of the non-refundable, non-transferable, and no carry forward restrictions. To form the Program flexibility index, we sum these 16 variables and then standardize the index by subtracting its mean and dividing by its standard deviation prior to interacting it with our treatment variables.
VC supply	State-year level aggregate venture capital investment amount (excluding angel and seed rounds identified in our main sample) scaled by the total number of young firms (of age 0-5) in that state-year. This variable is standardized by subtracting its mean and dividing by its standard deviation. Source: VentureXpert, BDS.
Ln(Emp. Young All Industries)	The logarithm of one plus state-year level aggregate of employment across all industries in young firms (of age 0-5). Period covered: 1993 -2017 (but different states do not report in some of earlier years). Source QWI.

Ln(Emp. Young Manufact. High Tech)	The logarithm of one plus state-year level aggregate of employment for manufacturing and high-tech in young firms (of age 0-5). High-tech is defined following Appel et al. (2017), as NAICS: 3254 3341 3342 3344 3345, 3346, 3353, 3391, 5112, 5141, 5171, 5172, 5179, 5182, 5191, 5413, 5413, 5415, 5416 and, 5417. Period covered: 1993 -2017 (but different states do not report in some of earlier years). Source QWI.
Ln(Job Creat. Rate)	The logarithm of one plus state-year job creation rate across every industry. Period covered: 1993 -2016. Source: BDS.
Ln(Job Destr. Rate)	The logarithm of one plus state-year job destruction rate across every industry. Period covered: 1993 -2016. Source: BDS.
Ln(Job Creat. Rate Young)	The logarithm of one plus state-year job creation rate across every industry in young firms (of age 0-5). Period covered: 1993-2014. Source: BDS.
Ln(Job Destr. Rate Young)	The logarithm of one plus state-year job destruction rate across every industry in young firms (of age 0-5). Period covered: 1993-2016. Source: BDS.
Ln(Small Est. Manufacturing)	The logarithm of one plus state-year establishment count in small (less than 20 workers) manufacturing firms. Period covered: 1995-2015. Source: CBP.
Ln(Small Est. High Tech)	The logarithm of one plus state-year establishment count in small (less than 20 workers) high-tech firms. High-tech is defined following Appel et al. (2017). Period covered: 1995-2015. Source: CBP.
Any Succ. Exit	Dummy equal to one if the state-year has any angel-backed firm that later had a successful exit, defined as IPO or high-valued M&A, defined as the sale price being at least 1.25 times the total invested capital. Source: CVV.
Ln(Quality Firms)	The logarithm of one plus the number of high-potential firms founded in each state-year, where high potential is predicted (nowcast) by firm characteristics at founding. This corresponds to the Regional Entrepreneurship Cohort Potential Index (RECPI) in Fazio, Guzman, and Stern (2019). Period covered: 1993-2016. Source: Startup Cartography project.
Ln(Patent Applications)	The logarithm of one plus state-year count of patent applications of granted patents. Period: 1993-2017. Source: USPTO.
Ln(Entry Rate Young)	The logarithm of one plus state-year entry rate of young firms (of age 0-5). Period: 1993-2014. Source: BDS.
Ln(Exit Rate Young)	The logarithm of one plus state-year exit rate of young firms (of age 0-5). Period: 1993-2014. Source: BDS.
Got Tax Credit	Indicator variable for whether a firm certified by the tax credit program has an investor receiving tax credit.
Raised VC 2 yrs post-TC	Indicator variable for whether a firm received any VC financing within two years after its investors received angel tax credit.
Emp. >10 2 yrs post-TC	Indicator variable for whether a firm had more than 10 employees within two years after its investors received angel tax credit.
Emp .>25 2 yrs post-TC	Indicator variable for whether a firm had more than 25 employees within two years after its investors receive angel tax credit.
Emp. >p75 2 yrs post-TC	Indicator variable for whether a firm's employment count was above the 75th percentile within two years after its investors received angel tax credit.
Emp. >10 in credit yr	Indicator variable for whether a firm had more than 10 employees in the year its investors received angel tax credit.
Emp. >25 in credit yr yr	Indicator variable for whether a firm had more than 25 employees in the year after its investors received angel tax credit.
Emp. >p75 in credit Yr	Indicator variable for whether a firm's employment count was above the 75th percentile within our sample in the year its investors received angel tax credit.
Finance pre-TC	Indicator variable for whether a firm received any other external finance before its investors received tax credit/
Ln(number of investors)	The logarithm of one plus the number of investors making investments in each startup state-year. Source: AngelList.
Ln(number of in-state investors)	The logarithm of one plus the number of investors investing in same-state startups in each startup state-year. Source: AngelList.
Ln(number of out-of-state investors)	The logarithm of one plus the number of out-of-state investors in each startup state-year. Source: AngelList.
Ln(number of new investors)	The logarithm of one plus the number of investors with less than a year of investment experience in each startup state-year. Source: AngelList.
Ln(number of experienced investors)	The logarithm of one plus the number of investors with more than a year of investment experience in each startup state-year. Source: AngelList.
Ln(number of investors with no exits)	The logarithm of one plus the number of investors with no prior successful exit in each startup state-year. Source: AngelList.
Ln(number of investors with exits)	The logarithm of one plus the number of investors with prior successful exits in each startup state-year. Source: AngelList.
Ln(number of investors with no founder exp.)	The logarithm of one plus the number of investors with no prior founder experience in each startup state-year. Source: AngelList.
Ln(number of investors with founder exp.)	The logarithm of one plus the number of investors with prior founder experience in each startup state-year. Source: AngelList.

Appendix C. Identifying Angel Investments in CVV

In Crunchbase, we include round types identified as "pre-seed," "seed," "convertible note," "angel," or "equity crowdfunding," in addition to rounds when the investor type is identified as "angel," "micro," "accelerator," or "incubator." In VentureXpert, we keep first rounds and rounds when the investment firm or fund type is identified as "individual," "angel," or "angel group." In VentureSource, we incorporate round types identified as "seed," "pre-seed," "crowd," "angel," or "accelerator."

For robustness, we also use a stricter definition of angel investments defined as follows:

1. All rounds in VentureXpert where the investment firm or fund type is identified as "individual," "angel," or "angel group."
2. All rounds in VentureSource where the round type is identified as "seed," "pre-seed," or "angel."
3. All rounds in Crunchbase where the round type is identified as "pre-seed," "seed," or "angel."

Appendix D. Identifying Insiders

In Section 5, we describe how a substantial share of angels using the tax credit are actually insiders of the beneficiary firms. In this Appendix, we present some of the methods we have used to identify insiders. As mentioned in the paper, 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). These five states are reasonably representative of states that employ angel tax credits, including some high-tech clusters (e.g. in New Jersey and Maryland), as well as rural areas (Kentucky, New Mexico), and the Rust Belt (Ohio). There are 628 unique companies in this group, and 3,560 investors.

We identify insiders in three ways. First, we check whether any of the investors is executive in the company, using data from 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.

Second, we repeat the same procedure using the listed executives in Form D. We can find Form D filings in the year of the tax credit for 186 of the companies, and we matched executive officers from the Form D to investors in the tax credit data. 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.

Lastly, we also check for investors that are potential family members of any of the executives. We first identify the 61 companies that had at least three investors with the same last name. For these investors, we searched websites to identify if they or a family member were an executive. Based on this process, 61 percent of these 61 companies were identified as having an insider investor.

The methods used are inherently imperfect. However, we think that the errors are likely to be false negative (i.e. fail to identify an investor as insider when she is actually an insider) rather than false negative (i.e. incorrectly identify an insider). As a result, we consider our estimates to be a lower bound for the presence of insiders in the beneficiary group. We refer to the paper for more details on the results.

Appendix E. Power Analysis of Aggregate Real Effects Results

In this appendix, we discuss the interpretation of our real effects in the context of Abadie (2019). We also present a power analysis of our tests.

Statistically null effects in economics are generally interpreted with cautious. In fact, a null effect does not prove that the effect is zero, but simply means that the researchers failed to show that the effect was different than zero. Therefore, in the presence of null effects, researchers usually rely on the magnitude of the point estimate to claim that the estimate is consistent with an economically small effect. This is what we have done in the body of the paper.

In a recent paper, Abadie (2019) studies the informativeness of a statistically null effect in a Bayesian framework. The key takeaway is that dismissing null effect as uninformative based on the fact that confidence intervals are not "tight enough" is generally misleading. In particular, he proves that, when we hold the prior that an experiment is successful in generating a result (i.e. the policy was effective), a statistical null effect is informative, and in some cases more informative than a statistically significant result. Intuitively, when evaluating such experiments, a null result moves the prior more than a significant result, bringing more evidence in favor of the possibility that the policy was ineffective. In particular, Abadie (2019) shows that non-significance is more informative than significance if the power of the test is at least 0.5.

Abadie (2019) has two implications for our work. First, statistical insignificance could be useful above and beyond the fact that the estimates are close around zero. Although our null point estimates are small enough to rule out significant impact of angel tax credits, this result helps us providing a better conceptual framework to think about these effects. Second, when the power of a test is sufficiently high (more than 0.5), a null effect changes our prior more than a significant effect does. This could be the case in our setting, given the widely-held view (in particular by policy-makers) that these programs can be effective in increasing entrepreneurship.

This discussion requires a careful discussion of the power of our analysis, since our sample sizes make the likelihood of having tests with small power on a single analysis is potentially high. Formally speaking, power is the probability that a null hypothesis will be rejected, conditioning on it being false. For our context, there are two particular challenges to overcome. First, we need to compute the power of our test for each of the outcomes. In particular, our panel difference-in-differences does not fit well with the traditional, simple (RCT) framework for power calculation. Second, we need to aggregate the power of our tests across the many outcomes examined in our analyses. Intuitively, testing our hypothesis across a large number of outcomes increases the probability of rejecting the null in at least one test, given the null is false. The actual aggregation, however, will depend on the correlation structure of different outcomes.

We address the first challenge by relying on the recent work by Burlig, Preonas, and Woerman (2020). This paper develops a method to calculate power in a difference-in-difference framework.[49] Their model, in addition to being directly applicable to our setting, also deals with some of the unique features of difference-in-differences, such as serial correlation in the error structure, which could be relevant in a power calculation.

In general, the framework by Burlig, Preonas, and Woerman (2020) fits well ours. However, there are some differences. First, their model assumes that the treatment happens only once, and that it does no reverse. In our setting, some states had terminated their tax credit programs, and in a few cases re-introduced them. This difference is likely going to bias our estimate of the power

[49] The authors also provide a Stata program to run their analysis: *pc_dd_analytic*. We thank them for the program as well as the careful documentation provided.

downward, because the method will assume a smaller number of treatment events than actually in our data. Second, Burlig, Preonas, and Woerman (2020) assume that treatment happens at the same time for all treated units. Therefore, their model simply requires the specification of the proportion of units treated and the number of pre- and post-periods. We define the proportion of units treated as the share of states that have ever introduced tax credit programs (62%). We proxy the number of post-periods (pre-periods) by multiplying the sample period length by the share of state-years that are treated (untreated).[50] We think this approximation is reasonable, and we find that altering these parameters around the baseline does not significant impact the inference discussed later. Lastly, the model does not allow us to add controls, but – as shown in the paper – this does not affect our estimate of the real effect. Since controls seem to improve inference, not having control is also likely to bias downward the actual power. Using these assumptions, we then calculate the power for each outcome variable assuming an effect of 3% (small) or 5% (medium), and a significance level of 10%. Importantly, we have log-transformed all outcomes, and therefore our effect can be interpreted as a percentage change in increase relative to the baseline.

The second challenge is to combine the power across different outcomes. This is important because in the limited sample that is provided in state-level analysis, the power is not always high in one single specification, and therefore examining several dimensions is crucial to establish credibility in the analyses. Recall that power can be thought as the inverse the likelihood of a false negative. Intuitively, a way to reduce the likelihood of a false negative is to repeat the experiment across different outcomes, which capture different aspects of entrepreneurship activities in a state. The idea is that, while one may be unlucky to fail to detect an effect for one outcome, the probability of failing to detect any effect across all outcomes decreases as the number of outcomes increases.

While this is intuitive, a precise aggregation of power requires the knowledge of the correlation structure of different outcomes. While such a correlation structure is ultimately unobservable, we consider two limiting cases that – in our view – can help framing the discussion in an intuitive but compelling ways.

First, we consider a scenario where all outcome variables are independent (up to some random noise) from either other. This would imply that each measure captures a distinct aspect of the local economy and provides new and independent information. To be clear, we do not believe this limiting assumption to be true in the data, but it provides a useful thought experiment for our model. However, we do think that each of our measures does provide new and useful information on the underlying economics of entrepreneurship in the local market.

Under this assumption, it is easy to see that the probability of rejecting the null hypothesis in at least one of the tests, given that the null is false, is $1 - \prod_{i=1}^{N}(1 - p_i)$, where p is the power of the test for outcome i. This would yield a power that is well above 90% for both the 3% and 5% assumption. More generally, under this assumption, the overall power does not depend crucially on having particularly strong tests. Rather, the power is mostly coming from the high number of tests that are performed. The idea is that, even if an individual test does not have high power, once we repeat the test thirteen times, the likelihood of not detecting at least one positive effect given that there is an effect is quite low. The same result would in fact also hold with smaller expected size, like 1%.

[50] As we show in the variable definition (Appendix B), the different outcomes differ in the sample period covered. For those variables with a shorter period, we need to modify the assumption about the number of pre/post to match the total number of period (time dimension) in the sample.

We then consider the opposite scenario where all outcomes are perfectly correlated. In this case, each outcome is simply a "replica" of the other with a random noise. This implies that – net of the noise - additional outcomes do not bring new information. Also in this case, we also do not believe this case is likely in our data. For instance, measures of patenting at state level is likely to capture a very distinct economic aspect than measures of employment. Nevertheless, this provides a useful "worst case scenario" for the aggregation of power across tests. In fact, under this assumption having more tests does not necessarily help.

In this case, we can still calculate the lower bound of power. In particular, under this scenario, the probability of rejecting the null across all tests, given the null is false, is as at least high as the power of the most powerful test. In other words, if all tests are essentially the same and only differ in the level of noise, one can at least have the same level of confidence as the "best" test.[51] In our context, this implies we should look at the test with the highest power to determine the lower bound of the power of the overall analysis. If we consider the case of a 3% (5%) effect, our best test yields a power of 0.94 (0.99), which for the entry rate on young firm. This result does not crucially depend on this one variable, since we have five (nine) outcomes for which the power is above 0.5.

In general, we expect our tests lie between the above two limiting cases: our outcomes likely provide partially overlapping information, but we still learn new things as we add more and more outcomes. Together, the above analysis suggests that the likelihood of a false negative across all our outcome variables is relatively low, even when assuming a relatively small effect of 3%. Furthermore, this discussion highlights that our setting is likely to be above the threshold of 0.5 for an insignificant result to be informative (Abadie 2019).

The above conclusion is only made stronger by the fact that we find the same null effect across extra outcomes, as well as considering different specification with and without controls, and excluding Massachusetts and California (Figure A.3). While our power analysis is specific to our setting, this discussion could be also useful to other scholars interested in understanding the power of studying staggered introductions of policies in a difference-in-differences setting.

[51] To explain this idea with an example, this situation is akin to a case where one conduct ten tests for a disease. Assume that nine tests are bad, in that they are unlikely to detect the disease even when the person is sick, and one is excellent. If you administer all ten tests, the likelihood of detecting the disease on a sick person is at least as high as the detection rate of the good test. In principle, you might also learn something from the nine bad tests, but having these extra tests will not lower your power across all tests.