Economic Development Quarterly
2020, Vol. 34(2) 188–208

DOI: 10.1177/0891242420920926
journals.sagepub.com/home/edq
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The Impact of State-Level Research and Development Tax Credits on the Quantity and Quality of Entrepreneurship

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Abstract

U.S. states often cite the acceleration of start-up activity as a rationale for the research and development (R&D) tax credit. While a strong empirical base links the R&D tax credit to increased innovation, prior work provides no causal evidence that the credit effects the rate of formation and growth potential of new businesses. This article combines data from the Startup Cartography Project with the Panel Database on Incentives and Taxes to implement a difference-in-differences estimate of the impact of state R&D tax credits on the quantity and quality-adjusted quantity of entrepreneurship. The authors find that the R&D tax credit is associated with a significant long-term impact on both. In contrast, the authors observe that state investment tax credits have no impact on the quantity of entrepreneurship and lead to a marked decline in the rate of formation of growth-oriented start-ups over time. The results indicate the potential of state R&D tax credits to stimulate entrepreneurship.

Keywords

entrepreneurship, incentives, economic development

Introduction

The promotion of entrepreneurship is a central priority of regional economic development (Lerner, 2009). New firm formation plays a pivotal role in regional economic performance: The growth of young firms is the source of nearly all net new employment (Haltiwanger et al., 2013) and a high rate of local entrepreneurship serves to maintain the competitiveness of local markets (Andersson & Henrekson, 2015). There is likewise increasing appreciation for the role that start-up firms play in the overall innovation and commercialization process (Acs et al., 2009). However, the outcomes from entrepreneurship are highly skewed, with a small number of firms accounting for the vast bulk of economic impact (Decker et al., 2014). Consequently, assessing the role of policy on entrepreneurship depends on evaluating not only its impact in terms of the number of new companies founded but also on its potential for generating and increasing the realization of meaningful growth outcomes (Guzman & Stern, in press).

One of the principal instruments that policy makers use to impact entrepreneurship is tax policy. There is considerable evidence that the incentives to start and invest in the expansion of a business depends on the overall rate and convexity of taxation (Cullen & Gordon, 2006; Gentry & Hubbard, 2004). Indeed, an oft-cited justification for lower rates of taxation is the general encouragement of entrepreneurship (Gurley-Calvez & Bruce, 2013; Holtz-Eakin, 2000; Reynolds et al., 1999). As the outsized role of innovation-driven start-ups in harnessing local knowledge spillovers and enhancing the comparative advantage of regions has come to the fore (Delgado et al., 2016; Lanahan & Feldman, 2018), policy makers have increasingly deployed focused tax policies such as the research and development (R&D) tax credit for dual purposes: (1) to spur investment in innovation by larger and more established companies (their original intended purpose) and (2) to encourage the formation of growth-oriented

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ventures and accelerate their performance (Bartik & Eberts, 2012; Miller & Richard, 2010; Wu, 2008).

The primary contribution of this article is to provide novel empirical evidence regarding the impact of state R&D tax credits on the quantity, quality, and performance of entrepreneurship (i.e., the realization of significant growth outcomes by new firms). On one hand, an emerging empirical literature has documented the impact of state R&D tax credits on R&D investment, innovation, and overall economic performance (Lucking, 2019; Moretti & Wilson, 2014; Wilson, 2009; Wu, 2005). At the same time, since the work of Cullen and Gordon (2006) and Gentry and Hubbard (2004), there has been attention toward the overall impact of the tax system on the formation of new enterprises (Bruce, 2000; Cullen & Gordon, 2006; Gentry & Hubbard, 2004; Gurley-Calvez & Bruce, 2013). And, there have been a small number of studies that have linked the R&D tax credit to the overall growth of high-technology sectors (Wu, 2008), or linked the adoption of such credits to the movement toward entrepreneurship for individuals working in companies impacted by the credit (Babina & Howell, 2018). However, to date, there has been no article that directly examines the overall impact of the R&D tax credit on the rate, nature, and scaling of new business formation.

At least in part, this gap in understanding arises from the fact that, among all new business starts, the nature of growth-oriented entrepreneurship is elusive. The majority of new firms are founded with the intention to remain small businesses (Pugsley & Hurst, 2011). Only a very small fraction of start-ups experiences the explosive growth (in terms of jobs, revenue, or valuation) that propels the economy and motivates economic development policy (Guzman & Stern, in press; Haltiwanger et al., 2013). At the time a company is founded, one cannot observe whether that particular firm will experience explosive growth. Evaluating the effectiveness of fiscal incentives such as the state R&D tax credit thus requires confronting a measurement quandary: How do we identify whether state R&D tax credits are generating the formation and accelerating the performance of the types of start-ups that have the potential for exponential growth (Fazio et al., 2016)?

We overcome this impasse by extending the earlier work of Guzman and Stern (in press), who measured the quality and quantity of entrepreneurship across regions with a novel data set on tax incentives (Bartik, 2017) to examine the impact of state R&D tax incentives on entrepreneurship. Building on the methodology of Guzman and Stern (in press), we combine business registration records and predictive analytics to leverage founding choices that signal growth intention and model the relationship of these choices to later growth outcomes. We use this mapping to prospectively account for differences in the growth potential (or *quality*) of start-ups at or near the time of founding and develop systematic measures of the quantity, quality-adjusted quantity, and scaling potential of entrepreneurship in a region (Guzman & Stern, 2015, 2017, in press). We then consider the respective interactions of those measures with the availability (or absence) of state-level R&D tax credits.

More specifically, we combine data from the Startup Cartography Project (SCP), tracking the quality, quantity, and performance of entrepreneurship with data from the W.E. Upjohn Institute's Panel Database on Incentives and Taxes (PDIT; Bartik, 2017), tracking the availability and effective rates of state-level tax incentives. Our resulting data set includes entrepreneurship measures for all counties in 25 states from 1990 to 2010. Using a difference-in-differences approach at the county level, with year, county, and pretrend fixed effects, our core analysis evaluates how changes in the R&D tax credit impact the quantity, quality, and performance of entrepreneurial activity. In addition, as an exercise to consider the impact of tax credits that are more distant from the incentives for innovation-driven entrepreneurship, we repeat our analysis examining the impact of state-level investment tax credits using a similar difference-in-differences framework.

We find striking evidence for the long-term impact of the introduction of state R&D tax credits on the quantity and quality-adjusted quantity of entrepreneurship in a region. Accounting for county and year fixed effects, as well as lagged state gross domestic product (GDP), we find that the introduction of state R&D tax credits is associated with around a 7% increase in the rate of net new business formation (both in terms of raw quantity and accounting for the heterogeneous firm potential for growth). Moreover, this effect may underestimate the incentive's actual long-term impact. While state-level R&D tax credits have little to no effect on the rate or composition of new firm formation in the first few years following their introduction, these incentives lead to a 20% increase in the quantity and quality-adjusted quantity of entrepreneurship over a 10-year period (in the absence of any meaningful preadoption trend).

State R&D tax credits, thus, appear to have indirect effects on business dynamism and new firm formation and to "set the table" more generally for increased entrepreneurship over the long term (Lerner, 2009). Such credits, for example, may stimulate local R&D expenditures (perhaps even at the expense of other regions) and create a higher knowledge base from which start-ups of all types can be created. Our results also offer insights into the local supply of entrepreneurs in states that adopt tax credits. More specifically, the absence of any initial impact on the rate or composition of new firm formation following the introduction of a state R&D tax credit suggests that there is no pent-up supply of local entrepreneurs at the margin who are being deterred from entry by the cost of capital. Instead, state R&D tax credits improve the overall entrepreneurial ecosystem over the long term.

Notably, these impacts stand in sharp contrast to the effects of other contemporaneous state fiscal incentives supporting established firms—state-level investment tax credits.[1] For the investment tax credit, we see at best a neutral impact in terms of the overall quantity of entrepreneurship and a longer-term decline in the quality-adjusted quantity of new firms founded. This suggests that, by enhancing the competitiveness of established businesses, the investment tax credit might serve to deter growth-oriented entrepreneurship over time.

We conclude by observing that these results are informative for policy design. Though initially aimed at fostering innovation by established enterprises, state R&D tax credits also increase the rate of entrepreneurship, and importantly, the formation of high-growth-potential start-ups needed to achieve economic development objectives. However, the R&D tax credit does not offer a "quick fix" for states seeking to catalyze regional economic growth through entrepreneurship. Importantly, increases in the formation of high potential growth firms only materialize over time in response to R&D credits. Thus, it may take a decade or more for state R&D tax credits to have an impact on the economy through entrepreneurship. Overall, our findings counsel in favor of "patient" and targeted policy—offering long-standing tax incentives to encourage investment in innovation and encouraging investment in initiatives, including public–private partnerships, that support this important category of newly founded firms.

R&D Tax Incentives and Regional Entrepreneurship: A Review of the Evidence

Originally introduced at the federal level in 1981, state R&D tax credits permit companies to claim a credit against their tax liability for qualified spending on research and experimentation (Wu, 2008). Many, but not all, state R&D tax credits are incremental (e.g., may only be claimed on qualified spending above a base amount). While state R&D tax credits can only be applied against taxes owed (and—with one exception—not refunded independent of tax liability), holders are typically permitted to carry credits forward for terms of 15 to 20 years for future use (in the event companies do not owe sufficient taxes against which to claim them in the years that research expenses were incurred). Some, but not all states, also impose a tax liability floor, below which R&D tax credits cannot be applied.

State R&D tax credits and other types of fiscal incentives have proliferated since their counterpart at the federal level was first introduced (Wilson, 2009).[2] Between 1981 and 2006, 32 states introduced R&D tax credits and the average effective credit rate grew fourfold (Wilson, 2009). Although originally adopted as an economic development tool to support existing firms already conducting R&D (Miller & Richard, 2010), many state governments expected R&D tax credits would also help to advance their innovative capacity and industrial competitiveness either by creating or attracting new companies (Bartik & Eberts, 2012; Wu, 2008). Today, R&D tax credits have increasingly been positioned as a catalyst of start-up activity—a mechanism to spur growth in the states' respective high-technology sectors by directly helping prerevenue start-ups—above and beyond simply supporting established firms (Miller & Richard, 2010).

However, despite the significant and growing state fiscal investment to foster entrepreneurship through R&D credits, the empirical evidence evaluating their impact is sparse. While an extensive literature investigates the impact of R&D tax credits on innovation, and another complementary literature considers how taxes broadly effect entry into entrepreneurship, there appears to be a lack of evidence on the question at the intersection of the two: How R&D fiscal incentives change the local production of entrepreneurship in those locations that adopt them. To the best of our knowledge, our article is the first to empirically evaluate this important issue.[3]

To bridge this gap, we build on three related strands of economic literature that closely inform our area of study. First, there is a large and productive literature on the impact of R&D tax credits on established firms. This work has established that such tax credits have a significant influence on R&D investment as well as wider economic effects (Bloom et al., 2002; Branstetter & Sakakibara, 2002; Grossman & Helpman, 1991; Hall & Van Reenen, 2000; Jaffe, 1986; Katz, 1986; Mansfield, 1986; Moretti & Wilson, 2014; Pless, 2019; Rao, 2013; Wilson, 2009; Wu 2005).[4] While large firms account for the bulk of private R&D investment, recent research likewise suggests "that small, private firms are quite responsive to R&D tax incentives" (Agrawal et al., in press). Furthermore, at a macroeconomic level, R&D tax credits appear to increase establishment-level dynamism among incumbent R&D-performing firms (Acemoglu et al., 2018; Lucking, 2019). However, the aggregate impact of state-level R&D tax credits on R&D spending at the national level may be zero. Wilson (2007, 2009) found that R&D spending in one state is negatively impacted by R&D tax credits in others, creating a zero-sum dynamic in aggregate impact at the national level. Wilson's findings suggested that the impact of state R&D credits, to the extent they exist, may instead center in *local* economic activity (such as entrepreneurship) and localized spillovers (e.g., Jaffe, 1986).

Second, there is a body of literature considering how tax policy in general (rather than R&D fiscal incentives specifically) impacts entry into entrepreneurship. The findings of this literature are mixed, and the effects often depend on the relative level of tax rates, structure of tax policy, risk tolerance of investors, and the start-ups' stage of growth, although some general patterns do emerge. Generally speaking, entry into self-employment increases in response to lower marginal taxes (Bruce, 2000). Cuts in relative and across-the-board tax rates faced by entrepreneurs would likewise increase entrepreneurial entry (Gurley-Calvez & Bruce, 2013). Conversely, higher marginal tax rates and a more convex tax system reduce entry into self-employment for people who were previously employed in innovative industries and occupations (Gentry & Hubbard, 2004). Progressive tax structures have countervailing effects for high-income agents, risk-neutral investors on one hand, and risk-averse individuals on the other. Since graduated rates tax gains more than subsidize losses, such rates discourage individuals from the former group from moving to the entrepreneurial sector and encourage it for the latter (Cullen & Gordon, 2006). However, tax policy aimed at encouraging small business entry may come at the expense of discouraging later growth as preferential treatment is phased out and the government claims a larger share of payoffs for successful entrepreneurs (Gentry & Hubbard, 2004; Holtz-Eakin, 1995). Further, an across-the-board cut in tax rates would have a net positive impact on entrepreneurial spell length (Gurley-Calvez & Bruce, 2008).[5] Based on this literature, we would expect the structure of state R&D tax credits to affect the production of local entrepreneurship.

Finally, third, there are a small number of articles that have touched more directly upon the topic of R&D tax credits and entrepreneurship, even if not squarely looking at the impact of the former on the latter. Babina and Howell (2018) used changes in state and federal R&D tax credits to study varying incentives to knowledge production in large firms and their spillovers into new start-ups. Lokshin and Mohnen (2007) estimated the tax-price elasticity of R&D spending in the Netherlands across firm sizes, finding larger elasticities for smaller firms and hypothesizing that the credit plays a major role in helping small firms increase R&D expenditures in the face of more pressing capital constraints. The article that is closest to ours is Wu (2008), which links state R&D tax credits to the growth of the high-tech sector. Wu (2008) found that state R&D tax credits have significant and positive impacts on the number of *active* high-technology establishments and as a share of business establishments overall within states. However, Wu (2008) left open the question as to whether any temporal rise observed reflects an increase in entrepreneurship, survival, or other aspects. In conclusion, while much research has been done in adjacent areas, the empirical evidence on the impact of R&D tax credits on entrepreneurship continues to be largely missing.

Studying this question presents not only challenges in systematic empirical analysis but also the need to solve fundamental data issues at the core of entrepreneurship measurement. As emphasized in Guzman and Stern (2017), ecosystem entrepreneurship cannot simply be summarized by the count of new firms, but instead represents three distinct margins, each varying independently across locations: the regional *quantity*, representing the number of firms being created in a location; the regional *quality*, representing the heterogeneous underlying potential of firms at founding and their regional distribution; and *ecosystem effects*, representing the better or worse performance across locations for start-ups founded with the same quality. State R&D tax credits could impact entrepreneurship across any one of these margins, or all of them, potentially even with each moving in different directions. Without accounting systematically for each of these effects, the net impact of state R&D tax credits on entrepreneurship (from the policy maker's perspective) cannot be assessed.

Therefore, developing an approach to create systematic regional measures of the quantity of entrepreneurship, its quality, and the ecosystem performance in a way that can be done comprehensively across the United States (or another large geography) is a central and necessary requirement to careful study. This is the question to which we now turn.

Empirical Framework

In our empirical framework, we build on the earlier work of Fazio et al. (2016) and Guzman and Stern

(2015, 2017, in press), using business registration records and predictive analytics to measure the quality and quantity of entrepreneurship across regions. Then, we use these regional measures to setup a difference-in-differences empirical specification that takes advantage of the staggered introduction of tax credits to measure their impact on regional entrepreneurship outcomes.

Measuring Regional Entrepreneurship: An Entrepreneurial Quality Approach[6]

Our entrepreneurship measurement approach builds from Guzman and Stern (2019), who developed a way to measure the founding quality of start-ups using predictive analytics and business registration records. The approach combines three interrelated insights. First, as the challenges to reach a growth outcome as a sole proprietorship are formidable, a practical requirement for any entrepreneur to achieve growth is business registration (as a corporation, partnership, or limited liability company). This practical requirement allows us to form a population sample of entrepreneurs "at risk" of growth at a similar (and foundational) stage of the entrepreneurial process. Second, we can potentially distinguish among business registrants through the measurement of founding choices observable *at or close to the time of registration*. For example, we can measure start-up characteristics (which result from the initial entrepreneurial choices in our model) such as whether the founders name the firm after themselves (eponymy), whether the firm is organized to facilitate equity financing (e.g., registering as a corporation or in Delaware), or whether the firm seeks intellectual property protection (e.g., a patent or trademark). Third, though rare, we observe meaningful growth outcomes (such as achieving an initial public offering [IPO] or high-value acquisition) for some firms. Combining these insights, we estimate entrepreneurial quality by estimating the relationship between observed growth outcomes and start-up characteristics.

That is, for a firm i born in region r at time t, with at-birth start-up characteristics $K_{i,r,t}$, we observe growth outcome $g_{i,r,t+s}$ s years after founding and estimate:

$$\theta_{i,r,t} = P\left(g_{i,r,t+s} | K_{i,r,t}\right) = f(\alpha + \beta K_{i,r,t})$$

We use the *predicted* value of this regression as our measure of entrepreneurial quality.

As long as the process by which start-up characteristics map to growth remain stable over time (an assumption which is itself testable), this mapping allows us to form an estimate of founding characteristics to entrepreneurial quality for any business registrant within our sample.

We use these estimates to generate three entrepreneurship statistics capturing the level of entrepreneurial quality for a given population of start-ups, the potential for growth entrepreneurship within a given region and start-up cohort, and the performance over time of a regional entrepreneurial ecosystem in realizing the potential performance of firms founded within a given location and time period.

The Entrepreneurial Quality Index. To create an index of entrepreneurial quality for any group of firms (e.g., all the firms within a particular cohort or a group of firms satisfying a particular condition), we simply take the average quality within that group. Specifically, in our regional analysis, we define the Entrepreneurial Quality Index (EQI) as an aggregate of quality at the region-year level by simply estimating the average of $\theta_{i,r,t}$ over that region:

$$EQI_{r,t} = \frac{1}{N_{r,t}} \sum\nolimits_{i \in \{I_{r,t}\}} \theta_{i,r,t},$$

where $\{I_{r,t}\}$ represents the set of all firms in region r and year t, and $N_{r,t}$ represents the number of firms in that region year. To ensure that our estimate of entrepreneurial quality for region r reflects the quality of start-ups in that location rather than simply assuming that start-ups from a given location are associated with a given level of quality, we exclude any location-specific measures from the vector of observable start-up characteristics.

The Regional Entrepreneurship Cohort Potential Index. From the perspective of a given region, the overall inherent potential for a cohort of start-ups combines both the quality of entrepreneurship in a region and the number of firms in such region (a measure of quantity). To do so, we define the Regional Entrepreneurship Cohort Potential Index (RECPI) as simply EQI multiplied by the number of firms in that region-year:

$$\mathrm{RECPI}_{\mathrm{r,t}} = \mathrm{EQI}_{\mathrm{r,t}} \times \mathrm{N}_{\mathrm{r,t}}$$

Since our index multiplies the average probability of a firm in a region-year to achieve growth (quality) by the number of firms, it is, by definition, the expected number of growth events from a region-year given the start-up characteristics of a cohort at birth. This measure of course abstracts away from the ability of a region to realize the performance of start-ups founded within a given cohort (i.e., its ecosystem performance), and instead can be interpreted as a measure of the "potential" of a region given the "intrinsic" quality of firms at birth, which can then be affected by the impact of the entrepreneurial ecosystem, or shocks to the economy and the cohort between the time of founding and a growth outcome.

The Regional Ecosystem Acceleration Index. While RECPI estimates the expected number of growth events for a given group of firms, over time we can observe the realized number of growth events from that cohort. This difference can be interpreted as the relative ability of firms within a given region to grow, conditional on their initial entrepreneurial quality. Variation in ecosystem performance could result from differences across regional ecosystems in their ability to nurture the growth of start-up firms, or changes over time due to financing cycles or economic conditions. We define the Regional Ecosystem Acceleration Index (REAI) as the ratio of realized growth events to expected growth events:

$$REAI_{r,t} = \frac{\#\ of\ growth\ events_{r,t}}{RECPI_{r,t}}.$$

A value of REAI greater than 1 indicates a region-cohort that realizes a greater than expected number of growth events (and a value below 1 indicates underperformance relative to expectations). REAI is a measure of a regional performance premium: the rate at which the regional business ecosystem supports high-potential firms in the process of becoming growth firms.[7]

Together, EQI, RECPI, and REAI offer researchers and regional stakeholders the ability to undertake detailed evaluations (over time and at different levels of geographic and sectorial granularity) of entrepreneurial quality and ecosystem performance.

Empirical Specification. Building on this setup, we take advantage of the staggered introduction of tax incentives across different states in the United States to measure the difference in the average creation of local entrepreneurship for counties that have a tax incentive versus those that do not. Specifically, for a measure of entrepreneurship $Y_{r,t}$, estimated in county r at time t, we estimate the specification

$$Y_{r,t} = \alpha + \gamma_r + \lambda_t + \beta\ D_{r,t} + \epsilon_{r,t}$$

where $D_{i,t}$ is an indicator variable equal to 1 if a tax incentive has been included and 0 otherwise, γ_r are individual county-level fixed effects, λ_t are year fixed effects, and $\epsilon_{r,t}$ is an error term. The coefficient of interest is β, which estimates the average change in entrepreneurship (either RECPI, quality, or quantity) with and without the tax incentive. After controlling for mean levels of county and year fixed effects, the key identifying assumption is lack of correlation between the imposition of the policy and the trend in county-level entrepreneurship.

Indeed, one common concern in difference-in-differences implementations for policy evaluation, like our case, is the existence of pretrends. Here, the concern would be that, for some unmeasured reason, counties already experiencing an upward or downward trend in entrepreneurship levels are also more likely to have R&D tax credits. For example, if urban settings that are more conducive to R&D policies also have more start-ups, localized changes in urbanization, rather than the availability of R&D tax credits, may be driving measured differences in entrepreneurship. When such unobserved factors exist and are not fully controlled for, then the observed impact of the R&D tax credit will be biased. We test for the existence of pretrends in several ways, such as by running models that estimate pretrends, by including additional controls that are most likely to be correlated with these pretrends (e.g., regional GDP), and by plotting individual coefficients for each lag/lead to the tax incentive.

Finally, a second concern is that the standard errors are biased downward when there exists correlation in the unobserved component across different observations in the same county (and which therefore are exposed to the same tax incentive), or between different counties in the same year. To account for these concerns, we use the multiway clustering approach (Cameron et al., 2011) and cluster our standard errors by both county and year.[8]

Data

To implement the empirical framework described earlier, we need to combine systematic measures of the quantity and quality of regional entrepreneurship with measures of tax policy and other control variables over time. We construct a data set including county-level measures of entrepreneurship from the SCP with measures of business tax credits from the Panel Database on Incentives and Taxes. We therefore review each of these data sources in turn.

The Startup Cartography Project Data Set[9]

The underlying data set consists of all new business registrations across 34 U.S. states (representing more than 80% of U.S. GDP) from 1988 through 2012 that satisfy one of the following conditions: (a) a for-profit firm in the local jurisdiction or (b) a for-profit firm whose jurisdiction is Delaware but whose principal office address is in the local state. Our analysis excludes nonprofit organizations as well as companies whose primary location is not in the state. The resulting data set contains 18,916,895 observations.

For each observation, we construct variables related to (1) growth outcomes (IPO or significant acquisition), (2) firm characteristics based on business registration observables, and (3) firm characteristics based on external data that can be directly linked to the firm (e.g., patents, trademarks).

1. Growth outcomes: The growth outcome, Growth, is a dummy variable equal to 1 if the firm has an initial public offering or is acquired at a meaningful positive valuation within 6 years of registration, as reported in the Thomson Reuters Securities Data Company (SDC) database.[10]
2. Firm characteristic measures based on business registration data: We first create two binary measures that relate to how the firm is registered: Corporation, which captures whether the firm is a corporation rather than an LLC or partnership, and Delaware, equal to 1 if the firm is registered in Delaware. We then create five additional measures based directly on the name of the firm. *Eponymous* is equal to 1 if the first, middle, or last name of the top managers is part of the name of the firm itself.[11] Our last measure relates to the structure of the firm name. Based on our review of naming patterns of growth-oriented start-ups versus the full business registration database, a striking feature of growth-oriented firms is that the vast majority of their names are at most two words (plus perhaps one additional word to capture the organizational form, such as "Inc."). We define *Short Name* to be equal to 1 if the entire firm name has three or less words, and 0 otherwise.[12] We then create several measures based on how the firm name reflects the industry or sector within which the firm is operating, taking advantage of the industry categorization of the U.S. Cluster Mapping Project ("US CMP"; Delgado et al., 2016) and a text analysis approach. We develop seven such measures. The first three are associated with broad industry sectors and include whether a firm can be identified as local (*Local*), traded (*Traded*) or resource intensive (*Resource Intensive*). The other five industry groups are narrowly defined high-technology sectors that are typically associated with high-growth firms, including whether the firm is within the biotech (*Biotech Sector*), e-commerce (*E-Commerce*), other information technology (*IT*), medical devices (*Medical Devices*), or semiconductors (*Semiconductor*) space.
3. Firm characteristic measures based on external observables: We also construct two measures related to quality based on data from the U.S. Patent and Trademark Office. Patent is equal to 1 if a firm holds a patent application within the first year and 0 otherwise. We include patents that are filed by the firm within the first year of registration and patents that are assigned to the firm within the first year from another entity (e.g., an inventor or another firm). Our second measure, Trademark, is equal to 1 if a firm applies for trademark protection within a year from registration.

Entrepreneurial Quality Logit Model. We use these data to estimate a logit regression model that allows one to examine how the presence or absence of a start-up characteristic correlates with the probability of growth. Table 1 reports our results for all start-ups between 1988 and 2006. The results are striking. We find an extremely strong (and robust) correlation between start-up characteristics and the probability of growth. Substantial changes in the predicted likelihood of a growth outcome are associated with characteristics observable in real time from business registration records as well as characteristics observable with a lag (e.g., patent and trademark applications). On one hand, start-ups founded as corporations are almost 390% more likely to grow. Similarly, firms with short names, and those using biotech industry descriptors, are (respectively) close to 90% and 130% *more* likely to grow. On the other, eponymous firms and those with local industry descriptors are 74% and 57% *less* likely to grow, respectively. Finally, these changes in predicted probabilities are multiplicative in nature: A start-up that registers in Delaware and applies for a patent in its first year is 210 times more likely to grow than a firm that only registers in its home state and does not apply for intellectual property protection.[13,14]

Quantitative Estimates of Entrepreneurial Quantity and Quality-Adjusted Quantity. These findings can be used to construct, for every registered firm in the data set, its underlying probability of growth at founding. The probability of growth for an average firm is very low (on the order of 1 in 3,500). However, for those firms with multiple start-up characteristics that positively predict growth, the probability of growth is dramatically higher (the top 1% of firms have a better than 1 in 100 chance of achieving growth outcomes). These estimates of

Table 1. Entrepreneurial Quality Logit Model.

	(1)
Eponymous	0.259*** (0.0257)
Short name	1.883*** (0.0406)
Corporation	4.916*** (0.204)
Trademark	4.280*** (0.264)
Delaware patent interactions	
Delaware	33.21*** (1.059)
Patent	49.44*** (2.970)
Delaware and patent	211.9*** (10.40)
Industry descriptors	
Local industries	0.465*** (0.0300)
Traded industries	1.152*** (0.0326)
Biotechnology	2.354*** (0.197)
E-commerce	1.075 (0.0511)
Medical devices	1.297*** (0.0664)
Semiconductor	1.862*** (0.337)
State FE	Yes
N	18,916,895
pseudo R^2	.264

Note. FE = fixed effect. All start-ups founded between 1988 and 2006. Dependent variable: IPO or acquisition within 6 years. Incidence rate ratios reported. We report the incidence rate ratios of a logit model performed on all companies born between 1988 and 2008 in 34 U.S. states. The predicted value of this regression is our measure of quality for individual firms, which we aggregate into regional statistics. The outcome variable of the regression is Growth a binary variable equal to 1 if the firm achieves an IPO or acquisition within 6 years and 0 otherwise. The regressors are all binary measures observed at or near the time of firm registration. Patent and Trademark are indicators developed by matching our data to USPTO records. They are equal to 1 if owns a patent or trademark within 1 year of founding (both granted and applied). All other measures are developed directly from our business registration records. Robust standard errors in parenthesis. The regression and data are described in further detail in Guzman and Stern (in press).
***$p < .01$.

entrepreneurial quality at the firm level can, in turn, be used to develop economic indices that simultaneously account for both the quantity and the quality of entrepreneurship (and that are outlined in the "Empirical Framework" section):

- *EQI*—the Entrepreneurial Quality Index—the *average* growth potential (or "quality") of any given group of new firms
- *RECPI*—the Regional Entrepreneurship Cohort Potential Index—the number of start-ups within a particular location or region expected to later achieve a significant growth outcome
- *REAI*—the Regional Entrepreneurship Acceleration Index—the ability of a region to convert entrepreneurial potential into realized growth

Each index calculates a different quantitative measure that incorporates the quality of entrepreneurship. The EQI, RECPI, and REAI indices are a better indication than possibly traditional methods as to how skewed the distributions are of growth potential and likely growth outcomes (and whether and to what extent a greater number of small- to medium-sized businesses could be expected to catalyze the same growth outcomes as a high-potential-growth firm).[15] Additionally, REAI systematically quantifies the ratio of r*ealized* to *expected* growth events for a given cohort of new firms, providing an indication of whether the ecosystem in which a cohort of new firms is located is conducive to growth. As such, these indexes offer policy makers and stakeholders a better view of whether and to what extent their regions are attracting/generating start-ups with high growth potential versus helping/hampering these firms' efforts to realize their potential.

Aggregating Across Locations. Finally, we aggregate our estimates for all firms in our sample. To do so, we use the registered ZIP code of each company to identify each county using the HUD USPS ZIP code crosswalk files. We then aggregate across each county and year to estimate quality, quantity, RECPI, and REAI based on the observed outcomes in each one. Our resulting data set is made publicly available on the SCP website.

Measuring R&D Tax Credits: The Panel Database on Incentives and Taxes[16]

To incorporate the incidence and existence of R&D and investment tax credits into our study, we take advantage of a new data set, the Panel Database on Incentives and Taxes, created by Bartik (2017). PDIT "estimates, from 1990 to 2015, marginal taxes and business incentives for an average firm in each of 47 cities in 33 states (reported in Figure 1B), and 45 industries over 26 years" (Bartik, 2017, p. 1). It simulates average taxes and incentives by considering the following scenario:

> a business in some industry i creates a new branch facility. That new facility is set up in some particular city c, in some state s, and starts operation in some year t. Taxes and incentives for the new facility are projected for the facility's first 20 years of operation, and the facility is assumed to operate at the same scale during that time.[17] ... To calculate state and local taxes for this new facility, data based on industry averages are used for the firm's balance sheet [(including for value-added, pretax profits, mix of property assets, employment, wages, and R&D spending).] From this balance sheet information, and from information on state and local

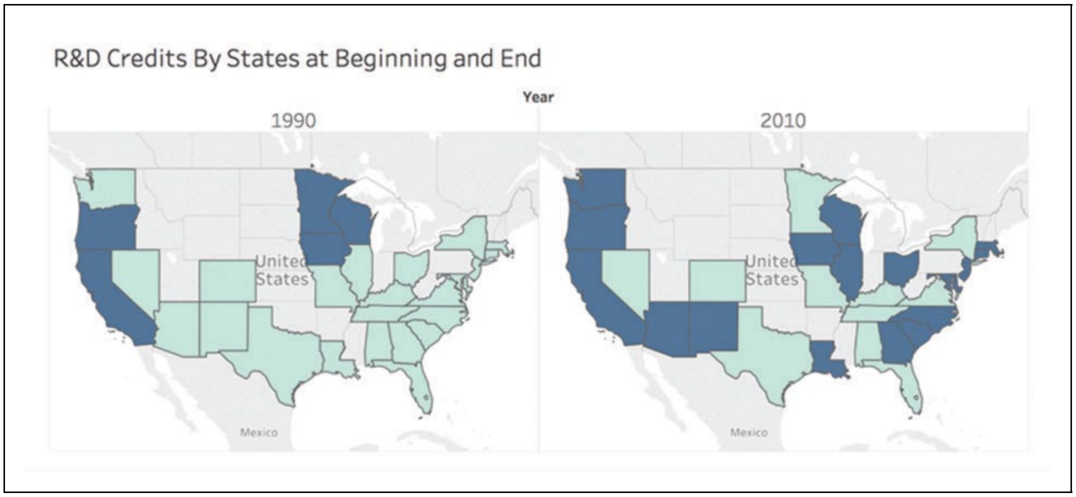

Figure 1. Distribution of tax credits.

Table 2. Summary Statistics.

	Count	*M*	*SD*
Startup Cartography Project			
Obs (quantity of entrepreneurship)	30,093	397.107	1947.699
RECPI (quality-adjusted quantity of entrepreneurship)	30,093	0.358	2.03
REAI (ecosystem effects)	30,093	0.637	6.529
Panel Database of Incentives and Taxes (PDIT)			
Has R&D credit	29,224	0.461	0.499
Has investment credit	29,372	0.383	0.486

Note. RECPI = Regional Entrepreneurship Cohort Potential Index; REAI = Regional Ecosystem Acceleration Index.

> business tax rates, and information on rules for how incentives are determined based on firm characteristics, state and local taxes and incentives are calculated for each year of the assumed 20 years of operation of the new facility. The present value of the 20-year stream of such taxes and incentives is calculated using a discount rate of 12%. (Bartik, 2017, p. 10)

The database thus describes "how business incentives vary over the term of a new business investment (from Year 1 to Year 20), and it breaks down incentives into different types," including investment tax credits and R&D tax credits[18,19] (Bartik, 2017, p. 2). It allows these incentives to be subjected to descriptive analyses, including "an examination of time trends in different types of incentives, and analysis of how incentives vary with a state's economic prosperity or with an industry's wage rates" (Bartik, 2017, p. 2).

Descriptive Statistics

Our data set merges the SCP data with PDIT, creating a complete panel of 25 overlapping U.S. states from 1990 to 2010 with 30,093 observations and 5 variables. Table 2 reports summary statistics. *Obs*, represents the count of individual registrations in each county-year. There are 397 new business registrants on average in a county and year. However, the distribution is highly skewed, with a standard deviation of 1,948. *RECPI* represents our headline index, the quality-adjusted quantity of entrepreneurship. It indicates the expected number of growth events given the founding characteristics of new businesses in a specific county and year. The mean is 0.37 with a standard deviation of 2. *REAI* indicates the ecosystem performance index, which is the ratio of realized growth events versus predicted growth ones. The mean is 0.64 with a standard deviation of 6.

We create two measures from PDIT reflecting the presence or absence of the indicated tax credits in the states in question. *Has R&D Tax Credit* is a binary variable equal to 1 if the county has an R&D tax credit during that year and 0 otherwise. Forty-six percent of the county-year observations have an R&D tax credit, allowing well-balanced variation in our data. To avoid issues particular to the transitioning year when the tax credit is introduced, we drop all county-year observations when the tax credit is introduced ($N = 869$), therefore, simply observing the time before and after the credit. *Has Investment Credit* is a binary variable equal to 1 if the county has an investment credit during the year of the observation and 0 otherwise. Thirty-eight percent of the observations in our sample have an investment credit. We drop the 721 observations representing county-year observations in which the credit is introduced.

Empirical Results

We now proceed to estimate the impact of R&D tax credits on the level of regional entrepreneurship through our difference-in-differences approach. In Table 3, we report the difference in the quantity of newly founded companies (*Obs*), the difference in the quality-adjusted quantity of companies (*RECPI*), and difference on the performance of companies conditional on being founded (*REAI*), for those counties that have an R&D tax credit versus those that do not. For *Obs* and *RECPI*, we use the logarithms as our dependent variables to control for skewness in the variables and to allow easier interpretation of our estimates as elasticities. However, we do not log *REAI* as it is already a ratio that can be directly interpreted. Standard errors are clustered two ways (by year of observation and county) to account for correlation in the error terms across either of those dimensions.

Model 1 is a naïve model without any controls. It reports the cross-sectional differences in the levels of entrepreneurship between locations that have R&D tax credits and those that do not. In a way, they represent the perceived differences in entrepreneurship for the casual policy observer or for those who might be doing a comparative analysis between regions at a point in time. We observe substantially more entrepreneurship in counties with R&D credits than without. Column 1 indicates that counties with R&D credits have 48% higher total quantity of firms. Column 2 indicates that they have 64% higher total quality-adjusted quantity of firms. Interestingly, column 3 shows a negative relationship between REAI and the R&D credit. Firms in counties with R&D credits are 14% *less* likely to achieve growth outcomes compared with firms in counties that do not have the credit.

Of course, cross-sectional differences like those of Model 1 are likely to suffer from significant omitted variable bias. For example, it is likely that locations that are more urban simply have more economic development support (which will include tax credits) and more firms, so that R&D credits and entrepreneurship will be positively correlated due to the omitted variable of urbanization. As well, variation in the business cycle would also influence the founding and quality of new companies and policy introductions. Unless the business cycle is accounted for, the estimates will be similarly biased.

Model 2 is our preferred difference-in-differences estimate. In Model 2, we control for constant differences across counties by including county fixed effects, and for the business cycle effects and other national shocks by including year fixed effects. If the choice to introduce an R&D tax credit in any state is random after

Table 3. The Impact of R&D Tax Credits on Regional Entrepreneurship.

	(1) Ln(Obs)	(2) Ln(RECPI)	(3) REAI
Model 1: Naive model (no controls)			
Has R&D credit	0.477*** (0.102)	0.642*** (0.104)	–0.137** (0.0697)
Model 2: Difference-in-differences (county, year fixed effect)			
Has R&D credit	0.0745* (0.0389)	0.0760** (0.0376)	–0.0265 (0.159)
Model 3: Difference-in-differences + County level pretrends			
Has R&D credit	0.0927** (0.0366)	0.104*** (0.0381)	–0.0973 (0.139)
Model 4: Difference-in-differences + State GDP			
Has R&D credit	0.0651* (0.0337)	0.0641** (0.0302)	–0.0193 (0.163)
Log(state GDP)	1.016*** (0.116)	1.293*** (0.125)	–0.776 (0.856)
Model 5: Difference-in-differences + pre/post time effects			
Years before credit (negative values)	0.00242 (0.00726)	0.00802 (0.00695)	–0.00246 (0.0719)
Has R&D credit	–0.0281 (0.0426)	–0.0332 (0.0451)	–0.0252 (0.173)
Has R&D credit × Years after credit	0.0230*** (0.00744)	0.0224*** (0.00698)	0.000648 (0.0151)

Note. GDP = gross domestic product. County-level pretrends is the predicted value of entrepreneurship for each county based on the noncredit years. Standard errors clustered two ways by county and year.
*$p < .1$. **$p < .05$. ***$p < .01$.

controlling for these two sources of endogeneity, then our estimate is identified.

Highlighting the important role of omitted variables in determining which counties eventually offer R&D credits, our estimates decrease significantly from the naïve model to the difference-in-differences model. Column 1 reports an average difference in the quantity of entrepreneurship of 7.5% between counties with R&D credits compared to those without, conditional on the fixed effects. Column 2 reports a difference of 7.6% for the quality adjusted quantity of entrepreneurship. Finally, in column 3, we report our estimate of the effect of R&D tax credits on the ecosystem performance, which is now equivalent to zero. These results emphasize a meaningful main effect of R&D tax credits on the rate of entrepreneurship for counties in our sample. Notably, the introduction of R&D tax credits increases the rate of entrepreneurship, but changes neither its composition nor its acceleration. Both the *quantity* and the *quality-adjusted quantity* of entrepreneurship increase in equal proportion. While counties with an R&D tax credit enjoy an increase in the rate of business formation, that increase reflects the same mix of entrepreneurial quality previously found in the region. Moreover, counties with an R&D credit are no more effective at helping start-ups to realize growth outcomes (relative to initial quality) than those without. Lowering the capital cost of R&D leads to more employee departures for entrepreneurship (Babina & Howell, 2018). Beyond potential knowledge spillovers, however, it does not appear to have broader ecosystem effects.

Robustness Tests

We now consider the potential threats to the validity of our estimate. As in most difference-in-differences panel models, the main threat to validity is the potential role of pretrends in our treated counties. While we control for fixed characteristics of counties and time periods, there can potentially be region-specific omitted variables that drive both entrepreneurship levels and the introduction of R&D tax credits, making our results artificially higher. For example, localized economic and population growth would increase the level of entrepreneurship in a region and might lead to legislative choices such as the introduction of tax credits. Conversely, however, the process of policy making is often driven by state-level elements of politics that are more random and might be uncorrelated with trends of entrepreneurship. In Models 3 and 4, we evaluate some potential threats to validity in our estimates by considering two obvious potential confounders, pretrends and the state economy.

In Model 3, we control for county pretrends by estimating the predicted value of entrepreneurship for each county if it had not implemented the R&D tax credit. Specifically, for all counties we estimate a county-specific trend coefficient using only the observations where *Has R&D Credit* is zero, then *predict* the level of entrepreneurship (either quantity, quality-adjusted quantity, or ecosystem effects) on all observations based on this trend. We include these predicted values as individual county trends for all observations. The point estimates of the impact of R&D tax credits are close to those of Model 2 (in fact, slightly higher) and the differences are not statistically significant.

In Model 4, we control directly for the most obvious potential bias in the policy-making process of state legislatures, the state-specific economy, by including the state GDP as a control directly in our regression. Once again, the point estimates are quite close to those of Model 2 and the differences are not statistically significant.

We move to a graphical analysis of pretrends in Figure 2, where we report the year-specific trends in the 5 years preceding the introduction of the R&D tax credit. To do so, we estimate regressions with time-specific coefficients in the years before and after the introduction of the R&D tax credit. Consistent with our other results, we do not observe any pretrends in either the quantity or the quality-adjusted quantity of entrepreneurship.

Together, our results provide compelling evidence of a lack of pretrends in the introduction of state R&D tax credits. This evidence suggests that the threats to validity do not hold in our estimates and, therefore, they can be interpreted as causal.

The Impact of State R&D Tax Credits Through Time

While we have observed a mean difference in the effect of state R&D tax credits on regional entrepreneurship, there is reason to believe that this effect would vary over time. We particularly expect R&D tax credits to have long-term effects on a local start-up ecosystem. For example, the credit might change not only the marginal cost of starting a company for those ideas already existing but also the supply of new ideas themselves as entrepreneurs and investors are motivated by the expectation of lower capital costs, thus, leading to longer term effects on regional entrepreneurship.

We study this possibility in Model 5 of Table 3. To do so, we change our core difference-in-differences specification in Model 2 to include time-varying effects through two variables. The first variable, *Years Before Credit*, is equal to the (negative) number of years prior to the tax credit's introduction and zero when the tax credit

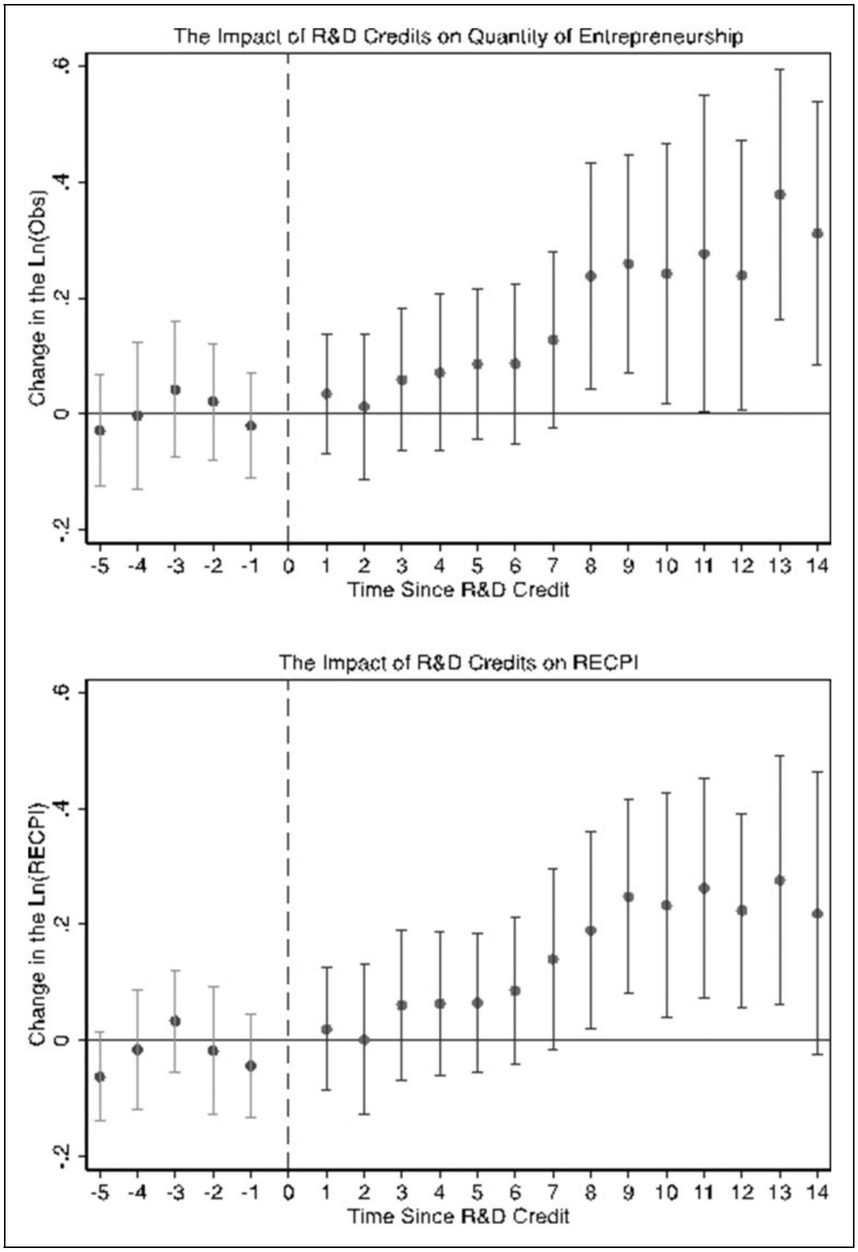

Figure 2. Year-by-year effects of R&D tax credits on entrepreneurship.

has been introduced. Its coefficient indicates the presence of pretrends in the data. The second variable *Years After Credit* is equal to the number of years after the tax credit is introduced and zero when it has not been included. We also include a level effect of R&D tax credit by keeping our main variable *Has R&D Credit*. Our estimates show no pretrends, highlighting once again that there is no conditional endogeneity in the introduction of the tax credit. We also show no effect on the main variable; however, we see a positive and significant coefficient of 0.023 of our time trend on the level of entrepreneurship for both quantity and quality-adjusted quantity. These estimates suggest that there is not an initial increase in entrepreneurship immediately following the introduction of a tax credit. There is, however, a subsequent improvement of 2% per year for every year the credit has been active.

We revisit these estimates with yearly coefficients after treatment in Figure 2 and observe the same increasing pattern. There is no increase in the level of entrepreneurship immediately following the introduction of the R&D tax credit. However, there is an upward trend that begins

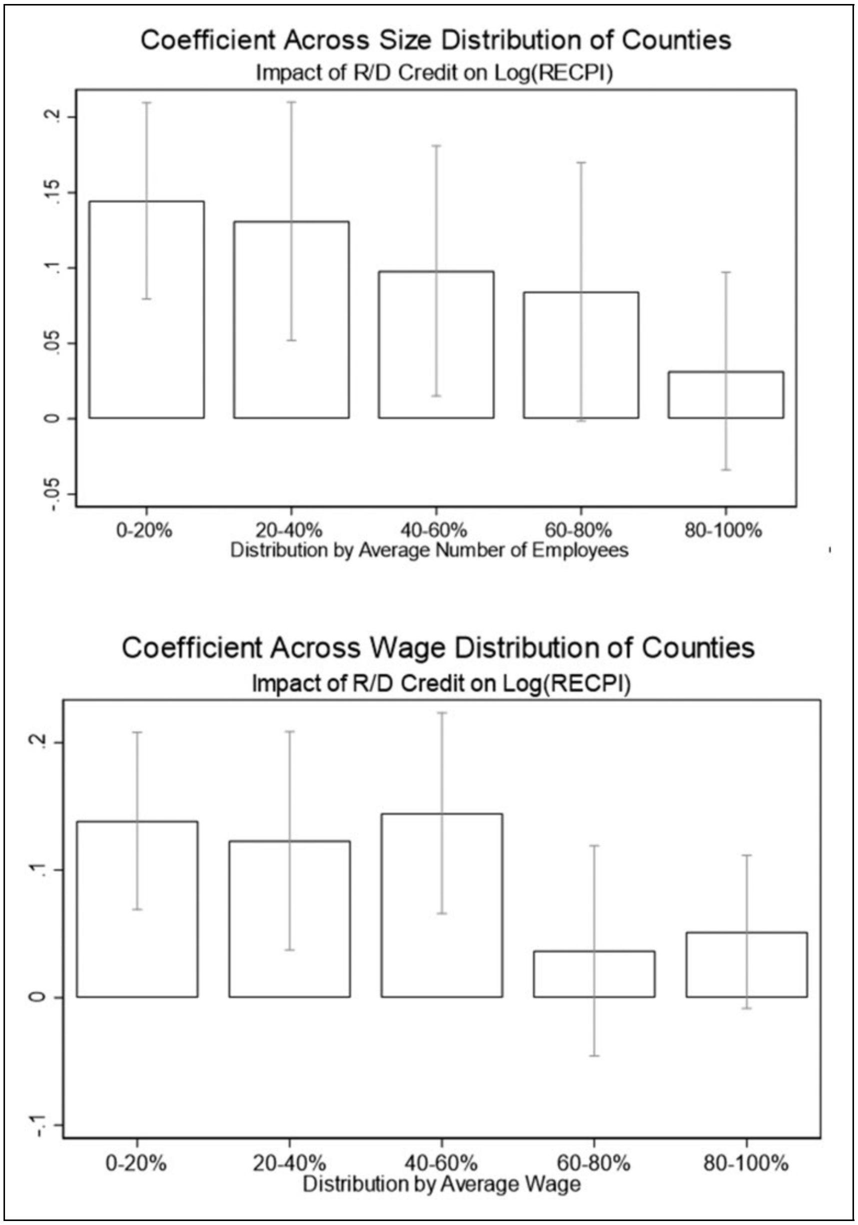

Figure 3. Tax credits across locations: (A) by county size and (B) by county average wages.

after Year 3 and continues up to Year 14. Consistent with our average increase of 2% per year in our regressions, we see a difference of about 20% in the level of entrepreneurship by Year 10.

Together, our results provide evidence showing that there is a significant effect of state R&D tax credits on the rate of entrepreneurship, but that this effect only accumulates through time. We believe that these differences provide important information on the nature and benefits of R&D tax credits for entrepreneurs. There is no pent-up supply of entrepreneurs that responds to a state R&D tax credit upon its introduction. Instead, the state R&D credit appears to improve the overall ecosystem making it more conducive to the incidence of entrepreneurship. For example, state R&D credits could increase the knowledge created within large companies, which could then lead to the spin-off of new start-ups down the line (Babina & Howell, 2018). Studying the specific channel for this indirect effect is an important question for future research.

Table 4. The Impact of Investment Tax Credits on Regional Entrepreneurship.

	(1) Ln(*Obs*)	(2) Ln(*RECPI*)	(3) *REAI*
Model 1: Naive model (no controls)			
Has investment credit	0.705*** (0.123)	0.352** (0.141)	−0.0586 (0.115)
Model 2: Difference-in-differences (county, year fixed effect)			
Has investment credit	−0.0527 (0.0385)	−0.0912** (0.0392)	0.104 (0.150)
Model 3: Difference-in-differences + County-level pretrends			
Has investment credit	−0.0465 (0.0380)	−0.0874** (0.0394)	0.264 (0.181)
Model 4: Difference-in-differences + State GDP			
Has investment credit	−0.0331 (0.0333)	−0.0661* (0.0348)	0.0901 (0.143)
Log(state GDP)	0.938*** (0.140)	1.199*** (0.146)	−0.664 (0.812)
Model 5: Difference-in-differences + Pre/post time effects			
Years before credit (negative values)	0.0154 (0.0175)	0.0122 (0.0147)	−0.0172 (0.0617)
Has investment credit	−0.0397 (0.0565)	−0.0359 (0.0554)	0.220 (0.161)
Has investment credit × Years after credit	−0.00608** (0.00244)	−0.0114*** (0.00268)	−0.0124 (0.0141)

Note. County-level pretrends is the predicted value of entrepreneurship for each county based on the noncredit years. Standard errors clustered two ways by county and year.
$^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

Who Benefits From the R&D Tax Credit? Heterogeneity Across Locations. Finally, we consider who benefits from R&D credits by looking at differences across locations. To do so, we match our data set to the U.S. Census County Business Patterns and consider two versions of heterogeneity: the size of the county (by total employment) and the average wage paid in the county.

Figure 3 presents our results. We split the sample across quintiles in the heterogeneity distribution and reestimate our main specification (Model 2) for each subsample independently. Our analysis indicates that poorer and smaller counties benefit more from state R&D tax credits than richer or larger counties. While the effect is high at the bottom of the distribution of each variable, it is not significantly different from zero at the top.

Investment Tax Credits

As an additional exercise, we repeat our analysis studying the impact of a different type of tax credit, the investment tax credit, on entrepreneurship. Table 4 repeats our estimates using the variable *Has Investment Tax Credit* as the independent variable. The regressions are otherwise the same.

Model 1 reports the naïve model, representing the cross-section correlation that would be observed by simply comparing the levels of entrepreneurship between those counties that have investment tax credits and those that do not. As is the case with R&D tax credits, the correlation is positive and substantial. Counties with investment tax credits have 71% higher quantity of entrepreneurship and 35% higher quality-adjusted quantity.

The relationship changes in Model 2, where we introduce county and year fixed effects. The relationship to entrepreneurship is now negative. Investment tax credits are associated with a decrease of 5% in the quantity of entrepreneurship, though not statistically significant, and a decrease of 9% in the quality-adjusted quantity, which is statistically significant. This is in sharp contrast to R&D tax credits, which showed a positive relationship to regional entrepreneurship.

Models 3 and 4 perform robustness tests on our data by including county pretrends (as explained for Table 3) and state level GDP. The results are mostly unchanged. The coefficients are close to the baseline estimate of Model 2 and are not statistically different from them. Figure 3 also shows the pretrends for the 5 years prior to the introduction of the credit. While slightly noisier than the R&D credits, we do not observe any pretrends on the process to introducing investment tax credits.

Model 5 considers the time-specific impact of investment tax credits on entrepreneurship. Our estimates indicate that there is no main effect from investment tax credits on the level of entrepreneurship, but that there is a negative trend, which is significant. For each year that the investment tax credit is active, there is a decrease of 0.7% in the quantity and 1.1% in the quality-adjusted quantity of entrepreneurship.

We look at these effects in more detail in Figure 4, which reports time-specific level coefficients for each outcome. There is a negative trend in the quantity of companies following the credit, but the pattern appears quite

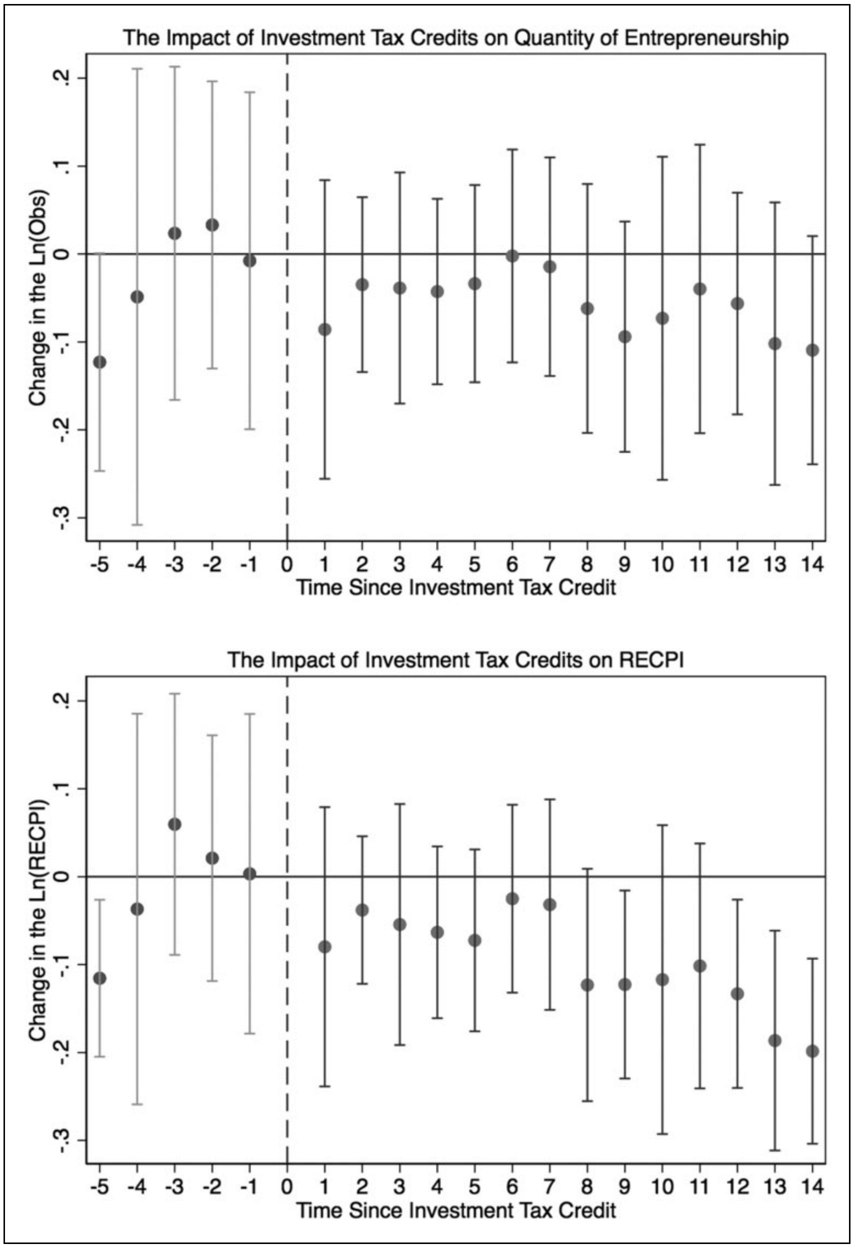

Figure 4. Year-by-year effects of investment tax credits on entrepreneurship.

noisy. It is more precise when considering the quality-adjusted quantity of entrepreneurship, where there is a negative trend that becomes more significant through time.

Generally, we conclude that the effects of the investment tax credit are negative on entrepreneurship and, more specifically, high-growth-potential firms. A potential interpretation of this effect is that these credits create a "crowding out" effect on investment in the region as the investment tax credit is taken advantage of by large companies. This stands in sharp contrast to the positive effects we identified for R&D credits, painting a nuanced picture of the role of tax incentives on entrepreneurship and its subsequent development, with both positive and negative effects being possible.

Conclusion

Innovation and entrepreneurship are central to economic growth and an increasing focus of state-level economic development policy. States are offering R&D tax credits to both encourage innovation and support high-technology clusters within regions. With the locus of innovation shifting to start-ups in high-tech industries and the majority of net new job creation resulting from the expansion of young high-potential-growth firms (Guzman & Stern, in press; Haltiwanger et al., 2013), state-level R&D tax credits must create high-growth entrepreneurship (either directly or through spillovers) to be an effective tool for economic development.

R&D tax credits appear particularly well suited for the creation of endogenous high-growth entrepreneurship in a region. These incentives lower the cost of capital and the incremental expense of research, encouraging investment in innovation and generating spillovers strengthening high-technology sectors within regions (Wu, 2008). Historically, such tax credits were designed for and used by established industries, leaving open the question of whether and to what extent R&D tax credits generate the type of entrepreneurship needed for economic growth and/or greater realization of growth outcomes. Our findings on state R&D tax credits offer a new lens through which to understand the impact of these fiscal incentives on both the rate of entrepreneurship and its composition, as well as the time it takes for effects to emerge. Our results on investment tax credits present an interesting counterpart against which the impacts of R&D tax credits may be compared and understood.

While state R&D tax credits increase the *quantity* and the *quality-adjusted quantity* of new firms founded in equal proportion, investment tax credits change the mix of new firm formation, decreasing the rate of high-growth-potential entrepreneurship credited with the majority of new job creation. The causal impact of R&D and investment tax credits on entrepreneurship take time to emerge and build over time. Over the long term, R&D tax credits empower regions to significantly increase both the quantity of entrepreneurship and number of expected growth outcomes. Counties with R&D tax credits experience a rise in the rate of new firm formation and the number of expected growth outcomes by 2% per year and 20% over a 10-year period. Similarly, the negative impacts of investment tax credits on the quality-adjusted quantity of entrepreneurship build over time, decreasing the incidence of expected growth outcomes by 1.2% per year and 12% in total over a 10-year period.

At the same time, our findings dampen expectations of states achieving an indirect ecosystem effect from the issuance of state R&D tax credits on the performance of start-ups found there. While state R&D tax credits "set the table" for increased rates of entrepreneurship, we find no causal relationship between the introduction of credits and later start-up performance.

Last, but not least, our results have important limitations. We do not study variation in the size of state R&D tax credits or their interaction with other credits in the economy. Our results are likewise estimated in the United States—a large and developed economy. They may or may not expand well to other smaller or less developed countries. In these respects, the evidence presented in our article represents a first pass to understand the impact of state R&D credits on local entrepreneurship and an opportunity for follow-on work.

Even with these limitations, our findings shed further light on the dynamics of growth entrepreneurship and the role that corporate investment in innovation has, albeit indirectly, on sustaining it. Our results lend support to the literature finding that growth entrepreneurship is a function of the ecosystem in which it takes root (Delgado et al., 2010). The rate and form of business dynamism experienced in an ecosystem is sensitive to the type and level of corporate investment made there. Indeed, poorer and smaller counties tend to gain more entrepreneurship from state R&D tax credits than richer or larger ones. Entrepreneurship spillovers from corporate investment are broad (in terms of impact on entrepreneurial *quantity* and *quality*), location based (in terms of the place of impact), and cumulative over the long term. The rate of new business formation responds to the ripple effect of increased corporate investment in their ecosystem, not the tax incentives itself.

Our findings also have important implications for policy design. First, and not surprisingly, the impact of tax incentives on entrepreneurship and its subsequent development is neither uniform nor unidirectional. Both positive and negative effects are possible. R&D tax credits generate the form of entrepreneurship needed for economic growth, while investment tax credits retard it. States offering both R&D and investment tax credits to stimulate high-growth entrepreneurship may be offering incentives that work at cross purposes.

Second, the differential impact of R&D and investment tax credits on the composition of entrepreneurial entry (i.e., the rate of formation of main-street vs. high-growth-potential start-ups) suggests that the structure of such incentives matters to later outcomes. State R&D tax credits generate substantial increases in the quantity and quality-adjusted quantity of new firms founded. By contrast, investment tax credits offered to established firms appear to crowd out the formation of new high-growth-potential start-ups.[20] Our findings leave open the prospect that policy experimentation with the intensity and terms of these fiscal incentives could identify structures that better amplify the type of entrepreneurship most needed for later economic growth.

Third, R&D tax credits offer no universal salve for accelerating entrepreneurial ecosystems. R&D tax credits do generate meaningful increases in the formation rates of growth-oriented start-ups. Indeed, recent research confirms labor reallocation as one important mechanism through which this effect occurs (Babina & Howell, 2018). However, counties with R&D credits are no more effective at helping start-ups to realize growth outcomes than those without. Thus, while R&D tax credits will lead to the creation of more growth-oriented start-ups, policy makers cannot also count on R&D tax credits to improve those start-up's performance. Policy makers should consider complementing R&D tax credits with other programs and initiatives to support start-ups as they scale.

Finally, our findings suggest a time horizon over which policy impact from R&D and investment tax incentives may reasonably be expected. R&D tax credits do not offer a "quick fix" for states seeking to stimulate regional economic growth through entrepreneurship (nor will investment tax credits spark a rapid decline in the number of expected growth outcomes from start-ups). Higher entrepreneurial entry does not immediately follow the introduction of a state R&D tax credit. There exists no pent-up supply of high-growth-potential start-ups discouraged from entering, at the margin, by the high cost of capital. Instead, our cross-sectional results suggest that regional variation, and innovation and entrepreneurship initiatives, likely are stronger contributors to near-term growth in the formation rates of high-growth-potential start-ups. And, the impact of R&D and investment tax incentives compound to substantial levels (albeit in opposite directions) over a 10-year period.

Overall, our research indicates that fiscal incentives have the potential to play a key role in sustaining and enhancing entrepreneurial ecosystems. Our findings counsel in favor of leveraging R&D tax credits as one arrow in the quiver of a long-term "patient policy" at the ecosystem level and experimenting with alternative incentive designs geared toward prerevenue and innovation-driven start-ups.

Acknowledgments

We thank Evan Absher, Brian Asquith, Tim Bartik, George Erickcek, Lee Flemming, Evan Mast, and Peter Orazem for helpful comments, as well as participants in the Upjohn Institute Conference on the Effects of State and Local Tax Incentives on Business Location Decisions and the Kauffman Uncommon Methods and Metrics meetings. Yu-Ting Chen and Yupeng Liu did excellent research assistantship in this project. All errors and omissions are of course our own.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: We acknowledge and thank the Kauffman Foundation for its support of our research agenda, including the Uncommon Methods and Metrics grant that supported this project. We also thank the Jean Hammond (1986) and Michael Krasner (1974) Entrepreneurship Fund and the Edward B. Roberts (1957) Entrepreneurship Fund at MIT for their support.

Supplemental Material

The supplemental material for this article is available online.

Notes

1. The PDIT panel centers on "incentives that are commonly used by medium to medium-large export-base firms" and excludes fiscal incentives geared toward incentivizing angel investment in prerevenue start-ups (Bartik, 2017).
2. State-level investment tax credits have similarly proliferated over the past four decades, notwithstanding the repeal of the federal investment tax credit upon which they were modeled. As of 2004, 40% of states offered a general, statewide tax credit on investment in machinery and buildings with an average rate exceeding 4% (Chirinko & Wilson, 2008; Figure 1). Research finds positive impact from these incentives on investment (although of varying magnitude; Bartik, 2018). We are not aware of research that considers the impact of general investment tax credits on entrepreneurial activity. However, in their evaluation of the federal investment tax credit prior to its repeal, Auerbach and Summers (1979) credited such incentives with "crowding out of non-favored investment" at a level sufficient "to offset a large percentage of the increase in the stock of equipment resulting from use of the credit." Accordingly, although likewise aimed at established firms, we would not expect state investment tax credits, as traditionally formulated, to have a positive impact on the creation of entrepreneurship. The effects of general investment tax credits on entrepreneurship, thus, offer a useful counterpart against which to compare similar analysis of the impact of state R&D tax credits.
3. The closest related article is Wu (2008), who considered how the introduction of state R&D credits changes the number of total active firms in the high-technology sector. However, Wu's data did not allow him to actually

separate between the entry and exit margins, or consider the varying quality of those firms that are marginally enticed to enter after the introduction of R&D credits.

4. Drawn from Mukherjee et al. (2017). *See* Hall and Van Reenen (2000) for a comprehensive survey on this topic. Because firms are known to relabel other costs as R&D in an effort to claim tax credits, it can be difficult to ascertain whether the R&D spending response to tax changes reflects changes in productive innovative inputs as opposed to creative accounting. Recent research establishes that firms differ widely in the productivity of their R&D investments (Hirshleifer et al., 2013) and these differences in innovative efficiency translate into differences in future sales (Cohen et al., 2013).
5. Drawn from Gale and Brown's (2013) survey of the literature considering how federal tax policy affects small business.
6. This section draws heavily from Guzman and Stern (2017, in press), where these measurement statistics were introduced.
7. A key assumption to interpret this coefficient is that the unexplained portion of the predicted performance is randomly distributed across locations. In our empirical setting, we cluster by location and year, thus, allowing for these two dimensions to be correlated but assume the rest is i.i.d (independent and identically distributed).
8. A different approach could instead be to cluster by state and year, rather than county and year. As indicated in Abadie et al. (2017), choices of clustering depend on the conceptual experiment being answered. In our case, the focus of our analysis is county-level entrepreneurship and its variation over time, and so we believe that county-level clustering is more adequate.
9. This section draws heavily from Guzman and Stern (in press), where business registration records and many of the measures used in this article were introduced.
10. Although the coverage of IPOs is likely to be nearly comprehensive, the SDC data set excludes some acquisitions. SDC captures its list of acquisitions by using over 200 news sources, SEC filings, trade publications, wires, and proprietary sources of investment banks, law firms, and other advisors (Churchwell, 2016). Barnes et al. (2014) compared the quality of the SDC data with acquisitions by public firms and found a 95% accuracy rate (Netter et al., 2011, also performed a similar review). While we know these data not to be perfect, we believe them to have relatively good coverage of "high value" acquisitions. We also note that none of the cited studies found significant false positives, suggesting that the only effect of the acquisitions we do not track will be an attenuation of our estimated coefficients.
11. Belenzon et al. (2017, 2018) performed a more detailed analysis of the interaction between eponymy and firm performance, finding an important negative relationship between an intent to use equity financing and eponymy.
12. Companies such as Akamai or Biogen have sharp and distinctive names, whereas more traditional businesses often have long and descriptive names (e.g., "New England Commercial Realty Advisors, Inc.").
13. It is very important to emphasize that these start-up characteristics are not the *causal* drivers of growth, but instead are "digital signatures" that allow us to distinguish firms in terms of their entrepreneurial quality. Registering in Delaware or filing for a patent will not guarantee a growth outcome for a new business, but the firms that historically have engaged in those activities have been associated with skewed growth outcomes.
14. The precision allowed by our definition of quality comes nonetheless at a cost. Our definition does not allow us to include all the richness of social outcomes through which companies help communities or individuals. In principle, however, a richer version of our approach that includes multiple outcomes and a larger number of observables might be able to achieve this result.
15. The level of skewness of entrepreneurial quality is highly informative. It indicates how much more likely a start-up at the high end of the entrepreneurial quality distribution is to grow than an average firm. If skewness were low, then adding several average firms could have as much regional impact as one high-growth-potential firm. But, if skewness is high (as the findings indicate), then a much larger number of firms with average growth potential is needed to generate the expected impact of one high-growth-potential firm. Given the level of skewness observed, almost 4,000 local limited liability companies (average firm) are needed to generate the same potential as only one new Delaware corporation with an early patent and trademark. Put another way, initial ambition/potential for growth is a key dimension of heterogeneity across new firms. The subset of high-potential-growth start-ups is very small and fundamentally different than the vast majority of new firms.
16. This section draws heavily (if not verbatim) from Bartik (2017).
17. "In assigning taxes and incentives to this new facility over the 20 years, the same incentive and tax rules in place for year t are assumed to remain unchanged through year $t+20$. This assumption can be seen as taking the perspective of a business that myopically projects current tax and incentive rules into the future. (When taxes and incentives are calculated for the same city and state in some future year t1, the tax rules and incentives for year t1 are carried forward for 20 years.)" (Bartik, 2017, p. 10)
18. We distinguish general state investment tax credits from ones targeted toward encouraging early-stage capital investment (which are not included in PDIT; Bartik, 2017), and therefore, not the subject of our analysis). Bell et al. (2013) found that more than 30 states offered targeted angel investment tax credits as of 2012 and that these incentives were correlated positively with an increase in the quantity of state-level entrepreneurial activity within 2 years after introduction.
19. PDIT does not include all tax incentives offered across all states. Instead, it centers on "incentives that are commonly used by medium to medium-large export-base firms." "The goal [of PDIT] is to measure the "standard deal" that

would be offered to a medium-sized export-base new facility that the state and city wished to attract. These incentives may not be offered to all firms, but they are commonly offered to many firms" (Bartik, 2017, p. 25). As such, investment tax credits targeted at specific sectors (such as the biotechnology sector) or start-up firms (such as angel investment tax credits) are not included in the PDIT panel.

20. Our findings do not foreclose the possibility, however, that more targeted investment tax credits, such as those specifically tailored toward supporting the biotech industry or angel investment, could have the opposite effect. Bell et al. (2013), for example, found an increase in the quantity of entrepreneurship in the 2 years following the implementation of an angel investment tax credit. Further research is needed to study the impact of more tailored investment tax credits on the composition of new firm formation and, more specifically, the quality-adjusted quality of entrepreneurship. Similarly, consideration of whether and to what extent the level of R&D credit offered and its terms impact the composition of entrepreneurship generated (i.e., its extensive margin), while beyond the scope of this article is likewise an important subject for future research.

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