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

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Abstract

Angel investor tax credits are used globally to spur high-growth entrepreneurship. Exploiting the staggered implementation of these tax credits in 31 U.S. states, we find that while they increase angel investment, they have no significant effect on entrepreneurial activity. Tax credits induce entry by inexperienced, local investors and are often used by insiders. A survey of 1,411 angel investors suggests that a "home run" investing approach alongside coordination and information frictions explain low take-up among experienced investors. The results contrast with evidence that direct subsidies to firms have large positive effects, raising concerns about using investor subsidies to promote entrepreneurship.

JEL Classification: E24, G24, H71, L26

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1. Introduction

Fostering high-growth entrepreneurship is crucial for long-term economic success. As a result, governments around the world deploy tools such as grants, loan guarantees, prize competitions, and tax subsidies. This paper studies a popular policy that has been adopted by more than 13 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 firm quality and could 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 for the government. Third, 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 investors with the experience and skill to allocate capital to high-quality startups increase their investment activity in response to the policy. That is, while tax credit programs offer attractive flexibility, there is no guarantee that they will support the startups that policymakers target.

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 appears to be unrelated to relevant local economic conditions. Based on available data for programs in our sample, subsidized investors received $8.1 billion in tax credits, which is large relative to state funding for entrepreneurship and local angel investment in states with these programs. The programs

[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, Singapore, 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.

also have a high take-up rate of 88% on average. Given an average tax credit percentage of 34%, these tax credits support up to $23.8 billion of angel investment over our sample period. We evaluate the impact of angel tax credit programs using data on angel activity from Crunchbase, VentureXpert, VentureSource, Form D filings, and AngelList. For a subset of states, we also received data from state governments on the identity of firms and investors benefiting from these tax credit programs.

In our baseline analysis, we use a difference-in-differences framework at the state-year level to identify the effect of tax credits. We find that angel tax credits increase the number of angel investments by approximately 18%. This effect is amplified when programs impose fewer restrictions and when the supply of alternative startup capital is more limited. Relatedly, angel tax credits increase the number of individual angel investors by about 31%.

Furthermore, we document that these new investments primarily flow to low-growth potential firms, measured by pre-investment employment, employment growth, and founder experience. Average ex-ante growth characteristics of angel-backed firms also deteriorate after the implementation of angel tax credits, which may be expected if relaxing financial constraints reduces the quality of firms financed at the margin (Evans and Jovanovic (1989)), and does not imply that the investments are not privately or socially valuable. However, the large declines raise concerns about the ability of angel tax credits to reach high-growth startups and have a significant impact on the local economy.

We test whether angel tax credits achieve the objectives stated in legislation, which typically include increasing employment, startup entry, and innovation. We find that the policies have no significant 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 find that the angel tax credits have an economically small and statistically insignificant effect on local entrepreneurship. At the firm level, we similarly find no effect when we compare firms backed by subsidized investors to firms certified for investors to receive a tax credit but whose investors never received a tax credit, suggesting that the aggregate results do not reflect small program scale.

These economically small null effects are informative. Abadie (2020) shows that insignificant results are *more* informative than significant results when there is a prior on finding a significant effect and sufficient power. Our analysis fits this framework well. First, since many studies of other innovation tax credits find large positive effects, a positive effect is a natural prior.[3] Indeed, the programs' popularity suggests that policymakers expect positive effects. Second, we follow Burlig, Preonas, and Woerman (2020) and calculate the power of our analysis, i.e., the probability of rejecting the null across all outcomes when the policy impacted at least one of the outcomes. We find sufficiently high power. Therefore, the null results offer useful new information about angel tax credits.[4] As DellaVigna and Linos (2020) discuss, reporting null results reduces publication bias in policy evaluation towards effective and significant policies, at the expense of evaluating ineffective ones.

To understand why angel tax credits increase investment yet have no effect on real activity, we study how they change investor behavior. A commonly cited goal of angel tax credit programs is to increase external investment by professional investors who would otherwise not invest in local firms. Professional investors may have access to high-quality deals and the ability to screen deals more effectively than less experienced investors. Also, non-professional investors may be more likely to invest for non-pecuniary reasons (Huang et al. (2017)) or to exploit tax credits to minimize their tax burdens. The ability of these programs to stimulate high-growth entrepreneurship could therefore depend on whether they attract professional, experienced angel investors.

We find that the increase in angel activity appears to be largely explained by more investment among non-professional investors. First, using data from the state tax credit programs, we examine characteristics of investors who have received the tax credits. We find that they are primarily younger, more local, and less experienced than the average angel investor. Second, we examine how angel tax credits affect the composition of investors. Following the introduction of these programs, we find that there is a surge of in-state, new, and inexperienced investors, while there is little entry of professional, arms-length angels. This suggests that non-professional investors respond to these tax incentives, while professional investors do not. Since non-professional investors have less access to high-

[3] This literature includes Hall (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).

[4] While there are likely some externalities of the programs both on government spending and on unsubsidized firms, these are beyond the scope of this paper. However, the null effects, particularly on measures of job and firm churning, suggest that such externalities are not first order for our analysis.

quality deals and lower ability to screen deals, the insignificant aggregate effect is consistent with investments in projects that are on average zero NPV without the tax subsidy.

Professional investors might have lower take-up if they use a different investment approach than non-professional investors. We consider two investment frameworks. The first relies on financial metrics such as IRR and NPV to evaluate deals. This framework is appropriate when cash flows can be forecast with reasonable accuracy, and it should lead investors to be sensitive to tax credit availability. However, professional angel investors considering potentially high-growth and very early-stage startups face expected returns that are extremely skewed and uncertain in the Knightian sense. Investors in this type of startup may find financial metrics less useful and instead focus on qualitative measures, such as the quality of the management and business model, which are perceived to be correlated with the right tail of outcomes. Angel tax credits may not change the selection of startups among investors employing this "Home Run" framework. Nevertheless, even if tax credits do not change angels' investment behavior *ex ante*, they might still be used *ex post* if their benefits exceed coordination, administrative, and information costs.

To assess how an investor's approach relates to the importance and use of angel tax credits, we conduct a survey of angel investors. Among 1,411 respondents, about 11% are from the state tax credit recipient data and the remainder are AngelList investors. We examine the importance of nine factors, one of which is angel tax credits. We find that 51% of respondents rate tax credits as not at all important (the lowest of five options), which increases to 71% among the most experienced investors. This contrasts with all other factors. For example, 97% of investors rate the management team as very or extremely important. When prompted to explain why credits are unimportant, 57% report that it is because they invest based on whether the startup has the potential to be a home run. In the words of one respondent, "I'm more focused on the big win than offsetting a loss." Among investors who never use angel tax credits, 15% selected coordination or administrative burdens as the reason, which increases among experienced investors. The survey results contribute to existing work on how early-stage investors make decisions (Bernstein, Korteweg, and Laws (2017), Ewens and Townsend (2019), and Gornall and Strebulaev (2019)).

An additional channel that can explain why tax credits increase angel investment yet have no significant real effects is relabeling. Investors may relabel transactions that would have happened regardless of the program as an angel investment in order to obtain the tax credit.[5] While this is relevant for all investors, it is particularly applicable to investors who are also firm insiders. They face negligible coordination frictions when investing in their own firms and may invest for non-financial reasons, particularly because tax credit programs do not restrict how firms use subsidized capital. We find that 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. The substantial share of insiders using angel tax credits indicates that relabeling may partially explain the contrasting findings.

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. Our findings point to a tradeoff between program flexibility and effective targeting. Angel tax credits do not appear to reach investors who have a comparative advantage in allocating capital to startups with high-growth potential. Sophisticated angels do not respond to intensive margin incentives and face coordination and information frictions to using tax credits. Instead, angel tax credits attract individuals with lower barriers to accessing the programs, for example because they are local or connected to firms. 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), Deshpande and Li (2019), and Zwick (2020)).

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)). To our knowledge, our survey offers the first large-scale evidence of how angel investors make decisions. In a related paper, Lindsey and Stein (2020) find that the Dodd-Frank Act reduced angel investment, leading to a decline in firm entry and a contraction in employment.[6] Also related is González-Uribe and Paravisini (2019), who

[5] Such relabeling would represent moral hazard due to information asymmetry between the investor and the government (Holmstrom (1979)).
[6] In Lindsey and Stein (2020), marginal investors are wealth constrained, but are experienced before losing accreditation status. In our context, marginal investors tend to be non-professional. This explains why a positive angel capital shock generates a null effect in our paper but a positive effect in Lindsey and Stein (2020).

study the combined effects of investor and capital gains tax credits on firm decisions in the U.K. They document a low take-up rate but large responses among beneficiary firms.[7]

More broadly, our paper is related to work on sources of financing for early-stage firms (Robb and Robinson (2012), Adelino, Ma, and Robinson (2017), Hochberg, Serrano, and Ziedonis (2018), Davis, Morse, and Wang (2019), Xu (2019), Babina, Bernstein, and Mezzanotti (2020), and Ma (2020)). Relative to this literature, our paper highlights the importance of angel investor heterogeneity. Differences between professional, sophisticated angels and inexperienced or insider investors create opportunities for individuals to use tax credits for reasons besides the intended purpose of additional investment in high-growth startups. While we are among the first to analyze this issue systematically, it is thought to be a challenge facing entrepreneurship policy (Acs, Astebro, Audretch, and Robinson (2016) and Lerner (2020)).

Finally, we contribute to the literature on government investment incentives, which overwhelmingly finds positive effects. For example, 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 (Cohen et al. (2019), Fehder and Hochberg (2019), González-Uribe and Leatherbee (2017), Howell (2019), and McKenzie (2017)). 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.[8] Despite being attractive to policymakers, the flexibility of tax incentives for investors could also limit its impact.

2. Angel Investor Tax Credits

[7] Unlike the U.S. programs, the U.K. policy specifically targeted new, external investors and included reductions in capital gains taxes. Additionally, the policy targeted a broader population of firms.

[8] 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 (2009), Brander, Du, and Hellmann (2015), and Denes (2019)).

This section describes angel investor tax credit programs (Section 2.1) and assesses whether local economic or political conditions predict their implementation (Section 2.2).

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.[9] Figure 1 shows the annual allocated expenditure on angel tax credits from 1989 to 2019, which totals $8.1 billion.[10] Take-up is high, at 88% of allocated funding by state legislatures. Based on an average tax credit percentage of 34%, these tax credits support up to $23.8 billion in angel investment. 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.[11]

Figure 2 (Panel A) 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. Panel B of Figure 2 shows the introduction and termination of these programs. The earliest was Maine's Seed Capital Tax Credit Program, introduced in 1988. A steady progression of states launched 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 program duration varies from just one year to three decades.

Tax credits are available to accredited investors and their pass-through entities.[12] They require both the firm and the investor to be certified by the state ex-ante as eligible for the credit, and then the investor may apply after the deal is complete. This requires

[9] In addition to these 31 states, Massachusetts and Delaware have also introduced these programs, but both states failed to launch them or attract qualified firms as of the time of this paper.
[10] New York and Oklahoma do not provide data on funds received by subsidized investors.
[11] For example, funding for angel tax credit programs in Ohio, Minnesota, and Wisconsin are respectively 19%, 58%, and 86% of annual state funding for high-tech jobs or small businesses.
[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.

substantial coordination between the firm and the investor over, typically, a months-long period. 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 after making an investment.

Policymakers state that they implement angel tax credits to increase local economic activity, particularly employment of high-skill workers. For example, Wisconsin notes that "the Qualified New Business Venture (QNBV) Program helps companies create high-paying, high-skill jobs throughout Wisconsin." The Louisiana program goals 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." 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."[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%). Programs often have eligibility criteria for both beneficiary companies and investors. They frequently do not allow investors to request cash in lieu of the credit if they do not have local state income tax liability (72%) or to transfer the credit (72%). Other restrictions include firm age caps (31% of programs), employment caps (39%), revenue caps (47%), assets caps (22%), and minimum investment holding periods (50%). Most programs target the high-tech sector, which guides our empirical design. While many programs do not allow participation by owners and their

[13] The tax credit available to a particular investor will depend on her state tax liability.
[14] See Wisconsin Economic Development Corporation 2013 Qualified New Business Venture Program Report; Louisiana legislation (http://www.legis.la.gov/Legis/Law.aspx?d=321880); "Startup investor camp out for Maine tax credit" (https://www.pressherald.com/2019/01/02/startup-investors-camp-out-for-maine-tax-credit).

families (61%), most states permit full-time employees, executives, and officers to receive tax credits. Tax credits reduce income tax liability for the current year, but most programs have a carry-forward provision (89%). Appendix Table A1 provides comprehensive details for all programs.

2.2 Predictors of Angel Tax Credit Program Implementation

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, innovation, and economic growth.[15] 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 assess whether economic, political, fiscal, and entrepreneurial factors explain the introduction of angel tax credit programs using a predictive regression. The outcome, *ATC*, is an indicator variable equaling one if a state introduces an angel tax credit program in a given year. We include year fixed effects and omit the years after a program starts. Appendix A defines the state-level variables included in each specification.

Table 2 presents the results. 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. We find that these variables do not have significant predictive power. When we include state fixed effects (even columns), there is an economically small relation between the maximum state personal income tax rate and *ATC*. 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 and implementation of these programs. Several states passed legislation for angel tax credits after years of failed initiatives and amid persistent lobbying efforts.[16] Some

[15] 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.
[16] Local businesses and trade associations advocated for angel investor tax credits in Kentucky for many years, which were eventually adopted in 2014 (Campbell (2014)). In New Jersey, Governor Chris Christie signed legislation for angel investor tax credits in 2013, despite vetoing the bill two years earlier (Linhorst (2013)).

states discussed introducing these programs, but never proposed a law (e.g., Idaho and Montana). Other state legislatures proposed bills, but did not pass them (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]

3. Data

This section explains the data we use to assess state-level outcomes (Section 3.1) and firm-level outcomes (Section 3.2). Last, it describes the angel investor survey that we conduct (Section 3.3).

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

Angel investments are difficult to observe in the U.S. as 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)). 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. We identify angel investments from these two databases based on round type and investor type.[18] We also collect angel investment data from Form D filings. Form D is a notice of an exempt offering of securities under Regulation D and allows startups to raise capital from accredited investors without registering their securities (Ewens and Farre-Mensa (2019)).[19] To identify angel

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

[18] In Crunchbase, we include round types "pre-seed," "seed," "convertible note," "angel," or "equity crowdfunding," and investor types "angel," "micro," "accelerator," or "incubator." In VentureXpert, we keep 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."

[19] Offerings under Regulation D preempt state securities law. Before March 2008, Form D filings were paper based. We use a FOIA request to obtain non-electronic Form D records from 1992 to 2008.

rounds, we drop all financial issuers and focus on the first Form D filing that is not a VC round.[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 123,399 angel investments from 1985 to 2017. While not all angel investments trigger a Form D filing or appear in the databases described above, our data set represents one of the most comprehensive sources of angel deals available.

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 88,200 angel-backed firms over time. We only use actual, non-imputed employment and employment growth in the year before angel investment to address concerns about estimated data (Crane and Decker (2020)).[22] 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)).[23]

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 drawback of AngelList is that the coverage increases in more recent years.

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-

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[20] Specifically, we drop all financial issuers and pooled investment funds. Further, we match all first rounds in Form D with VC rounds in CVV based on firm name, location, and round date within three months of each other. We discard rounds that are identified as VC rounds.

[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.

[22] We do not use sales from NETS because 90% of the sales data are imputed.

[23] The NETS-matched sample period is 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 ex-ante growth characteristics. 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.

growth firms (based on Startup Cartography data from Fazio, Guzman, and Stern (2019)), and number of successful startup exits (based on CVV data). 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 4.1.

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, about 25% of state-years have an active angel tax credit program. The average angel-backed firm has eight employees and an employment growth rate of 39% in the year before investment. On average, 5% of the founders on a founding-team are serial entrepreneurs.

3.2 Applicant Company and Investor Data

We obtain data on startups receiving subsidized investment ("beneficiary companies") for 12 states from public records or privately from state officials. Among these, we also received identities of tax credit recipient investors for seven states. For ten states, we also observe companies that were certified to receive subsidized investment, but for which no investor 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 complete for a given program-year, though we do not observe all years for all programs. Appendix Table A2, Panel A, shows the number of unique companies by state. In total, there are 1,823 beneficiary companies and 1,404 failed applicants. Using name and location, we match 1,227 firms to financing data and 808 startups to NETS.

3.3 Angel Investor Survey

Our final data source is a survey of angel investors. We develop the sample from two sources described above: the state-provided list of angel tax credit recipients and all investors on AngelList as of early 2020 who had made at least one investment.[24] We sent each investor an email containing a personalized survey link. This email is in Appendix D, and the

[24] The authors are grateful to Will Gornall for his willingness to share these AngelList data.

complete survey is in Appendix E.[25] In total, we emailed just over 12,000 individuals and obtained 1,411 responses, out of which 1,384 are complete, representing a response rate of 11.6%, which is in line with other recent investor surveys.[26] Among respondents, about 11% are from the state tax credit recipient data and the remainder are from AngelList. Details on responsiveness are in Appendix Table A7, Panel A.

While the survey allows us to directly test for mechanisms, a downside of survey evidence is that it is subject to sample selection. In Appendix Table A7, Panel C, we find no evidence of selection on key variables related to tax credits, including residing in a state with a tax credit program or living in the hub states of California and Massachusetts. However, investors with more deals are more likely to respond and investors who are company insiders are less likely to respond. In addition, tax credit recipients are less likely to respond. While these relationships are not large in magnitude, they point towards respondents being somewhat more experienced investors.

4. Effects of Angel Investment Tax Credits

This section first explains the estimation approach for evaluating state-level effects of angel tax credits (Section 4.1), and then discusses the results from this analysis on angel investment (Sections 4.2 and 4.3). Effects on real outcomes are presented in Section 4.4. Last, we estimate the firm-level effect using data from state program offices in Section 4.5.

4.1. Identification Strategy

Our empirical approach is a difference-in-differences design, exploiting the staggered introduction and expiration of 36 angel tax credit programs in 31 states from 1988 to 2018. Specifically, we estimate the following specification:

$$Y_{st} = \alpha_s + \alpha_t + \beta \cdot ATC_{st} + \gamma' \cdot X_{s,t-1} + \varepsilon_{st}, \tag{1}$$

[25] We obtained approval from the NYU IRB for this survey.

[26] Twenty-seven responses are either incomplete or cannot be matched back to our investor data due to response from a different email address. Our response rate is in line with the previous literature conducting other large-scale surveys. Gompers et al. (2020) survey VC investors and obtain a response rate of 8.3%, Bernstein, Lerner and Mezzanotti (2019) obtain a response rate of 10.3% from PE investors, Graham and Harvey (2001) obtain a response rate of 8.9% from CFOs, and Da Rin and Phalippou (2014) obtain a response rate of 13.8% from private equity LPs. Our absolute number of responses is also high relative to other surveys of private equity investors. For example, Gompers, Kaplan and Mukharlyamov (2016) survey 79 buyout investors and Gompers et al. (2020) survey 885 VC investors.

where ATC_{st} is an indicator equaling one if state s has an angel tax credit program in year t. The dependent variable is angel investments or a real outcome. $X_{s,t-1}$ is a vector of state-year controls.[27] 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 is β, which captures the marginal effect of angel tax credits on angel investments and real outcomes.

We extend our baseline analysis along two dimensions. First, we estimate the following dynamic difference-in-differences specification:

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

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.[28] Second, for robustness, we exploit variation in the size of tax credits across programs by replacing 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.

4.2. Effect of Angel Tax Credits on Angel Investments

We begin by studying the effect of angel tax credit programs on the number of angel investments. Table 4, Panel A, reports the difference-in-differences estimates using equation (1). In column 1, we show that the programs increase angel investments by 18.5%.[29] In column 2, we find that a 10-percentage-point rise in the tax credit increases the number of angel investments by 5.5%. These estimates indicate that angel tax credits lead to an economically significant in angel activity.

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[27] In particular, we include the following controls: lagged Gross State Product (GSP) growth, natural log of income per capital, natural log of population, an indicator for whether a state has personal income tax, and the maximum state personal income tax rate.
[28] Section 4.4 discusses additional identification tests, including a triple difference (DDD) approach that compares the high- and low-tech sectors.
[29] When the outcome is a natural logarithm, we report the exponentiated coefficient minus one.

A key identifying assumption for our empirical design is that, in the absence of angel tax credits, there would be parallel trends in states with these programs relative to those without them. We use equation (2) to estimate a dynamic difference-in-differences specification to assess this assumption. In Figure 4, Panel A, we find no pre-treatment differences in angel investment volume before the introduction of angel tax credits. Notably, the effect only appears in the years following the implementation of these programs.

We also examine the effect using AngelList data, which include investor identities. In Appendix Table A3, Panel A, we find that angel tax credits significantly increase the number of angel investments, the number of angel-backed firms, and the number of unique angel investors 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 the programs induce entry of new angel investors.[30]

Next, we evaluate heterogeneity in program design. We define *Program flexibility* to measure the presence and strictness of the 17 restrictions in Table 1.[31] If the increase in investment is driven by angel tax credits, we expect more flexible programs to have larger effects. In Table 4, Panel B, we find that a one-standard-deviation increase in program flexibility leads to an additional 13.2% increase in the quantity of angel investments (column 1). When we use the tax credit percentage as the treatment, we find similar and significant results (column 3). These results also highlight the importance of the program design.[32]

We also ask whether the supply of local capital is related to the impact of angel tax credits on angel investment volume. We construct a state-year level measure of venture capital supply relative to the number of young firms, *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 years) in a state-year. We standardize *VC supply* by subtracting its mean and dividing by its standard deviation.

[30] We do not examine investment amount because it is observed for only a relatively small subset of our sample. Additionally, the data do not distinguish angels and other investors that co-invest in the same round.

[31] 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 17 variables and then standardize the index by subtracting its mean and dividing by its standard deviation prior to interacting it with our treatment variables.

[32] We also examined individual program restrictions, such as firm size, and did not find significant heterogeneity in these requirements.

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 (2017) and Ersahin, Huang, and Khanna (2020)) and angel tax credit programs being particularly effective when firms face more limited options in raising early-stage capital. This could also suggest that angel tax credits do not support high-growth potential firms, which are more likely to have access to venture capital funding.

The results thus far show that angel tax credits significantly affect capital deployment. Next, we examine the type of firms receiving this additional financing, focusing on measures of growth potential. We divide angel investments by ex-ante characteristics of the firms being financed around the median and re-estimate equation (1). In Table 5, columns 1 and 2 find that angel tax credit programs have an insignificant effect on the amount of capital allocated to high-employment firms, but the programs significantly increase the capital invested in low-employment firms. Columns 3 and 4 show similar effects for angel-backed firms with high and low employment growth. An important determinant of startup success is founders' prior entrepreneurship experience (Hsu (2007) and Lafontaine and Shaw (2016)). We find that angel tax credits flow to firms founded by fewer serial entrepreneurs (columns 5 and 6). Consistent with these results, in Appendix Table A3, Panel B , we show that angel-backed firms on average have lower growth characteristics and fewer serial entrepreneurs after a state implements angel tax credits.

It is possible that the average decline in ex-ante growth characteristics reflects higher risk tolerance or willingness to experiment among investors (Manso (2011) and 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, conditional on eventually having a program. Appendix Figure A1 shows that, consistent with our regression estimates, the distribution of angel-backed firms shifts to the left towards lower growth characteristics and exit outcomes. Importantly, this shift occurs across the distribution without substantial differences in the dispersion of the distributions or the tails. This implies that higher risk tolerance or experimentation are unlikely to explain our results.

Overall, we show that tax credits lead to investments in firms with relatively low growth potential. This result has two important implications. First, the decline in high-growth investments supports our empirical design. One potential concern about our identification is that states introduce tax credits in response to a boom in local demand. Since we find that marginal investments flow to lower-potential firms, our results are more consistent with angel tax credit programs shifting the supply of angel financing, rather than reflecting changes in demand. Second, our results suggest that the increase in angel activity is not driven by the discovery of startups with high-growth potential. This finding raises questions about whether angel tax credits can have a substantial impact on the local entrepreneurial ecosystem, which we examine in Section 4.4.

4.3. Robustness of Effect on Angel Investments

We examine the robustness of the effect of angel tax credits on angel investments. 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:

$$Y_{stj} = \alpha_{sj} + \alpha_{jt} + \alpha_{st} + \beta \cdot ATC_{st} \cdot High\text{-}tech_j + \varepsilon_{stj}, \tag{3}$$

where $High\text{-}tech_j$ is an indicator for sector j being high-tech, which we define as information technology, biotech, and renewable energy based on program requirements. We include state-sector fixed effects (α_{sj}), sector-year fixed effects (α_{jt}), and state-year fixed effects (α_{st}), which absorb ATC_{st} and the state-year controls $X_{s,t-1}$. Standard errors are clustered by state.

In Appendix Table A3, Panel C, we find that angel tax credits significantly increase the number of angel investments in the high-tech sector relative to the non-high-tech sector. The magnitudes are similar to those estimated in Table 4 using the difference-in-differences specification. Importantly, angel investments do not decline in the non-high-tech sector, suggesting that our results are not driven by a reallocation of existing capital.[33] Rather, angel tax credits induce new investment in the high-tech sector.

We also evaluate the robustness of our results to several different sample restrictions in Appendix Table A3, Panel D. First, we limit our sample to 2001 to 2016, when our data have better coverage of angel investments. The effect on angel investment volume in this period is similar to the main sample (column 1). Second, we separately estimate our results for the CVV sample (column 2) and the Form D sample (column 3), and again find similar estimates.[34] Third, the main result is robust to dropping angel investments from VentureXpert and VentureSource, which tend to capture angel-backed firms that eventually received institutional capital (column 4). Last, column 5 shows that the result is similar without including California and Massachusetts in the sample.

4.4. The Effect of Angel Tax Credits on Real Outcomes

States introduce angel tax credit programs primarily to stimulate the local economy and entrepreneurial ecosystem. Support for employment, business creation, and innovation are often cited as goals of angel tax credits. To evaluate whether these programs achieve their stated objectives, we use six data sources: first, the Quarterly Workforce Indicators (QWI) to measure the total employment by start-ups in a state and year across all industries, in addition to the high-tech sector; second, the Census' Business Dynamics Statistics (BDS) to measure job destruction and creation rates for all and young firms as well as establishment entry and exit rates; third, the Census' County Business Patterns (CBP) to measure establishment counts of small firms (less than 20 employees) in the manufacturing and high-tech sectors; fourth, financing data to measure successful exits through IPO or acquisition; fifth, entry of high-growth firms based on Startup Cartography data (Fazio, Guzman, and Stern (2019)); and sixth, patent data to measure innovation activity.[35] In total, our analysis

[33] This is also 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.
[34] This addresses a concern that the Form D data might capture some investments by other types of investors or that tax credits may induce investors to file a Form D.
[35] 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.

uses 13 state-year variables.[36] To interpret the result as a percentage change, we log-transform all outcomes except the probability of a successful exit.[37]

Estimates of equation (1) are in Figure 3 and Appendix Table A4. For each variable, we report the coefficient and the 95% confidence interval. The models in Figure 3 Panel A have no controls, while those in Panel B include state-level controls. Across a broad array of outcomes, we consistently find that an insignificant and economically small impact of the policy. For instance, based on Panel B, employment in young firms decreases by 0.3%, while job creation rate in young firms increases by 0.7%, neither of which are statistically different from zero.

These results are robust to a variety of alternative specifications and samples. First, the estimates are similar with and without the inclusion of controls, reducing concern about omitted variables. Second, the null effects are not driven by angel tax credits reversing a pre-existing negative trend in entrepreneurial activity. Figure 4 Panels B to F show the results of a dynamic difference-in-differences model (equation (2)), which demonstrate no pre-trends and show that the estimates remain statistically and economically insignificant for several years following the introduction of angel tax credits. Third, the results hold when we drop California and Massachusetts (Appendix Figure A2), use alternative definitions of the outcomes (Appendix Figure A3), or use an event study including six years before and after program introductions (Appendix Figure A4).

Overall, we do not find evidence that angel tax credits significantly impact state-level entrepreneurial activity. While we cannot reject the possibility that the policies have some effect, the null results are informative for two reasons. First, our coefficient magnitudes are economically small, in stark contrast to estimates of the effects of other tax credits. One relevant benchmark is the R&D tax credit that many states and the federal government offer to firms performing R&D. Existing literature documents large positive effects of R&D tax credits. For example, 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 firms in the UK increased

[36] These variables and the sample period are described in Appendix A. For each variable, we use the largest sample available between 1993 and 2017.

[37] The log transformation also makes effect sizes more comparable across outcomes, a feature that is particularly useful in the power analysis in Appendix C.

patenting by 60%. In both cases, the value of the R&D tax credit relative to payable taxes is smaller than the average angel tax credit percentage in our data.[38]

Second, as shown in Abadie (2020), 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 (2020)). We calculate the power of our analysis across all outcome variables based on Burlig, Preonas, and Woerman (2020). Under the conservative 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 outcome – is substantially higher than 0.5. Appendix C provides details about this power analysis.

A final point regarding the aggregate results concerns potential externalities from angel tax credit programs. While calculating such externalities is beyond the scope of this paper, they are important to consider. For example, governments might fund angel tax credits rather than directly support new startups through programs such as R&D tax credits, grants, or accelerators. Angel tax credits could also be associated with more borrowing or higher taxes, which have long-term social costs. On the firm side, angel tax credits could cause reallocation of capital from unsubsidized to subsidized firms. However, we find no negative impact of these programs on angel investments in the untargeted non-high-tech sector (Appendix Table A3, Panel C). We also show that there is no effect on job creation or destruction and firm entry or exit, suggesting that the null effect does not reflect externality-induced churning. Overall, while they may exist, externalities seem unlikely to have first-order implications for our analysis.

4.5. Angel Tax Credits and Recipient Firms

One potential concern about the null aggregate finding is that angel tax credit programs might not be large enough to generate a significant impact on aggregate outcomes.

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

As discussed in Section 2, this is unlikely to explain our results since angel tax credits are large relative to other tax incentives, such as R&D tax credits, and are substantial compared to local angel investments. However, to further rule out this explanation, we present additional analyses using firm-level data. If the null aggregate effects simply reflect program size, we should expect to observe an effect at the firm level.

We evaluate the effect of angel tax credits on startups by comparing firms financed by subsidized investors ("beneficiary companies") to firms 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 indicate interest in the tax credit. However, failed applicants are likely to be of relatively lower quality because they either failed to raise angel financing or applied after the state ran out of funding for the tax credits.[39] 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.[40] We estimate the following equation:

$$Y_{i,t+k} = \alpha_{jt} + \alpha_{st} + \beta \cdot TC_{it} + \theta Y_{i,t+k-1} + \varepsilon_{i,t+k}, \qquad (4)$$

where the dependent variable $Y_{i,t+k}$ is the outcome for startup *i* in year *t+k*. Year *t* is the year that the startup either first had an investor receive a tax credit or applied for an investor to receive a tax credit for the first time. TC_{it} is an indicator for startup *i* having an investor receive a tax credit in year *t*. $Y_{i,t+k-1}$ is the outcome variable in the previous year. The specification includes sector-year (α_{jt}) and state-year (α_{st}) fixed effects. Standard errors are clustered by state-year.[41]

Table 6 shows the relationship between receiving a tax credit and subsequent venture capital financing and employment growth, which are common proxies 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. 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

[39] 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).
[40] Appendix Table A2, Panel B, provides summary statistics on beneficiary firms and failed applicants.
[41] We cluster by state-year because there are limited clusters by state. The results are quite similar with other approaches, including robust standard errors.

several measures of firm-level employment. Subsidized investment has no effect on the probability of having at least 10 employees in the second year after the tax credit (column 3), at least 25 employees (column 4), or employment greater than the 75th percentile among certified companies (column 5). In Appendix Table A5, we show similar results using a matching estimator comparing beneficiary companies to similar control firms in nearby states without tax credit programs.

In sum, beneficiary companies do not raise more money or grow more than certified companies in which no investor received a tax credit. This suggests that angel tax credits support investments in poor quality projects or reflect tax arbitrage. The results imply that, conditional on applying, receiving subsidized investment does not alleviate constraints relative to certified firms that did not receive subsidized capital. This does not mean that firms in states with tax credits are not constrained. Instead, it indicates that firms applying for tax credits are relatively less constrained compared to their investment opportunities. More importantly, these findings are consistent with the null effect of angel tax credits on local economic activity and demonstrate that the scale of these programs is not responsible for the null effect.

5. Mechanism

To understand why angel tax credits have no real effects despite increasing angel investments, this section examines the effect of angel tax credits on investor behavior. Program success depends on subsidized investors allocating funds effectively. A commonly cited goal of angel tax credit programs is to attract professional angel investors who would otherwise not invest in local firms. A large response by non-professional investors may limit the effectiveness of these programs in spurring entrepreneurship. These investors tend to be inexperienced and may have lower ability to screen deals or less access to high-quality deals. As a result, investments by non-professional investors may fail to reach firms with high-growth potential. This is consistent with our findings in Section 4.2 that angel tax credits flow to low-growth firms. Furthermore, non-professional investors may invest for non-pecuniary reasons (Huang et al. (2017)) or may be better positioned to utilize tax credits to minimize their tax obligations due to their close connection with the firm.

We first study which investors use and respond to angel tax credits (Section 5.1). We then use survey and observational data to understand the heterogenous response and to shed light on how angels make investment decisions (Section 5.2). We conclude with a discussion of these results (Section 5.3).

5.1. Investor Heterogeneity in Take-up and Response

We examine investor heterogeneity in who uses angel tax credits (take-up) and whether the programs change investment decisions (response). To start, we examine investors who received angel tax credits. For seven states, we obtain data on the identities of subsidized investors and connect them with LinkedIn information on investor characteristics. Table 7 reports the statistics for the 5,637 tax credit recipients who are individuals.[42] We find that 87% of the subsidized investors are male and 95% are white, consistent with the findings in Ewens and Townsend (2019) that the vast majority of angel investors are white males.[43] The average angel investor is 42 years old, which is somewhat younger than the average age of 58 years for angel investors in Huang et al. (2017).

Subsidized investors appear to be relatively non-professional. Just 0.7% self-identify on LinkedIn as professional investors. Only 6.2% have prior entrepreneurial experience. In contrast, Huang et al. (2017) find that 55% of angels have entrepreneurial experience, and these investors tend to finance more companies, take a more active role in their portfolio companies, and earn higher returns. The majority of tax credit recipients in our data are corporate executives (82%), and the next largest groups are doctors (7.3%) and lawyers (4.1%).

A large fraction (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)). This is partly by design as many programs restrict investors to be in-state. This restriction may limit the ability of the programs to attract sophisticated investors. In-state investors are less likely to come from entrepreneurial hubs, as California and Massachusetts do not have tax credit programs. Overall, we find that the average angel

[42] This excludes investors who provide capital through a fund.

[43] We coded the ethnicity or race using pictures. We also coded as Hispanic individuals who 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).

investor who receives tax credits is younger, more local, and less entrepreneurial than the typical angel investor.

To quantify the relative importance of different types of investors in explaining the increase in angel investment, we use AngelList data to examine the effect of angel tax credits on the composition of investors.[44] In Table 8, Panel A, we estimate equation (1) at the state-year level, where each dependent variable is the log number of investors making investments that year and who are in the particular category. Columns 1 and 2 show that angel tax credits increase in-state angel investors by 31.9%, while there is no effect on out-of-state investors. Column 3 finds that the programs increase the number of investors with no more than one year of investing experience by 30.0% and have no effect on more experienced investors. We observe a similar pattern for investors who had a portfolio company with a successful exit (columns 5 and 6) and with past entrepreneurial experience (columns 7 and 8).[45] 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 examine these results at investment level, rather than state-year level. For these specifications, the dependent variable is an indicator equaling one if the characteristic in the column header describes an investor in the financing round. We weight observations by the inverse of the number of deals in a state, which gives each state an equal weight and accounts for the overrepresentation of hub states. 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, angel tax credits increase the likelihood that investors have no successful exit (column 3) and no entrepreneurial experience (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 suggest that a change in investor composition explains why marginal investments flow to lower-growth firms. While subsidies might

[44] We find similar results if we restrict the sample to start in 2010 to mitigate a potential concern about backfilled data.
[45] We verify in Appendix Table A6 that our measures of non-professional investors are correlated with worse startup exit outcomes.

weaken an investor's incentive to find potentially high-growth companies, it is not the case that the tax credits simply lead the same set of investors to alter their investing approach. Instead, we observe a change in composition, and high take-up among individuals who do not appear to be representative of U.S. angel investors described in prior research. Since non-professional investors have less access to high-quality deals or lower ability to screen deals, the null aggregate effects suggest that they invest in projects that have a limited impact on the growth of the firm and small or null spillovers in the rest of the economy.

5.2. What Explains Investor Heterogeneity?

Why do sophisticated, professional investors not respond to tax credits? Answering this question sheds light on why angel tax credits do not have their desired effects. It also provides new insights on how angel investors make decisions.

We hypothesize that differences in investment approaches could be one explanation. We consider two investment frameworks. In the first approach, which we term "Financial Metrics," investors use financial calculations such as IRR and NPV to evaluate deals and correspondingly invest if the returns are above a certain threshold. This framework is suitable when cash flows can be forecast such as when the firm has an operating history.

When investors are looking for the next Google, this approach may be less useful. For potentially high-growth and very early-stage startups, it is difficult to use financial metrics because returns are highly skewed and there is considerable Knightian uncertainty. Investors may instead focus on selecting firms using qualitative measures such as startup team and business model, which they believe to be correlated with the right tail of exit outcomes. We refer to this as a "Home Run" approach, since it leads to a binary decision process in which a startup either has the potential to be a huge success or not. In the latter case, the startup does not merit investment regardless of the particular deal terms. In this framework, changes in expected returns induced by angel tax credits may not impact startup selection.[46]

Importantly, the "Home Run" approach does not imply that investors leave money on the table. They may take up the tax credit *ex post*, even if the credit does not change their

[46] This does not imply that a tax credit never changes investment decisions using the "Home Run" approach. Rather, the sensitivity of investment decisions to tax credits is lower in this approach.

selection of startups *ex ante*. Investors using the "Home Run" approach likely apply for tax credits if the benefits exceed the costs, which include coordination, administrative, and information frictions.

5.2.1. Survey of Angel Investors

To assess how these investing approaches relate to tax credit use, we conduct a survey of angel investors. The survey is described in Section 3.3 and shown in Appendix E. The survey offers several insights. First, it indicates that investors do not consider angel tax credits to be important when evaluating investments. Investors were shown nine factors (randomly sorted for each investor) and asked to assign each factor one of five ratings, ranging from not at all to extremely important in affecting the decision to invest in a startup. Figure 5, Panel A shows that 51% of respondents rate tax credits as not at all important, and only 7% rate them as either very or extremely important. This distribution contrasts starkly with the other eight factors. For example, consistent with Bernstein, Korteweg, and Laws (2017), 97% rate the management team as very or extremely important, and 0% rate the team as not at all important. Only 2% rate valuation and gut reaction as not at all important, while over 50% rate these factors as very or extremely important.

Figure 5, Panel B, shows how the importance of the credits varies across respondent types. The top graph includes angel tax credit recipients based on data from state programs. Most of these respondents rate the credits as either slightly or moderately important, in contrast to those that have never used the credits in the second graph. The subsequent graphs of Panel B show that as we shift towards more professional investors, tax credits become more irrelevant to their investment decisions. Among respondents who identify as professional investors, 64% rate the tax credits as not at all important. For investors in the top decile by number of deals, 71% rate credits as not at all important. We also estimate the relationship between the importance of tax credits and being a professional investor. Table 9, Panel A, finds that there is a significant negative association between how important investors rate tax credits and a variety of proxies for investor sophistication and experience (columns 1-3). For example, being a professional investor reduces tax credit importance by 0.38, which is a 21% decrease relative to the sample mean.

The second insight from the survey concerns *why* angels do not view tax credits as important. If an investor rates tax credits as unimportant, we ask them to select one of five options to explain their answer.[47] Figure 5, Panel C, shows that the majority (57%) report that tax credits are unimportant because they invest based on whether the startup has the potential to be a home run or not. This view is summarized by many text-based responses, such as "If the deal is bad a tax credit will not make it good" and "If I believe in the business model/technology then a tax credit is largely irrelevant. Conversely, if I don't believe in the model then the tax credit is also irrelevant." Importantly, Table 9, Panel B, shows that there is a positive and significant correlation between investors with above-median deal experience and the choice of "Home Run" as the reason for why angel tax credits are unimportant (column 1). In sum, tax credits are not viewed by angel investors – especially professional ones – as relevant to their decision to invest in a startup in part because they use a "Home Run" investing approach, which explains our previous findings that professional investors do not use tax credits and why these programs do not promote high-growth entrepreneurship.

Third, the survey sheds light on barriers to using tax credits, conditional on deciding to invest in a particular startup. There are both administrative costs, such as coordinating certification with the startup and submitting forms to the state agencies, and information frictions, as an investor may not be aware of tax credits. Of the investors rating tax credits as unimportant, 11% report that the reason they are unimportant is coordination costs (Figure 5, Panel C). In the survey, we also ask whether an investor used angel tax credits and, if not, why. Figure 5, Panel D, shows that and 15% do not use tax credits because of coordination costs, and 60% are unaware the programs exist; indeed, even among investors whose states have a program, 19% report that tax credits are not available and 60% do not know about their availability, suggesting considerable information barriers. The importance of coordination and information frictions are corroborated by text responses, such as "The state is slow to act on applications and they do not have a system to remind you about the requirement for annual certifications" and "Tax credits seem so difficult to navigate and receive. Too many stars need to align for that to work!"

[47] They can also choose "Other" and fill in a text box.

Coordination costs are likely to be higher for professional arm-length investors as they typically do not have close ties with the startups before investing, face a fast-paced deal cycle, or have higher opportunity costs of their time. Consistent with this, Table 9 Panel B column 2 shows that professional investors are more likely to report coordination frictions. To illustrate, a respondent with a history of 21 deals and 5 successful exits (both above the 90th percentile of our sample) wrote that: "I work with startups because I don't like dealing with red tape and bureaucracy. Tracking investments for tax credits sounds like a headache."

The final insight from the survey is that there is a significant and large positive association between the importance of tax credits and focus on financial returns (Table 9 Panel A column 4). The bottom graph in Figure 5, Panel C, shows that, among the few investors who found tax credits to be important, 81% report that tax credits make an investment financially viable (i.e., change the NPV from negative to positive). These results are consistent with use of the financial metrics approach among tax credit recipients.

5.2.2. Insider Investors

The survey results indicate that professional investors face larger information and coordination frictions. At the other end of the spectrum are firm insiders who face low information and coordination frictions when they invest in their own companies and claim tax credits. These investors should be in an advantageous position to use angel tax credits. However, they are not the ideal group of investors targeted by policymakers, in part because insiders may use the programs to take advantage of a tax arbitrage opportunity or because they have non-financial motives such as private benefits of control.

To explore this possibility, we assess the prevalence of insider investors in our tax credit recipient data.[48] Our data include 628 unique firms and 3,560 investors from 5 states.[49] In Table 10, we find that 35% of firms have at least one investor who is an executive or

[48] 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). 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 B provides additional details for identifying insiders.

[49] Interestingly, many states explicitly permit the investor to be employed at the company (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.

family member of 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. At the investor level, 14% of subsidized investors are the executives of the invested company or their family members. The corresponding benchmark in AngelList is only 2%. The take-up of angel tax credits by insider investors is consistent with insiders facing fewer information and coordination frictions.

5.3. Discussion

The evidence above, while from disparate sources and different perspectives, yields a single, coherent reason for why tax credits fail to increase local startup entry and growth: they have little impact on sophisticated, professional investment. First, angel tax credits depend on investors using financial metrics such as NPV to gauge returns, with investments occurring when expected returns exceed a particular threshold. We document for the first time that professional investors tend to use a "Home Run" approach when selecting startups, reducing their sensitivity to tax incentives.

Non-professional investors residing in-state who have both local tax liabilities and information about the programs appear primarily responsible for take-up. They likely face lower coordination costs, especially when they are firm insiders. This group likely has access to lower quality deals and may be more likely to invest for non-pecuniary or tax planning reasons. Since tax credits increase investment returns, non-professional investors who both respond to the tax credit program by investing more and who focus on NPV to make investment decisions are likely select projects that they perceive to be negative NPV without the subsidy. To the degree the types of projects selected by these NPV-focused investors are relatively low-growth, this pattern helps to explain why the impact on the local economy might be limited.

Another channel that can reconcile the increase in angel investment with the null real effects is relabeling. Investors may relabel transactions that would have happened regardless of the program as an angel investment in order to receive the tax credit. This seems particularly applicable to firm insiders, but it could also apply to other investors. Investors using a state tax credit may be more likely to file a Form D because they are required to demonstrate that a legal equity round occurred. While Form D filing is in many cases technically necessary to exempt an equity round from national security registration requirements, it is widely known that many startups do not file, in large part to avoid the accompanying disclosure.[50] Ewens and Malenko (2019) show that no Form D is ever filed for more than 20% of VC-backed startups. Relabeled investments would appear in our sample as an angel investment when they might not have otherwise. The sizeable proportion of insiders, who might be relatively more likely to relabel, highlights that relabeling may also partially explain these contrasting findings.

It is crucial to note that our results cannot tell us about startups' financial constraints. There may be constrained, potentially high-growth startups in states with tax credits, but investors who select them do not appear to use the credits. The results also are not informative about the financing capacity of angels broadly (Lindsey and Stein (2020)). Since there are frictions to using the tax credits and they are not available in states with the highest concentrations of angels and startups (Massachusetts and California), we cannot know whether alternative policy implementations that involved no frictions would affect investment differently.

Our mechanism analysis does shed light on how angel investors make decisions. To the best of our knowledge, the survey is the first to elicit novel information about investment approaches among a wide and arguably representative swathe of angel investors, a group known to be important to early-stage entrepreneurial finance but that is difficult to observe with conventional data sets. While we have surveys about how VCs make decisions (Gompers et al. 2020), we know relatively little about angel decision making.

6. Conclusion

There is substantial government interest in supporting startups, with investor incentives being a particularly appealing option. Understanding angel tax credits is important for both academics and policymakers, as more regions propose implementing such tax credits and

[50] See https://techcrunch.com/2018/11/07/the-disappearing-form-d. While there could be penalties for failing to file a Form D, they appear to be rarely enforced. Additionally, U.S. courts and the SEC have ruled that failing to file a Form does not cause a startup to lose its security exemption status. See https://www.sec.gov/divisions/corpfin/guidance/securitiesactrules-interps.htm. Our results on angel investments are robust to using only deals from CVV and not from Form D.

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.[51] Yet there has been no systematic evidence on the effectiveness of these policies.

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 investment. This increase is connected to a decline in the ex-ante growth characteristics of marginal startups funded by angels. Second, we find no evidence that these policies had any significant impact on the real effects that policymakers focus on, such as new business starts or young firm employment. Third, we show that the increase in angel investments is mostly driven by a surge in inexperienced, young, and new investors, with no change in professional angel activity. Non-professional investors may face fewer frictions in accessing tax credits and 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.

A survey helps to explain these results. We find that angel tax credits are a relatively unimportant factor for professional investors when deciding whether or not to invest in a startup. Instead, experienced investors focus on whether or not a startup has the potential to be a home run. These investors tend not to use tax credits even when they are available because of information, coordination, and administrative costs.

Taken together, our findings raise questions about the ability of 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 problems of its own as the targeted investors may not be sensitive to the policy.

Our emphasis on the importance of targeting is relevant for other entrepreneurship programs, such as matching funds that also subsidize investors at the time of investment. Israel's Yozma is an example of a highly successful venture capital matching fund that targeted expert foreign investors. In contrast, China's Government Guidance Fund Initiative that also matched outside capital did not enjoy the same success, which Lerner (2020) attributes to the fact that much of its matching capital came from local governments and

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

state-owned companies. 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 government programs focused on subsidizing capital for high-growth 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 Appendix 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.

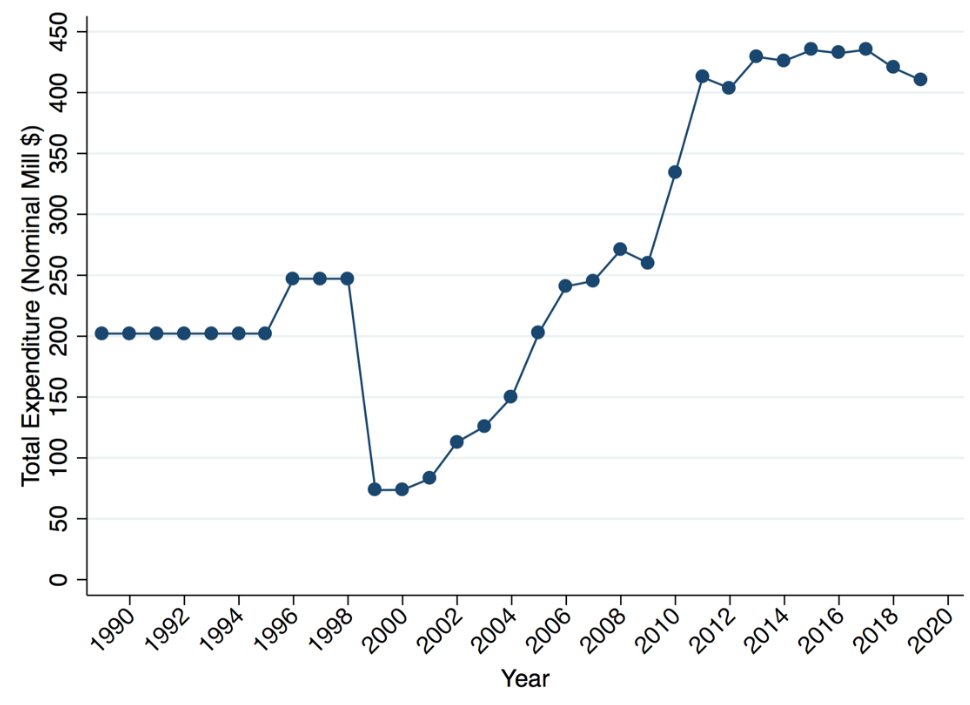
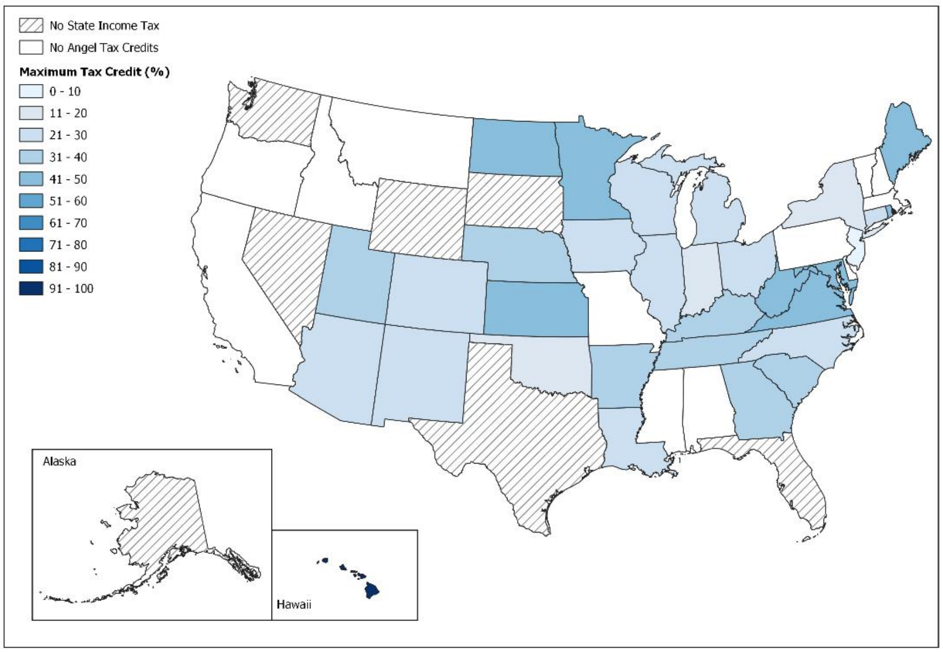


Figure 2. State Angel Tax Credit Programs

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

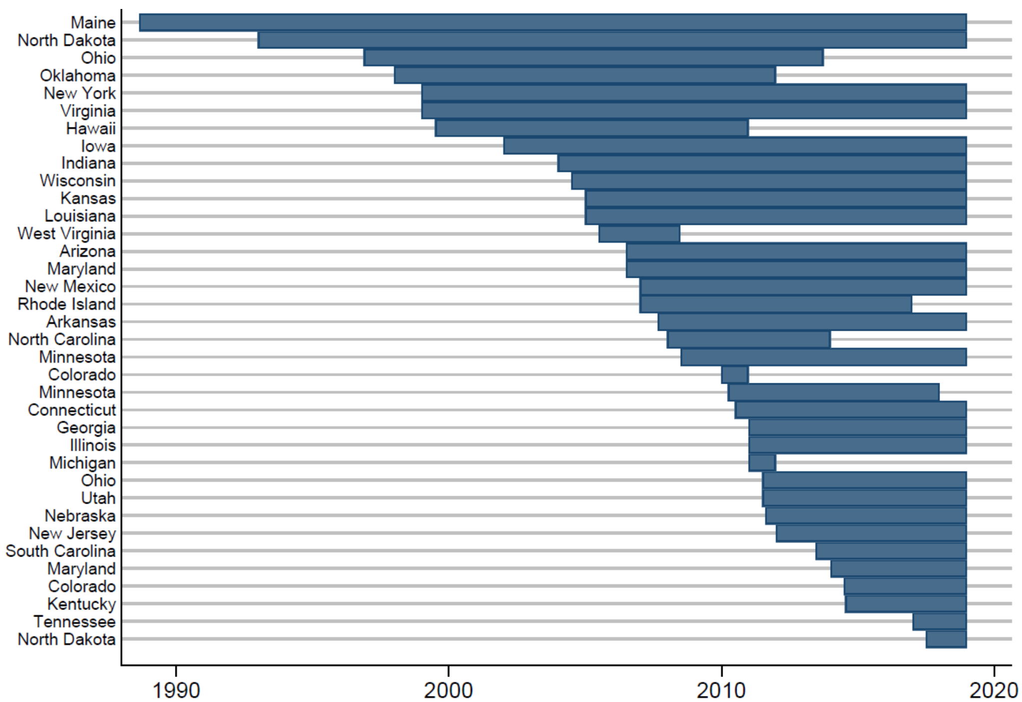
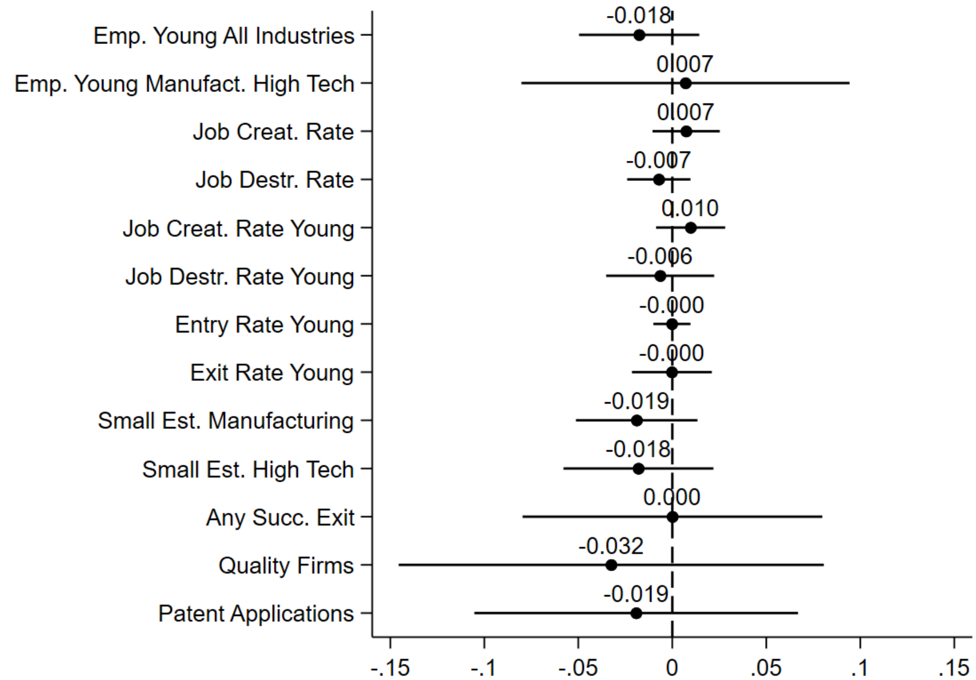


Figure 3. Aggregate Real Effects of Angel Tax Credits

Panel A reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using the specification in equation (1) with no controls. Panel B reports the same estimates with controls. All outcome variables except the probability of having successful exits (Any Succ. Exit) are log-transformed to facilitate comparison of magnitudes across outcomes. All variables are defined in Appendix A.

Panel A. Effects of Angel Tax Credits, without Controls



Panel B. Effects of Angel Tax Credits, with Controls

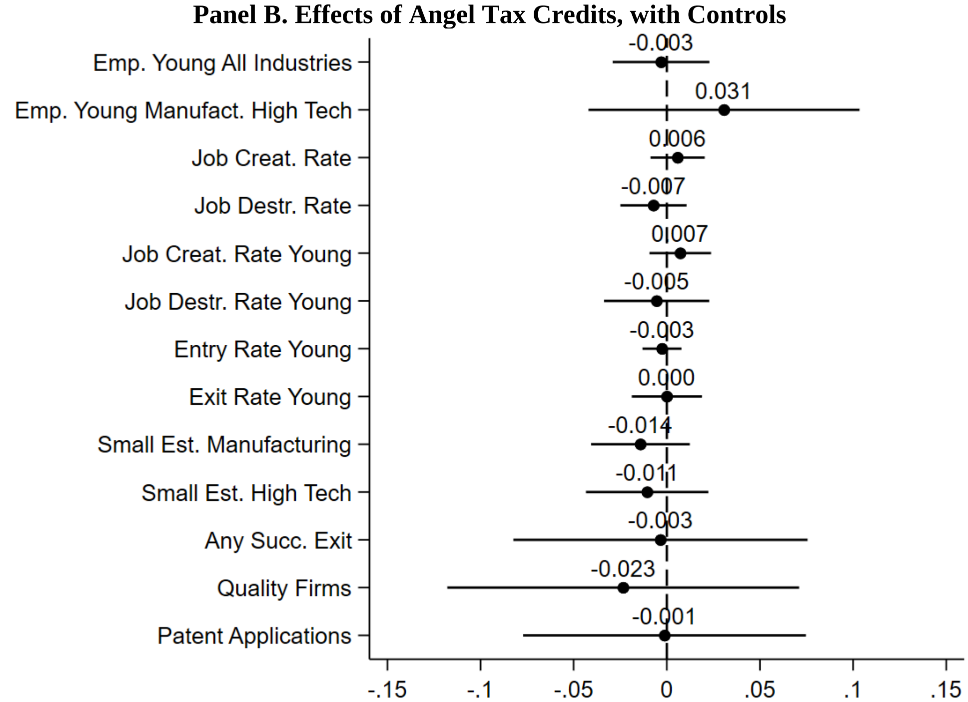
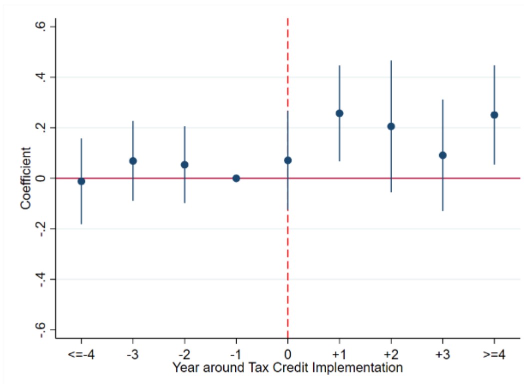


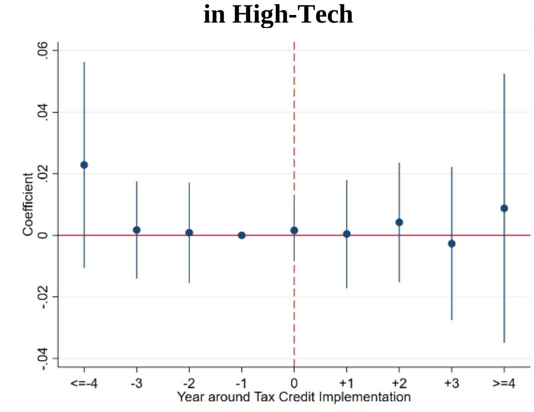
Figure 4. Dynamic Effects of Angel Tax Credit Introduction on Real Outcomes

This figure shows the dynamic effect of a state introducing angel tax credits using equation (2). The samples are the same as in 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 1 to 19) in the high-tech sector; Panel C shows total employment in young firms of age 0 to 5; Panel D shows job creation rate (in percentage points) among young firms of age 0 to 5; 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. All outcome variables are log transformed, except for Panel F. All variables are defined in Appendix A. Standard errors are clustered at the state level. 95% confidence intervals are shown.

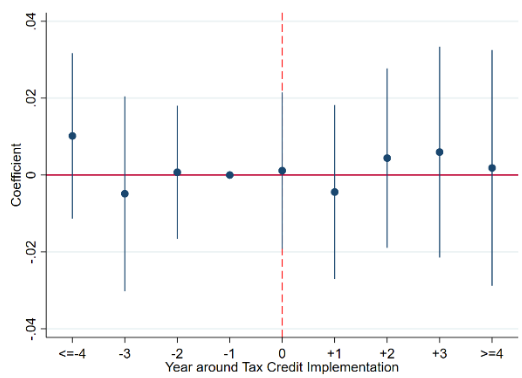
Panel A. Number of Angel Investments



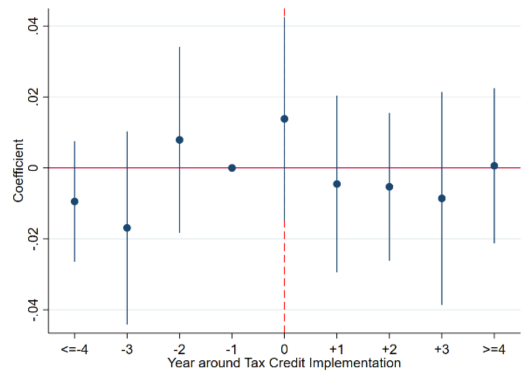
Panel B. Number of Small Establishments in High-Tech



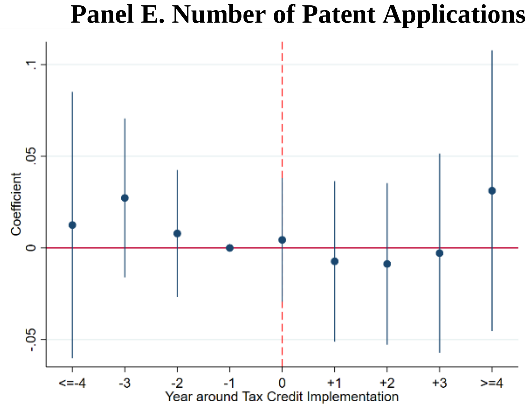
Panel C. Aggregate Employment in Young Firms



Panel D. Job Creation Rate in Young Firms



Panel E. Number of Patent Applications



Panel F. Probability of Successful Exit

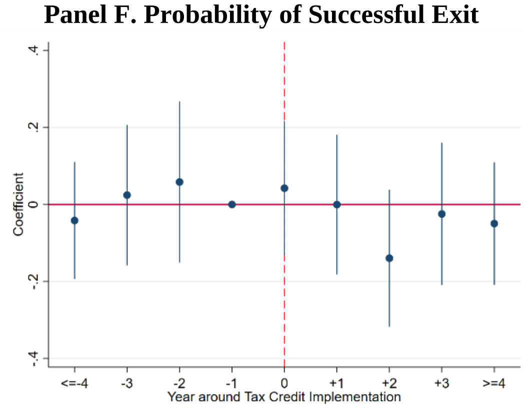
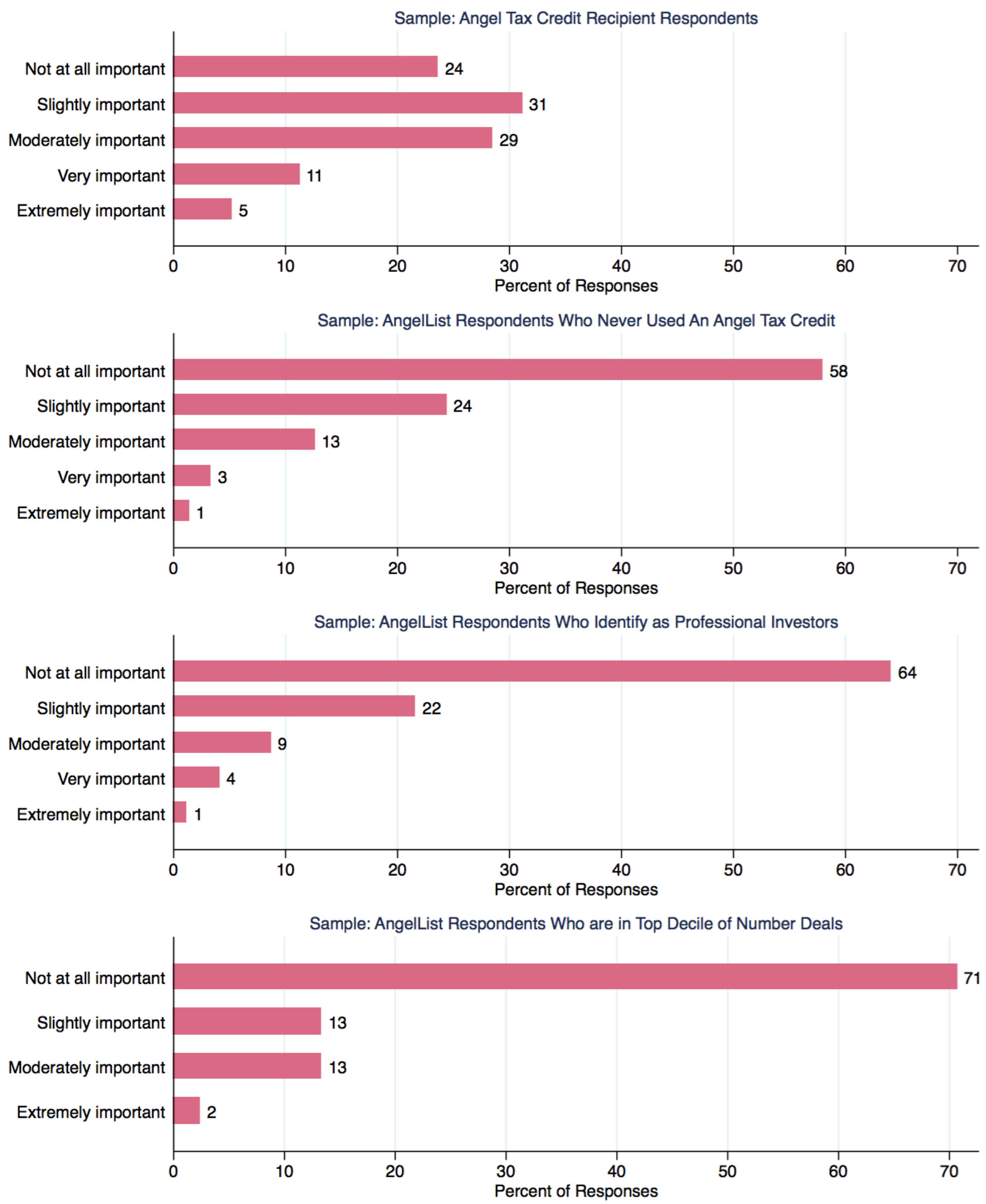


Figure 5: Survey Results

Panel A. Distribution of Responses to Factor Importance Question

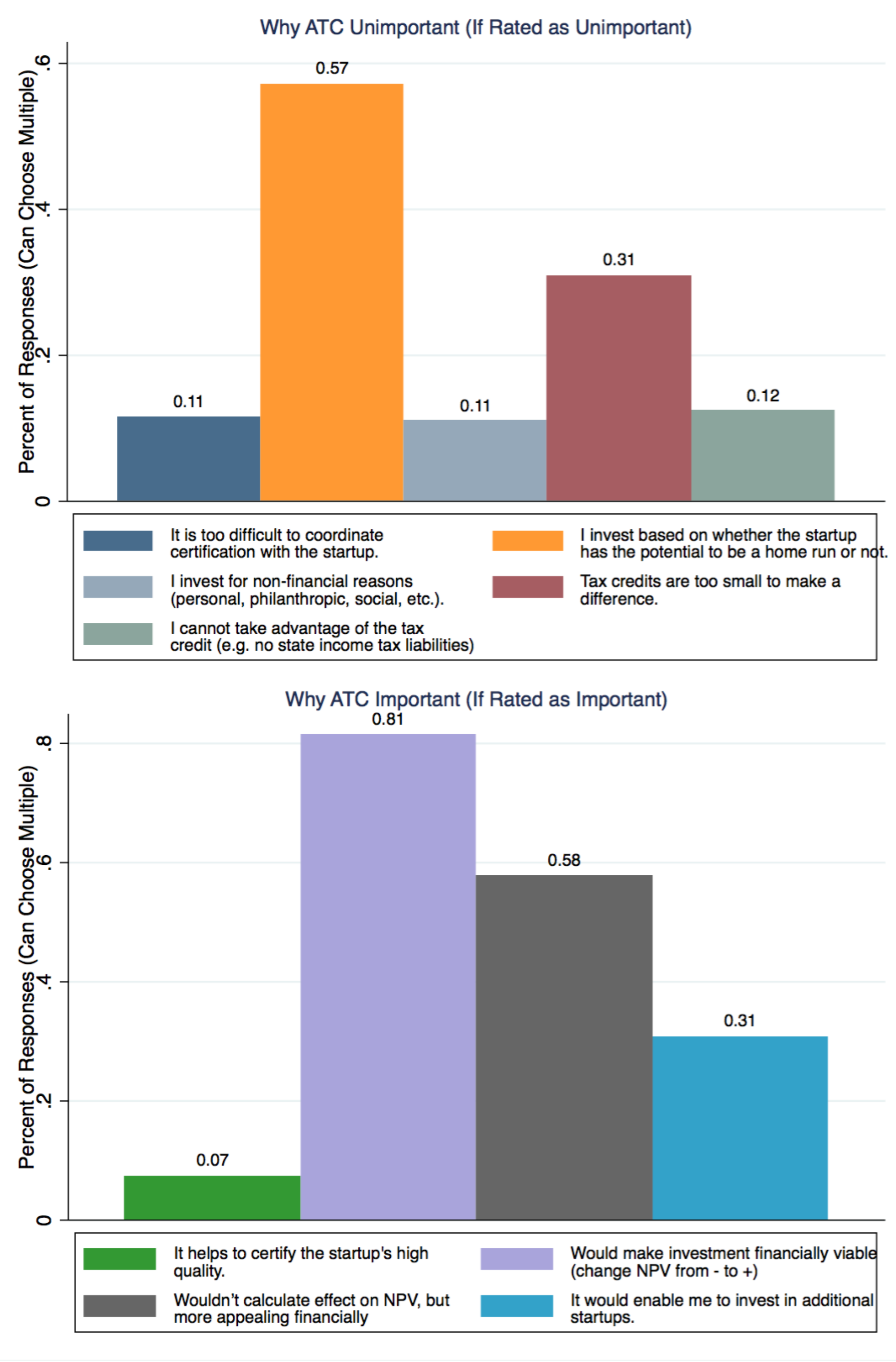
These graphs show the distribution of responses to question 1 in the survey for each of the nine factors. Respondents could only choose one importance level for each factor. The order in which the factors were presented was randomized across survey participants. N=1,364.

Panel B. Distribution of Responses to Importance of Angel Tax Credits by Respondent Type



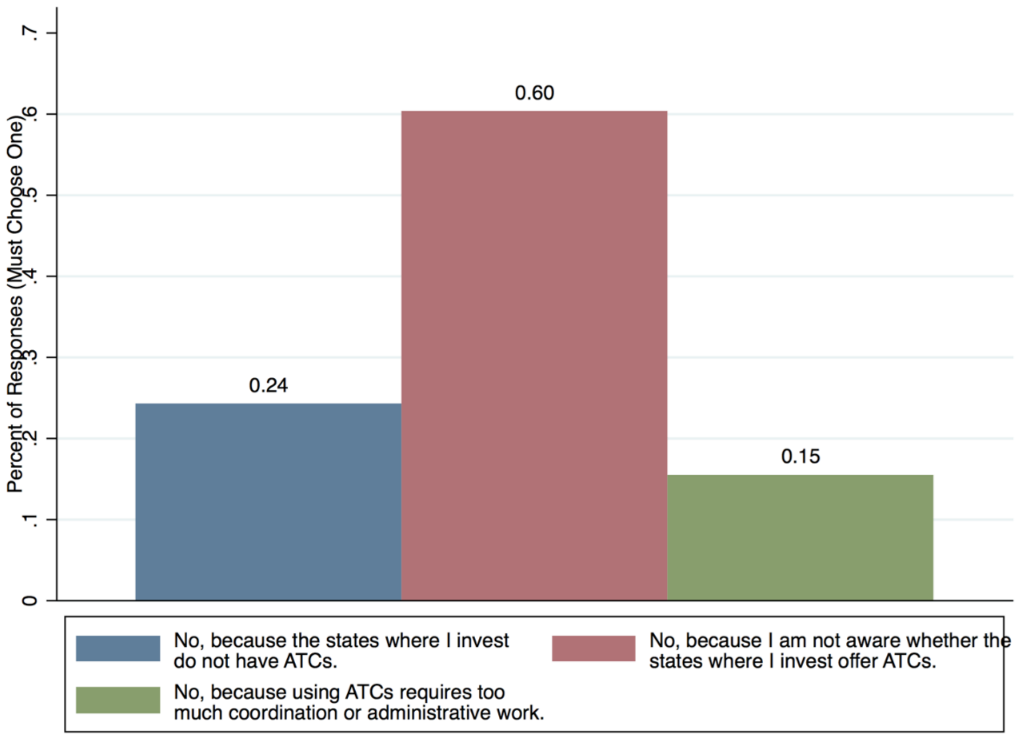
These graphs show the distribution of responses to the question of whether angel tax credits are important to the decision to invest in a startup. Each graph presents a different sample. The top graph shows the subset of respondents who were either angel tax credit recipients from our state-provided data, or who reported having used an angel tax credit in the survey (N=268). The second graph shows the subset of respondents from AngelList data who reported having never used an angel tax credit in the survey (N=1,028). The third graph shows the subset of respondents from AngelList data who identify as professional investors (N=241). The bottom graph shows the subset of respondents from AngelList data whose number of deals are in the top 10% among all AngelList responders (N=84). Respondents could only choose one importance level. The order in which the factors were presented was randomized across survey participants.

Panel C. Distribution of Responses to Why Angel Tax Credits are (Un)important



These graphs show the distribution of responses to the question of why angel tax credits are unimportant (top, N=948) or important (bottom, N=338) to the decision to invest in a startup. Respondents were prompted to answer the question of why the credits are unimportant if they rated them as not at all or slightly important. Similarly, respondents were prompted to answer the question of why the credits are unimportant if they rated them as at least moderately important. Respondents could only choose one importance level. The order in which the factors were presented was randomized across survey participants.

Panel D. Distribution of Responses to Why Have Not Used Angel Tax Credits



These graphs show the distribution of responses to the question of why an investor has not used angel tax credits, conditional on not using them. The sample is restricted to the subset of respondents from AngelList data who reported having never used an angel tax credit in the survey (N=1,028). Respondents could only choose one option.

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 program 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 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	1,343	1,343	1,343	1,343	1,343	1,343	1,343	1,343
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 state-year level variables used in our analyses. All variables are defined 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 investment					
Ln(number of angel investments)	1,200	2.19	1.36	0.00	2.20	4.37
	Average ex-ante characteristics of angel-backed firms					
Pre-investment ln(employment)	1,200	2.20	0.68	1.27	2.12	3.30
Pre-investment employment growth	1,200	0.39	0.46	0.00	0.31	1.08
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
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
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
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	0.10	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	0.00	1.00	1.00
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

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 number of angel investments in the high-tech sector (IT, biotech, and renewable energy). 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 percentage 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 17 that measures the presence and strictness of the 17 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. 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	0.170**	
	(0.075)	
Tax credit percentage		0.539***
		(0.176)
Controls	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,200	1,200
Adjusted R^2	0.911	0.912

Panel B. Heterogeneity

	Ln(Number of angel investments)			
	(1)	(2)	(3)	(4)
ATC	0.157**	0.168**		
	(0.069)	(0.066)		
ATC × Program flexibility	0.124*			
	(0.065)			
ATC × VC supply		-0.182***		
		(0.050)		
Tax credit percentage			0.394***	0.370**
			(0.142)	(0.154)
Tax credit percentage × Program flexibility			0.359***	
			(0.083)	
Tax credit percentage × VC supply				-0.286***
				(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	0.912	0.913	0.914	0.913

Table 5. Angel Investments by Ex-Ante Growth Characteristics

This table 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 at the median (employment, employment growth, and the fraction of serial entrepreneurs on founding team). 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.

	High employment	Low employment	High employment growth	Low employment growth	High fraction of serial entrepreneurs	Low fraction of serial entrepreneurs
	(1)	(2)	(3)	(4)	(5)	(6)
ATC	-0.004	0.247***	0.078	0.185**	0.083	0.177*
	(0.075)	(0.083)	(0.067)	(0.082)	(0.116)	(0.094)
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	0.879	0.872	0.891	0.860	0.735	0.879

Table 6. Angel Tax Credits and Firm-Level Outcomes

This table reports the 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 has more than 10 (25) (75^{th} percentile) employees within two years after first applying to have an investor receive a tax credit. *Finance pre-TC* is indicator variable for whether a firm received any other external financing before its investors received a tax credit. All specifications include state-year and sector-year fixed effects. Standard errors are clustered at the state-year level. ***, **, and * denotes significance at the 1%, 5%, and 10% level, respectively.

	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***	
				(0.11)	
Emp. > p75 in credit yr					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	3,227	3,227	3,227	3,227	3,227
Adjusted R^2	0.31	0.11	0.46	0.50	0.41

Table 7. Characteristics of Investors Receiving Tax Credits

This table describes characteristics of investors who receive angel tax credits. We gather information from LinkedIn on angel investors from seven states that publicly release the names of individual investors who received angel tax credits. Corporate Executive is an investor who lists their current occupation as President, Vice President, Partner, Principal, Managing Director, or Chief Officer other than CEO. Gender and race are identified from pictures. 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 in the sample, which is 2013.

	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			

Table 8. 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) who 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 observations in each state. The dependent variables are dummies indicating that an investor was in-state, new, had no prior exit, or had no prior founder experience. 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 * denotes 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 9. Survey Analysis

This table examines investors' perception of the importance of angel tax credits based on survey data. In Panel A, the dependent variable is ATC importance, a score that takes a value of 1 to 5 (1 being "not at all important" and 5 being "extremely important"). Column 1 examines whether a respondent has done an above median number of angel deals since January 2018. Column 2 focuses on investor experience measured by matching respondents to AngelList data. Column 3 examines investor profession. Column 4 examines surveyed importance of other investment factors. Panel B examines how deal experience correlates with the reasons a respondent perceives angel tax credit as unimportant. All regressions include state fixed effects. Standard errors are clustered by state. ***, **, and * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A. ATC Importance

	ATC importance			
	(1)	(2)	(3)	(4)
Above median # of deals since 2018	-0.229***			
	(0.041)			
AL_has exit		-0.199***		
		(0.039)		
AL_has founder experience		-0.118*		
		(0.061)		
AL_has invested as insider		0.103**		
		(0.049)		
AL_top school		-0.138***		
		(0.033)		
Profession_corporate executive			-0.144	
			(0.110)	
Profession_entrepreneur			-0.193*	
			(0.105)	
Profession_investor			-0.375***	
			(0.136)	
Importance_team				-0.103**
				(0.040)
Importance_business				0.127***
				(0.034)
Importance_location				0.055*
				(0.031)
Importance_financial return				0.117***
				(0.020)
Importance_add value				0.041**
				(0.017)
Importance_valuation				0.001
				(0.031)
Importance_gut reaction				-0.02
				(0.021)
Importance_deal terms				0.141***
				(0.029)
State FE	Yes	Yes	Yes	Yes
Observations	1,202	1,199	1,242	1,331
Adjusted R^2	0.126	0.048	0.121	0.170

Panel B. ATC Unimportance for Different Reasons

	Home run	Coordination	Non-financial	Too small	Cannot use
	(1)	(2)	(3)	(4)	(5)
Above median # of deals since 2018	0.046**	0.051**	0.006	-0.021	0.003
	(0.020)	(0.024)	(0.016)	(0.021)	(0.021)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	1,202	1,202	1,202	1,202	1,202
Adjusted R^2	0.018	0.025	-0.007	0.018	0.090

Table 10. The Role of Insider Investors

This table reports summary statistics for tax credit recipients who are insider investors, defined as angel investors who also serve as executives or managers at the firm for which they receive angel tax credits. For company-level statistics, the unit of observation is a unique tax credit beneficiary company for which we observe an investor-company link. For investor-level statistics, the unit of observation is a unique investor for which we observe an investor-company link.

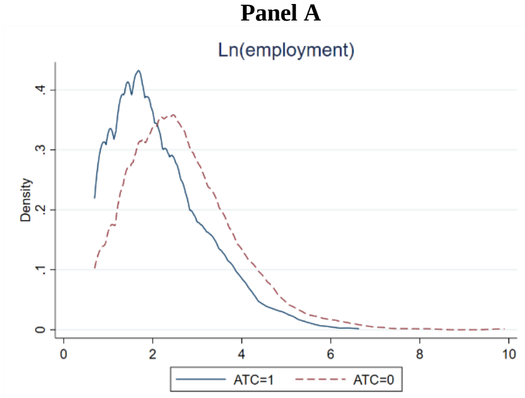
Company Level	N	Fraction
≥1 investor is executive or has family member who is executive	628	0.35
Among Kentucky companies	77	0.04
Among Maryland companies	81	0.38
Among New Jersey companies	63	0.24
Among New Mexico companies	61	0.26
Among Ohio companies	346	0.44
At least one investor is an executive	628	0.33
Investor Level	N	Fraction
Investor is executive or has family who is executive	3,560	0.14
Investor is executive	3,560	0.11

Appendix Figures and Tables

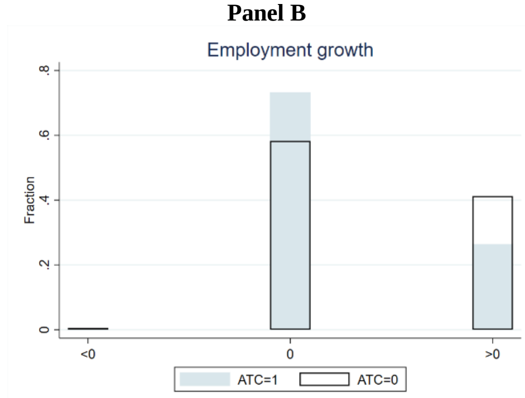
Figure A1. Distributions of Ex-Ante Growth Characteristics: State-Years with vs. without ATC

Panel A (B) compares the distributions of ex-ante employment (employment growth) of angel-backed firms in state-years with an angel tax credit program to state-years without a program, restricting to states that ever had an angel tax credit program. Employment and employment growth are measured in the year before angel investment. In Panel A, the solid line (dotted line) represent the estimated kernel density for firms that received angel investments in state-years with (without) an angel tax credit program. Panel B shows the histogram where employment growth is discretized into negative growth, zero growth, and positive growth. Panel C compares the histograms of exit outcomes by angel-backed firms in state-years with an angel tax credit program to those in state-years without a program, restricting to states that ever had an angel tax credit program. The blue bars (empty bars) represent the fraction of angel-backed firms achieving each exit outcome by the end of 2018 and that received angel investments in state-years with (without) an angel tax credit program from 1985 to 2016. Panel D 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 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. All variables are defined in Appendix A.

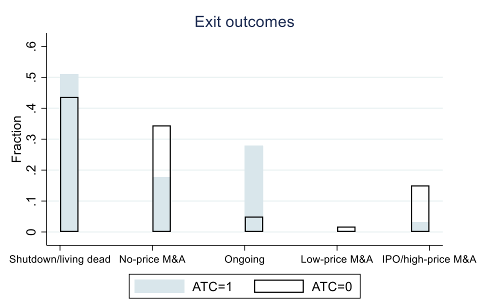
Panel A



Panel B



Panel C



Panel D

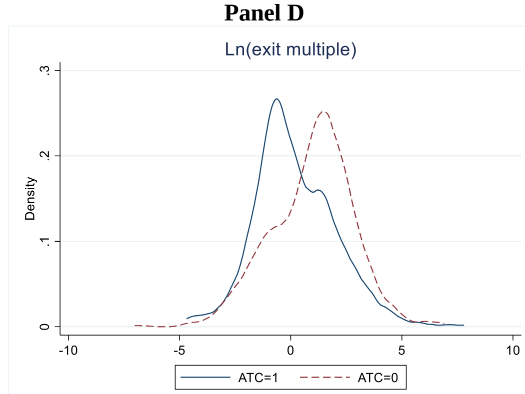
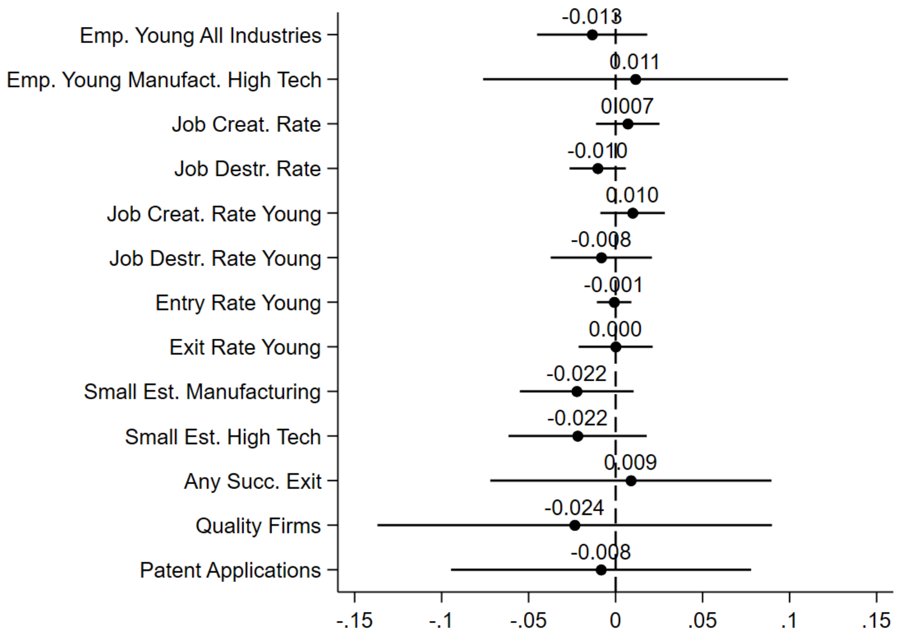


Figure A2. Aggregate Effects Robustness: Dropping CA and MA

This figure re-estimates the specification in Figure 3, dropping California and Massachusetts. Panel A reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using the specification in equation (1) with no controls. Panel B reports the same estimates with controls.

Panel A. Effects of Angel Tax Credits, without Controls



Panel B. Effects of Angel Tax Credits, with Controls

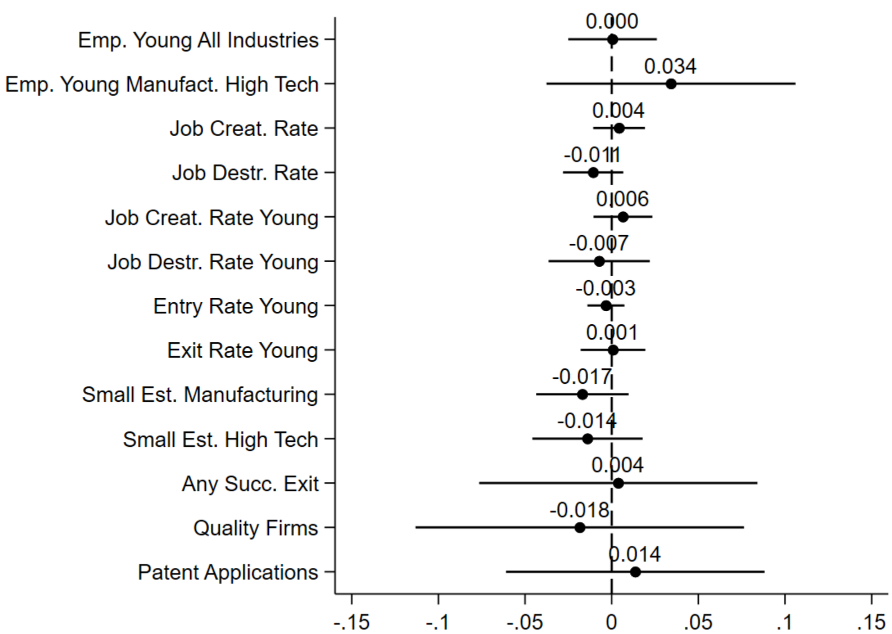
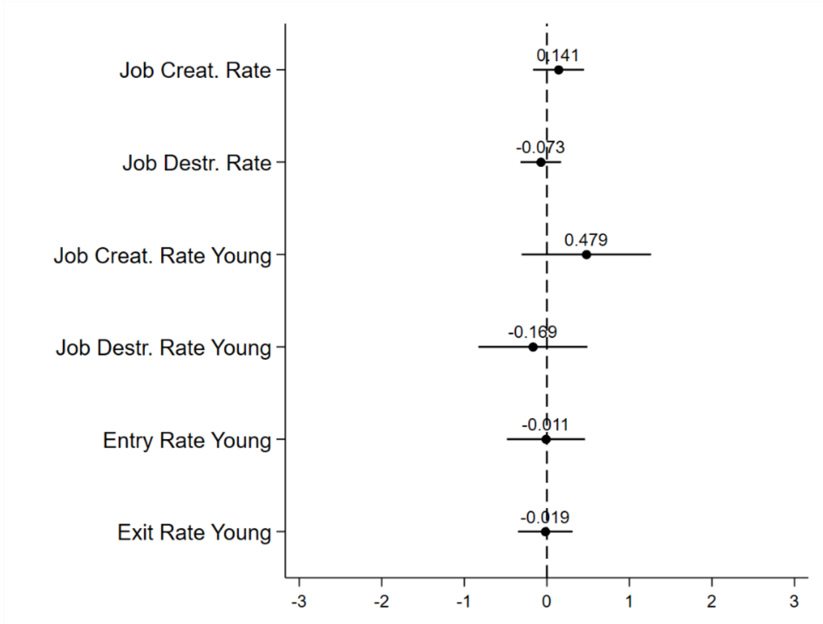


Figure A3. Aggregate Effects Robustness: Rate Variables in Percentage Points

This figure provides a robustness to the results in Figure 3. We consider the outcomes that are rates (in percentage points) and show the results without log-transforming these variables. Panel A reports the difference-in-differences point estimates and confidence intervals of the aggregate effects of angel tax credits using the specification in equation (1) with no controls. Panel B reports the same estimates with controls. The horizontal axis is in percentage points.

Panel A. Effects of Angel Tax Credits, without Controls



Panel B. Effects of Angel Tax Credits, with Controls

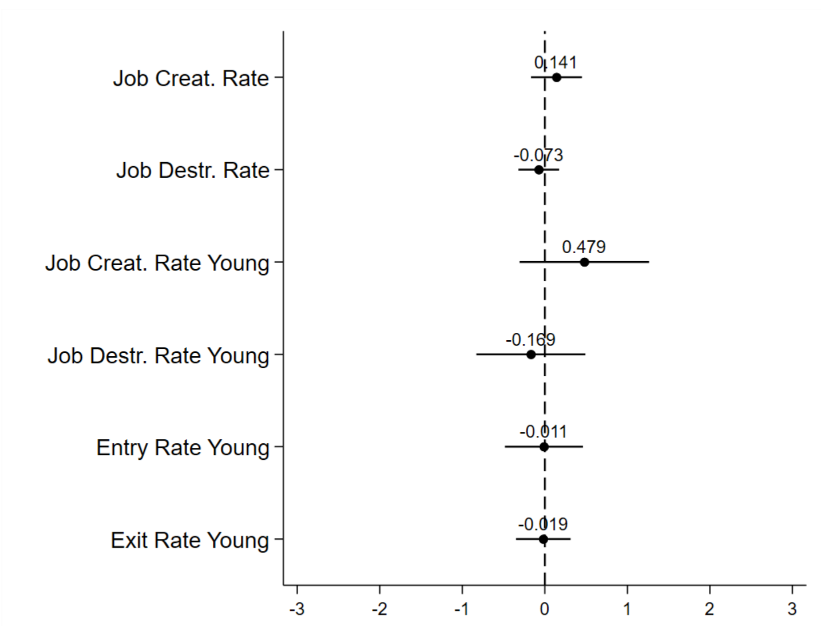
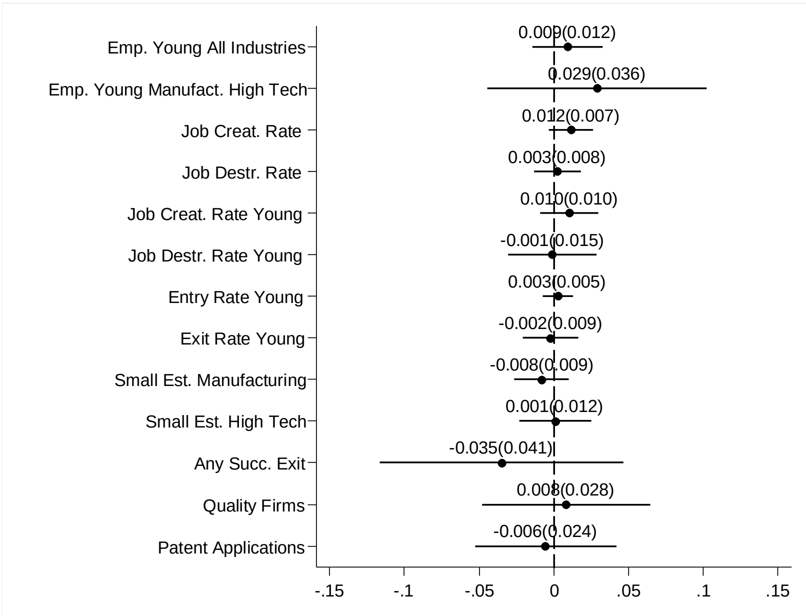


Figure A4. Aggregate Effects Robustness: Event Study

This figure reestimates the specifications in Figure 3 using an event study approach. Instead of using the full panel of state-years, we focus on six years before and after program introductions and expirations, and use the states that never adopted the tax credit as the control group. Panel A reports the main coefficients and 95% confidence intervals without control variables. Panel B reports those with control variables.

Panel A. Effects of Angel Tax Credits, without Controls



Panel B. Effects of Angel Tax Credits, with Controls

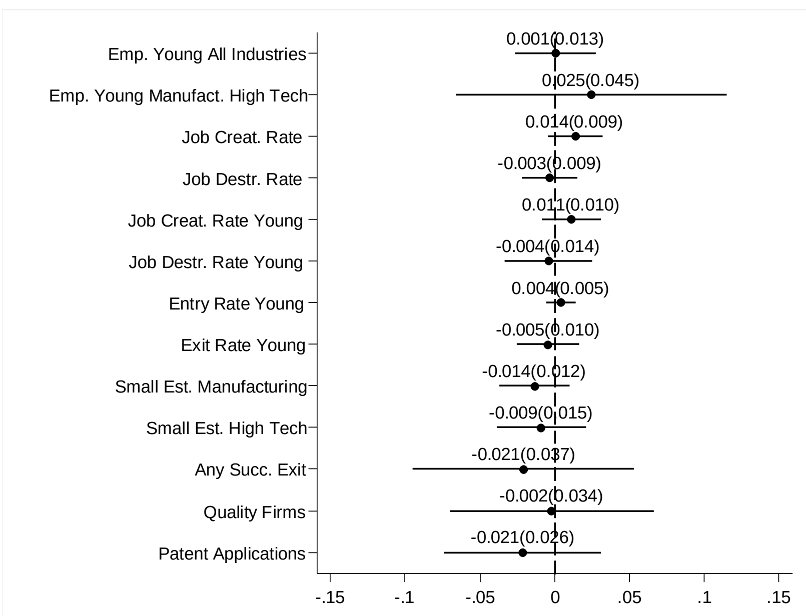


Table A1. Tax Credit Program Details

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	Max tax credit percentage
Arizona	Angel Investment Program	2006	2021	Both	0.3–0.35
Arkansas	Equity Investment Incentive Program	2007	2019	Both	0.333
Colorado	Innovation Investment Tax Credit	2010	2010	Both	0.15
	Advanced Industry Investment Tax Credit	2014	2022	Both	0.25–0.3
Connecticut	Angel Investor Tax Credit Program	2010	2019	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	Innovation Fund Tax Credit	2002	ongoing	Both	0.2
Kansas	Angel Investor Tax Credit	2005	2021	Both	0.5
Kentucky	Angel Investment Act Tax Credit	2015	ongoing	Individuals	0.4–0.5
Louisiana	Angel Investor Tax Credit	2005	2021	Individuals	0.25
Maine	Seed Capital Tax Credit Program	1989	ongoing	Both	0.3–0.6
Maryland	Biotechnology Investment Incentive Tax Credit	2007	ongoing	Both	0.5
	Cybersecurity Investment Tax Credit	2014	2023	Both	0.33–0.5
Michigan	Small Business Investment Tax Credit	2011	2011	Groups	0.25
Minnesota	Angel Tax Credit	2010	2017	Both	0.25
	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	ongoing	Both	0.1
New Mexico	Angel Investment Credit	2007	2025	Individuals	0.25
New York	Qualified Emerging Technology Company Tax Credits	2000	ongoing	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	ongoing	Both	0.45
	Angel Investor Investment Credit	2017	ongoing	Both	0.35
Ohio	Ohio Technology Investment Tax Credit	1996	2013	Both	0.25–0.3
	InvestOhio	2011	ongoing	Both	0.1
Oklahoma	Small Business Capital Companies Tax Credit	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	ongoing	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	ongoing	Individuals	0.5
West Virginia	High-Growth Business Investment Tax Credit	2005	2008	Both	0.5
Wisconsin	Qualified New Business Venture Program	2005	ongoing	Both	0.25

State	Program	Asset cap ($ million)	Revenue cap ($ million)	Employment cap	Age cap (years)
Arizona	Angel Investment Program	Assets < 2 if before 2012; Assets < 10 otherwise			
Arkansas	Equity Investment Incentive Program				
Colorado	Innovation Investment Tax Credit	Assets < 5	2		5
	Advanced Industry Investment Tax Credit		5		5
Connecticut	Angel Investor Tax Credit Program		1	25	7
Georgia	Angel Investment Tax Credit		0.5	20	3
Hawaii	High Technology Business Investment Tax Credit				
Illinois	Angel Investment Credit Program			100	10
Indiana	Venture Capital Investment Tax Credit Program		10		
Iowa	Innovation Fund Tax Credit	Net worth < 3 before 2005; Net worth < 10 otherwise			3 before 2009; 6 otherwise
Kansas	Angel Investor Tax Credit		5		5
Kentucky	Angel Investment Act Tax Credit	Net worth < 10		100	
Louisiana	Angel Investor Tax Credit	Net worth < 2	10	50	
Maine	Seed Capital Tax Credit Program		3 before 2014; 5 otherwise		
Maryland	Biotechnology Investment Incentive Tax Credit			50	10
	Cybersecurity Investment Tax Credit			50	
Michigan	Small Business Investment Tax Credit	Pre-investment valuation < 10		100	10 years if business uses MI university research; 5 otherwise
Minnesota	Angel Tax Credit			25	20 if med tech or pharma; 10 otherwise
	Seed Capital investment Credit				
Nebraska	Angel Investment Tax Credit			25	
New Jersey	Angel Investor Tax Credit Program			225	
New Mexico	Angel Investment Credit		5	100	
New York	Qualified Emerging Technology Company Tax Credits		10		
North Carolina	Qualified Business Tax Credit Program		5		
North Dakota	Seed Capital Investment Tax Credit		10		
	Angel Investor Investment Credit		10		
Ohio	Ohio Technology Investment Tax Credit	Net book value < 2.5	2.5		
	InvestOhio	Assets < 50	10		
Oklahoma	Small Business Capital Companies Tax Credit	Net worth < 1			
Rhode Island	Innovation Tax Credit		1		
South Carolina	High Growth Small Business Job Creation Act				5
Tennessee	Angel Tax Credit		3	25	5
Utah	Life Science and Technology Tax Credits				
Virginia	Qualified Equity and Subordinated Debt Investments Credit		3		
West Virginia	High-Growth Business Investment Tax Credit		20		
Wisconsin	Qualified New Business Venture Program			100	10

State	Program	Min. investment per investor ($)	Min. holding period (year)	Ownership cap before investment	Exclude existing owners and their families	Exclude full-time employees	Exclude executives and officers	Reporting req. for investor's firm	Previous external financing cap ($ million)	Registration req. for business
Arkansas	Equity Investment Incentive Program							N		Y
Arizona	Angel Investment Program	25,000	1	30%	Y			N	2 in total inv	Y
Colorado	Innovation Investment Tax Credit	25,000		30%	Y			N		Y
	Advanced Industry Investment Tax Credit	10,000		30%	Y			N	10 in inv, debt, equity	N
Connecticut	Angel Investor Tax Credit Program	25,000		50%	Y			N	2 in angel financing	Y
Georgia	Angel Investment Tax Credit		2					N	1 in equity or debt inv	Y
Hawaii	High Technology Business Investment Tax Credit		5							
Illinois	Angel Investment Credit Program	10,000	3	50%	Y			Y	10 in PE, 4 TC inv	Y
Indiana	Venture Capital Investment Tax Credit Program			50%	Y			N		Y
Iowa	Innovation Fund Tax Credit		3 if before 2014; none if after	70%	Y			N		N
Kansas	Angel Investor Tax Credit					Y	Y	Y		N
Kentucky	Angel Investment Act Tax Credit	10,000		20%	Y	Y		Y	1 in TC angel inv	Y
Louisiana	Angel Investor Tax Credit		3	50%	Y		Y	N		Y
Maine	Seed Capital Tax Credit Program		4	50%	Y		Y	Y		N
Maryland	Biotechnology Investment Incentive Tax Credit	25,000	2	25%	Y			N		Y
	Cybersecurity Investment Tax Credit	25,000	2	25%	Y			N		Y
Michigan	Small Business Investment Tax Credit	20,000	3		Y		Y	Y		Y
Minnesota	Angel Tax Credit	10,000	3	20%	Y		Y	Y	4 in PE	Y
	Seed Capital investment Credit			50%	Y			Y		Y
Nebraska	Angel Investment Tax Credit	25,000	3	50%	Y		Y	Y		Y
New Jersey	Angel Investor Tax Credit Program			80%	Y			N		N
New Mexico	Angel Investment Credit					Y	Y	N		N
New York	Qualified Emerging Technology Company Tax Credits		4	10%	Y			N		N
North Carolina	Qualified Business Tax Credit Program		1	10%	Y	Y	Y	N		Y
North Dakota	Seed Capital Investment Tax Credit		3	50%	Y			N		Y
	Angel Investor Investment Credit		3					N		N
Ohio	Ohio Technology Investment Tax Credit		3	5%	Y	Y		N		Y
	InvestOhio		2-5					N		Y
Oklahoma	Small Business Capital Companies Tax Credit							Y		N
Rhode Island	Innovation Tax Credit									Y
South Carolina	High Growth Small Business Job Creation Act		2					N		Y
Tennessee	Angel Tax Credit	15,000						Y		Y
Utah	Life Science and Technology Tax Credits	25,000	3	30%	Y			N		N
Virginia	Qualified Equity and Subordinated Debt Investments Credit		3		Y	Y	Y	N	3 in equity or debt inv	Y
West Virginia	High-Growth Business Investment Tax Credit		5	5%	Y		Y	N		N
Wisconsin	Qualified New Business Venture Program		3	20%	Y			N	10 in PE	Y

State	Program	Aggregate tax credit cap ($ million)	Max tax credit per company ($)	Max tax credit per investor ($)	Max tax credit amount per investor per business per year ($)	"First come first served" policy	Refundable	Transferrable	Carry over	Carry forward (year)	Total angel inv. in state during eff. year ($ million)	State funding as share of total angel inv. in state
Arizona	Angel Investment Program	2.5	600,000	250,000		Y	N	N	Y	3	4.2	0.60
Arkansas	Equity Investment Incentive Program	6.25					N	Y	Y	9	0	≥ 1
Colorado	Innovation Investment Tax Credit	0.75		20,000		Y	N	N	Y	5	44.62	0.02
	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	500,000	250,000		Y	N	N	Y	5	33.04	0.09
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	1,000,000		500,000	Y	N	N	Y	5	49.87	0.20
Indiana	Venture Capital Investment Tax Credit Program	12.5		1,000,000		N	N	Y after 2012; N before 2012	Y	5	0	≥ 1
Iowa	Innovation Fund Tax Credit	2-4	500,000	100,000	50,000	Y	Y	Y	Y	3-5	8.33	≥ 1
Kansas	Angel Investor Tax Credit	6		250,000	50,000	Y	N	Y	Y	Unlimited	0	≥ 1
Kentucky	Angel Investment Act Tax Credit	3		200,000		Y	N	Y	Y	15	9.55	0.31
Louisiana	Angel Investor Tax Credit	3.6		362,880	181,440	Y		Y			6.51	≥ 1
Maine	Seed Capital Tax Credit Program	Lifetime cap 30 before 2014; 5 otherwise	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
	Cybersecurity Investment Tax Credit	2-4	250,000 to 500,000			Y	Y	N	N			
Michigan	Small Business Investment Tax Credit	9	1,000,000	250,000	250,000		N		Y	5	24.81	0.36
Minnesota	Angel Tax Credit	15		125,000			Y	N	Y		33.7	0.45
	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
New Jersey	Angel Investor Tax Credit Program	25			500,000	Y	Y	N	Y for corporate; N for individuals		46.17	0.54
New Mexico	Angel Investment Credit	2			62,500	Y	N	N	Y	5 years if after 2015; 3 years if before 2015	7.2	0.28
New York	Qualified Emerging Technology Company Tax Credits			150,000			Y		Y	Unlimited	279.57	
North Carolina	Qualified Business Tax Credit Program	7.5			50,000	N		N	Y	5	15.82	0.47

State	Program	Aggregate tax credit cap ($ million)	Max tax credit per company ($)	Max tax credit per investor ($)	Max tax credit amount per investor per business per year ($)	"First come first served" policy	Refundable	Transferrable	Carry over	Carry forward (year)	Total angel inv. in state during eff. year ($ million)	State funding as share of total angel inv. in state
North Dakota	Seed Capital Investment Tax Credit	3.5	225,000	112,500		Y	N	N	Y	4	0	≥ 1
	Angel Investor Investment Credit			45,000			N	N	Y	5		
Ohio	Ohio Technology Investment Tax Credit	45		62,500		Y	N	N	Y	15	0	≥ 1
	InvestOhio	50		500,000		Y	N	N	Y	7	46.66	≥ 1
Oklahoma	Small Business Capital Companies Tax Credit						N	N	Y	3 years if after 2006; 10 years if before 2006	0	
Rhode Island	Innovation Tax Credit	0.5			100,000		N	N	Y	3	6.18	0.08
South Carolina	High Growth Small Business Job Creation Act	5		100,000			N	Y	Y	10	11.2	0.45
Tennessee	Angel Tax Credit	4		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		50,000		N	N	N	Y	15	35	0.14
West Virginia	High-Growth Business Investment Tax Credit	1	500,000	50,000		Y	N	N	Y	4	0	≥ 1
Wisconsin	Qualified New Business Venture Program	30	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 presents summary statistics on 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 tabulates these two groups by state. Panel B compares the characteristics between the two groups. All variables are defined in Appendix A.

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	P-Value
Tax credit (TC) amount ($ thou)	32.00	0.00	0.00
Finance pre-TC	0.37	0.12	0.00
Raised VC 2yrs post-TC	0.26	0.16	0.00
Exit	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. Angel Tax Credit and Angel Activities: Robustness

Panel A 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 percentage available in a state-year with an angel tax credit program. Panel B examines the effect of angel tax credits on the state-year average ex-ante characteristics of angel-backed firms. Dependent variables in columns 1 to 4 are based on firms that have non-imputed employment numbers from NETS. Panel C reports the triple-difference (DDD) estimation of the effect of angel tax credits on angel volume as described in equations (2) and (3). Each observation is a state-sector-year. *High-tech* is an indicator variable equaling one if the startup is in the high-tech sector (IT, biotech, and renewable energies). Panel D reports the effect of ATC on angel volume measured from the following subsamples: post year 2000, CVV deals, Form D deals, Form D and Crunchbase deals, and dropping deals in California and Massachusetts. Control variables are defined in equation (1). Each observation is a state-year. Standard errors are reported in parentheses and clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A. ATC and Angel Volume: Using AngelList Data

	No. of Investments		No. of Companies		No. of Investors	
	(1)	(2)	(3)	(4)	(5)	(6)
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

Panel B. ATC and Ex-ante Growth Characteristics of Angel-Backed Firms

	Ln(employment)		Employment growth		Fraction of serial entrepreneurs on team	
	(1)	(2)	(3)	(4)	(5)	(6)
ATC	-0.180**		-0.106**		-0.013*	
	(0.086)		(0.042)		(0.008)	
Tax credit percentage		-0.446**		-0.253***		-0.039**
		(0.174)		(0.087)		(0.015)
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	0.182	0.182	0.076	0.075	0.143	0.144

Panel C. ATC and Angel Volume: Triple-Difference

	Ln(Number of angel investments)	
	(1)	(2)
ATC	-0.037	
	(0.052)	
ATC × High-tech	0.206***	0.206***
	(0.062)	(0.062)
Controls	Yes	No
State × Sector FE	Yes	Yes
Year × Sector FE	Yes	Yes
State × Year FE	No	Yes
Observations	2,400	2,400
Adjusted R^2	0.914	0.926

Panel D. ATC and Angel Volume: Subsamples

	Ln(Number of angel investments)				
Sample:	Post-2000 Sample	CVV Sample	Form D Sample	Dropping VX and VS	Dropping CA and MA
	(1)	(2)	(3)	(4)	(5)
ATC	0.178**	0.141**	0.206***	0.166**	0.166**
	(0.071)	(0.070)	(0.071)	(0.072)	(0.075)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	800	1,200	1,200	1,200	1,152
Adjusted R^2	0.912	0.889	0.869	0.883	0.887

Table A4. Aggregate Real Effects of Angel Tax Credits

This table reports the difference-in-differences estimates of the aggregate effects of angel tax credits corresponding to Panel A of Figure 3. The specifications and variables are the same as those in Panel A of Figure 3. All outcome variables are defined in Appendix A. Standard errors are clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Emp. Young All Industries	Emp. Young Manufact. All Industries	Job Creation Rate	Job Destruction Rate
	(1)	(2)	(3)	(4)
ATC	-0.018	0.007	0.007	-0.007
	(0.016)	(0.043)	(0.009)	(0.008)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	970	970	1,200	1,200
Adjusted R^2	0.996	0.985	0.892	0.830

	Job Creation Rate Young	Job Destruction Rate Young	Entry Rate Young	Exit Rate Young
	(5)	(6)	(7)	(8)
ATC	0.010	-0.006	-0.000	-0.000
	(0.009)	(0.014)	(0.005)	(0.011)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,100	1,100	1,100	1,100
Adjusted R^2	0.604	0.464	0.422	0.668

	Small Est. Manufacturing	Small Est. High Tech	Any Successful Exit	Quality Firms	Patent Applications
	(9)	(10)	(11)	(12)	(13)
ATC	-0.019	-0.018	0.000	-0.032	-0.019
	(0.016)	(0.020)	(0.040)	(0.056)	(0.043)
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	900	900	1,300	1,166	1,250
Adjusted R^2	0.998	0.996	0.391	0.962	0.986

Table A5. Different-State-Matched Employment and Exit Outcomes

This table shows the nearest-neighbor matching estimates for Table 6. 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 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 in 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). As in Table 6, 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 controls discussed in the paper. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Emp. > 10 2yrs post-TC (1)	Emp. > 25 2yrs post-TC (2)	Emp. > p75 2yrs post-TC (3)	Exit (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	2,511	2,511	2,511	4,115
Adjusted R^2	0.52	0.46	0.44	0.079

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. Survey Summary Statistics and Sample Selection

Panels A and B present the summary statistics for our survey analysis. Panel A shows sample sizes for investors who we emailed and those who responded. Panel B presents the summary statistics for the variables used in our regressions. Panel C examines sample selection. Column 1 examines the roles of ATC usage, availability, and locations in California or Massachusetts. Column 2 additionally examines investor experience measured from AngelList. Standard errors are clustered by state. ***, **, and * denotes significance at the 1%, 5%, and 10% level, respectively

Panel A. Samples

	Tax credit recipient	AngelList Investors	Total
Emailed	2,508	9,566	12,074
Responded	158	1,226	1,384

Panel B. Summary Stats for Regression Variables

Variable	N	Mean	Std. dev.
Tax credit recipient	1,384	0.11	0.32
State has ATC	1,384	0.41	0.49
CA or MA	1,384	0.42	0.49
ATC unimportant_coordination	1,361	0.08	0.27
ATC unimportant_home run	1,361	0.40	0.49
ATC unimportant_non-financial	1,361	0.08	0.26
ATC unimportant_too small	1,361	0.22	0.41
ATC unimportant_cannot use	1,361	0.09	0.28
Importance_ATC	1,361	1.82	1.02
Importance_team	1,363	4.75	0.52
Importance_business	1,364	4.36	0.73
Importance_location	1,360	2.41	1.06
Importance_financial return	1,365	3.66	1.11
Importance_add value	1,364	3.39	1.16
Importance_valuation	1,362	3.48	0.97
Importance_gut reaction	1,363	3.94	0.96
Importance_deal terms	1,362	3.33	1.06
Profession_corporate executive	1,250	0.24	0.43
Profession_entrepreneur	1,250	0.37	0.48
Profession_investor	1,250	0.22	0.41
Above median # of deals since 2018	1,215	0.47	0.50
AL_above median # of deals	1,228	0.44	0.50
AL_has exit	1,228	0.30	0.46
AL_has founder experience	1,228	0.60	0.49
AL_has invested as insider	1,228	0.32	0.47
AL_top school	1,228	0.31	0.46

Panel C. Sample Selection: Who Responds?

	Responded	
	(1)	(2)
Tax credit recipient	-0.074***	0.114*
	(0.012)	(0.063)
State has ATC	0.012	0.010
	(0.013)	(0.012)
CA or MA	-0.001	-0.009
	(0.011)	(0.010)
AL_above median deal experience		0.066***
		(0.006)
AL_has exit		-0.015*
		(0.009)
AL_has founder exp		0.015**
		(0.007)
AL_has invested as insider		-0.031***
		(0.006)
AL_top school		0.020*
		(0.010)
Observations	12,073	9,572
Adjusted R^2	0.007	0.010

Appendix A. Variable Definitions

Variable Name	Definition
ATC	Indicator variable equaling one if a state has an 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.
Pre-investment employment	Number of employees in the year prior to receiving angel investment. Source: Non-imputed NETS.
Pre-investment employment growth	The percentage change in firm employment from year *t*-2 to *t*-1. Source: Non-imputed NETS.
Fraction of serial entrepreneurs	Fraction of founding team members who 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, SDC Platinum, and Kenney-Patton IPO Database.
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 in percentage points. Source: BEA.
Democratic control	Indicator variable for whether a state (both the legislative and executive branches) is controlled by Democrats. Source: NCSL.
Republication control	Indicator variable for whether a state (both the legislative and executive branches) 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 17 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 17 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 (some states do not report 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 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 (some states do not report earlier years). Source QWI.
Ln(job creat. rate)	The logarithm of one plus state-year job creation rate in percentage points. Period covered: 1993 -2016. Source: BDS.
Ln(job destr. rate)	The logarithm of one plus state-year job destruction rate in percentage points. Period covered: 1993 -2016. Source: BDS.

Ln(job creat. rate young)	The logarithm of one plus state-year job creation rate (in percentage points) for 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 (in percentage points) for 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 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: 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 an IPO or high-valued M&A (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 (in percentage points) for young firms of age 0-5. Period: 1993-2014. Source: BDS.
Ln(exit rate young)	The logarithm of one plus state-year exit rate (in percentage points) for 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. Source: state programs.
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. Source: state programs and CVV.
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. Source: state programs and Non-imputed NETS.
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. Source: state programs and Non-imputed NETS.
Emp. >p75 2 yrs post-TC	Indicator variable for whether a firm's employment count was above the 75^{th} percentile within two years after its investors received angel tax credit. Source: state programs and Non-imputed NETS.
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. Source: state programs and Non-imputed NETS.
Emp. >25 in credit yr	Indicator variable for whether a firm had more than 25 employees in the year after its investors received angel tax credit. Source: state programs and Non-imputed NETS.
Emp. >p75 in credit yr	Indicator variable for whether a firm's employment count was above the 75^{th} percentile within our sample in the year its investors received angel tax credit. Source: state programs and Non-imputed NETS.
Finance pre-TC	Indicator variable for whether a firm received any other external financing 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.
Ln(number of insider investors)	The logarithm of one plus the number of investors who are insiders of invested startups in each startup state-year. Source: AngelList.
ATC importance	An index variable that takes values of 1 to 5 (1 being "not at all important" and 5 being "extremely important") on the perceived importance of angel tax credits. Source: survey.
Above median no. of deals since 2018	Indicator variable equaling one if the number of deals made by the investor is above the median in our sample. Source: survey.
AL_has exit	Indicator variable equaling one if the investor has had at least one exit (IPO or M&A) in the past. Source: survey matched to AngelList.
AL_has founder experience	Indicator variable equaling one if the investor has prior founder experience. Source: survey matched to AngelList.
AL_has invested as insider	Indicator variable equaling one if the investor has invested in a startup as an insider. Source: survey matched to AngelList.
AL_top school	Indicator variable equaling one if the investor holds a degree from one of the Wall Street Journal Top 50 Universities or Wall Street Journal Top 50 MBA Programs. Source: survey matched to AngelList.
ATC_unimportant_home run	The respondent believed angel tax credit is unimportant because the investor invests based on whether the startup has the potential to be a "home run" or not. Source: survey.
ATC_unimportant_coordination	The respondent believed angel tax credit is unimportant because it is too difficult to coordinate certification with the startup. Source: survey.
ATC_unimportant_non-financial	The respondent believed angel tax credit is unimportant because the investor invests for non-financial reasons (personal, philanthropic, social, etc.) Source: survey.
ATC_unimportant_too small	The respondent believed angel tax credit is unimportant because the investor thinks tax credits are too small to make a difference. Source: survey.
ATC_unimportant_cannot use	The respondent believed angel tax credit is unimportant because the investor cannot take advantage of the tax credit (e.g. no state income tax liabilities). Source: survey.

Appendix B. 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 who 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 are executives in the company using data from Linkedin. Among investors for whom we observe LinkedIn employment histories, 20% 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 186 firms. 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 member 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 who 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 positive (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 C. Power Analysis of Aggregate Real Effects Results

In this appendix, we discuss the interpretation of our real effects in the context of Abadie (2020). We also present a power analysis of our tests.

Statistically null effects in economics are generally interpreted with caution. 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 (2020) 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 (2020) shows that non-significance is more informative than significance if the power of the test is at least 0.5.

Abadie (2020) has two implications for our work. First, statistical insignificance could be useful above and beyond the fact that the estimates are close to zero. Although our null point estimates are small enough to rule out significant impact of angel tax credits, this result helps us provide 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 policymakers) 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, conditional 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 that 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.[1] 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.

[1] 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.

In general, the framework by Burlig, Preonas, and Woerman (2020) fits well with ours. However, there are some differences. First, their model assumes that the treatment happens only once, and that it does not 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 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).[2] We think this approximation is reasonable, and we find that altering these parameters around the baseline does not significantly 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 a 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 our 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 of 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 captures 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 frame the discussion in intuitive but compelling ways.

First, we consider a scenario where all outcome variables are independent (up to some random noise) from each 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 provides 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

[2] As we show in the variable definition (Appendix A), 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.

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 sizes, like 1%.

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 random noise. This implies that – net of the noise - additional outcomes do not bring new information. Also, we do not believe this case is likely in our data. For instance, measures of patenting at the 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 that 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.[3] 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 is 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 (2020)).

The above conclusion is only made stronger by the fact that we find the same null effect across different alternative models. First, we find similar results when we measure the outcomes differently (Figure A.2). In particular, we show that the null effects remain when we do not log-transform the rates variables. Second, we find the same results when excluding Massachusetts and California (Figure A.3). Third, our results are robust to using an event-study approach, where we examine the effect of these programs in a narrower window around their introductions and expirations (Figure A.4).

Lastly, we note that while our power analysis is specific to our setting, it is also useful for those interested in understanding the power of studying staggered introductions of policies in a difference-in-differences setting.

[3] 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.

Appendix D: Angel Investor Survey Email

Re: Angel Investor Finance Professor Research

[redacted]

Jun 10, 2020, 9:18 PM (11 hours ago)

to Sabrina

Done - my pleasure.

On Wed, Jun 10, 2020 at 3:18 PM Sabrina Howell <showell@stern.nyu.edu> wrote:

> [redacted]
>
> I'm Sabrina Howell, a Professor of Finance at the NYU Stern School of Business, and I'm studying factors that are important to angel investors' decisions to invest in startups. This is joint work with professors at Northwestern, Carnegie Mellon, UNC, and UVA.
>
> We would really appreciate it if you could complete this brief survey:
> https://nyu.qualtrics.com/jfe/form/SV_9Ex6zwrbjQXOZFz?Q_DL=eQSLGCUu54q6MA3_9Ex6zwrbjQXOZFz_MLRP_4ON2oKGVA11cCC9&Q_CHL=gl
> I promise it will only take 3 minutes! Your response will be anonymous, and we will only report aggregated results in our research paper.
>
> I hope you and your family are doing OK during these difficult times.
>
> Thanks a lot for your time,
> Sabrina
>
> ______________________________
>
> Sabrina T. Howell
> Assistant Professor of Finance
> NYU Stern School of Business
> Phone: 212-998-0719
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> Website: www.sabrina-howell.com

Appendix E: Angel Investor Survey

Which of the following factors do you consider to be the most important in affecting your decision about **whether or not** to invest in a startup?

	Not at all important (1)	Slightly Important (2)	Moderately important (3)	Very important (4)	Extremely important (5)
Quality of the startup's management team (1)	○	○	○	○	○
Quality of the startup's technology or business model (2)	○	○	○	○	○
Location of the startup (3)	○	○	○	○	○
Expected financial returns (based on NPV/IRR/Multiple) (4)	○	○	○	○	○
My ability to add value to the startup and its alignment with my expertise (5)	○	○	○	○	○
My ability to benefit from a state-level angel investor income tax credit after investing (6)	○	○	○	○	○
Valuation (overall worth of the startup) (7)	○	○	○	○	○
My gut reaction after seeing the business plan or meeting the management (8)	○	○	○	○	○
Terms of the investment (e.g. board control, future participation rights) (9)	○	○	○	○	○

(*Display this question if answer to previous question "My ability to benefit from a state-level angel investor income tax credit after investing" <= 2*)
In the previous question, you rated your ability to benefit from a state-level angel investor income tax credit after investing as relatively unimportant. Why? (Select all that apply)

- [ ] It is too difficult to coordinate certification with the startup. (1)
- [ ] I invest based on whether the startup has the potential to be a "home run" or not. (6)
- [ ] I invest for non-financial reasons (personal, philanthropic, social, etc.). (2)
- [ ] Tax credits are too small to make a difference. (3)
- [ ] I cannot take advantage of the tax credit (e.g. no state income tax liabilities). (4)
- [ ] Other (please describe). (5) ____

Page Break

(*Display this question if answer to previous question "My ability to benefit from a state-level angel investor income tax credit after investing" >= 3*)

In the previous question, you rated your ability to benefit from a state-level angel investor income tax credit after investing as relatively important. Why? (Select all that apply)

- [ ] It helps to certify the startup's high quality. (1)
- [ ] It might make the investment financially viable (i.e., change NPV from negative to positive). (2)
- [ ] I wouldn't calculate the effect on the NPV, but it would make the investment more appealing financially. (3)
- [ ] It would enable me to invest in additional startups. (4)
- [ ] Other (please describe). (5) ____

Page Break

Have you ever received a state-level angel investor income tax credit? Choose one.

○ No, because the states where I invest do not have angel investor tax credits. (1)

○ No, because I am not aware whether the states where I invest offer angel investor tax credits. (2)

○ No, because making use of angel investor tax credits requires too much coordination or administrative work. (3)

○ Yes. (4)

What is your opinion of state-level angel investor income tax credits? Do you think they attract new investments into startups?

____

____

Page Break

Which of the following best describes your main approach to investing in a startup? Choose one.

○ After conducting financial analysis, I invest when the expected return is above a certain threshold. (1)

○ I focus on whether the startup is likely to experience dramatic growth over the next couple of years. (2)

○ I focus on whether the startup has a strong team, high quality technology, and/or good business model. (3)

○ I invest for non-financial reasons (personal, philanthropic, social). (4)

○ None of the above (please describe). (5) ____

Page Break

To close our survey, we would like to ask you for some background information.

How many investments in startups have you made since January 2018?

____

What is your average investment amount in a startup financing round (a rough estimate is fine)?

____

What is your main profession?

- ○ Corporate Executive (4)
- ○ Doctor (5)
- ○ Entrepreneur (6)
- ○ Lawyer (7)
- ○ Investor (8)
- ○ Other (please describe) (9) ____

Are you a member of an angel investment group?

- ○ Yes (1)
- ○ No (2)

End of Block: Default Question Block