The Policy Trade-off: How State R&D Incentives Affect Startups Pursuit of Federal Funding

April Burrage

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Abstract

Do state R&D policies shape entrepreneurial decisions regarding the pursuit of Federal funding? Using data from business registrations and firm enrollments in the Federal System for Award Management (SAM), this paper investigates how state policies influence the behavior of young high-tech firms *startups*. I employ a hazard rate model to examine in-state dynamics, focusing on how the implementation of state R&D tax credit adoption affects these startups' interest in federal funding. The findings reveal that state R&D tax credits significantly alter startup behavior, potentially substituting state incentives for federal funding opportunities. These results underscore the complex interaction between state and federal innovation policies, suggesting that more coordinated policy approaches may be necessary to ensure startups effectively access and leverage federal procurement.

JEL Codes: H25, L26, O31, O38

Keywords: Innovation policy, Entrepreneur Choice, R&D tax credits

1 Introduction

The funding landscape for startups has become increasingly constrained, particularly in the wake of the recent downturn in the technology sector (The New York Times, 2023). Entrepreneurs today face mounting challenges, including reduced access to venture capital and rising innovation costs. In 2023 alone, 3,200 venture-backed startups closed, marking a 58% increase in failure rates by mid-2024 (Edwards, 2024). The growing difficulty in securing private investment has made alternative funding channels, increasingly important for startup survival.

Using a novel dataset of state business registration records and federal firm registration database. This paper examines how state R&D tax credits influence firms' likelihood of registering in the System for Award Management (SAM), a necessary precursor to bidding on federal procurement opportunities. I propose that state R&D tax credits create a substitution effect, leading firms to prioritize state-level incentives over federal procurement opportunities. This effect may also resemble a crowding-out dynamic if startups, facing administrative or resource constraints, limit their engagement with multiple funding sources simultaneously. Firms optimize their R&D investment levels based on expected returns and the cost of available funding. When state tax credits reduce the cost of R&D capital, startups may reach their desired investment level without seeking interest in additional public funds, thereby decreasing their incentive to register for federal procurement.

Given well-documented market failures in R&D investment—where private markets systematically underinvest due to the public-good nature of innovation—governments often intervene with fiscal incentives such as R&D tax credits (Hall and Van Reenen, 2000). Prior research demonstrates that R&D tax credits stimulate firm-level R&D investment by lowering innovation costs (Agrawal et al., 2020; Johnson et al., 2022). However, little is known about whether these tax credits complement or substitute other public funding mechanisms, particularly federal grants and procurement programs. Since federal grants often involve extensive and competitive application processes, startups may strategically allocate their limited time and administrative resources, potentially bypassing federal opportunities in favor of less administratively burdensome state incentives.

To empirically test this hypothesis, I employ a Cox proportional hazards model using a novel panel dataset of 8,443 startup firms across 18 states from 2000 to 2021. I hypothesize that firms in states that introduce an R&D tax credit will be less likely to register in SAM compared to firms in states without such incentives. The findings confirm this hypothesis, showing that state R&D tax credits significantly reduce the likelihood of SAM registration, with firms being 46.9% less likely to register after their state introduces a tax credit. A

time-varying coefficient for the Post-R&D tax credit reveals that this effect remains stable over time.

Beyond this primary result, I find two additional key insights. First, the reduction in SAM registration is more pronounced as the are particularly responsive to state tax incentives, potentially foregoing federal procurement opportunities in favor of more immediate financial relief. Second, the effect is heterogeneous across industries, with firms in capital-intensive sectors such as manufacturing and semiconductor production exhibiting a stronger decline in registration compared to firms in service-based or software-focused industries. This industry variation suggests that tax credits may be disproportionately shaping funding strategies in sectors where upfront investment costs are highest.

This study contributes to the literature on entrepreneurial finance and public policy by empirically demonstrating how state-level innovation policies shape startups' strategic funding decisions. Much like uncertainty in intellectual property rights affects technology commercialization (Gans et al., 2008), the interplay between different policy incentives may unintentionally alter startup behavior, creating new trade-offs in how startups seek investment opportunities. Understanding these dynamics is critical for policymakers seeking to design complementary funding mechanisms that encourage broad-based participation in innovation-driven entrepreneurship.

The remainder of this paper is structured as follows: Section 2 provides background on innovation policy . Section 3 describes the data. Section 4 outlines the empirical strategy. Section 5 presents the results, and Section 6 concludes. Section 7 contains figures and tables, while Appendix A provide additional methodological details, the fuzzy matching procedure, and sample Python code for data processing.

2 Innovation Policy and Entrepreneurship Choice

Since the 1980s, U.S. states have become increasingly proactive in pursuing economic growth and innovation through dedicated R&D policies. Initially motivated by competition for attracting high-tech industries, these state-level interventions expanded significantly, reflecting a broader policy shift toward decentralized innovation strategies (**?**). State innovation policies primarily use supply-side mechanisms such as R&D tax credits, which reduce the effective cost of innovation activities, thereby incentivizing firms to increase investment. By contrast, federal-level policies often employ both supply-side incentives (grants, tax breaks) and demand-side mechanisms (such as procurement contracts), which directly create or stimulate markets for innovation (Mulligan et al., 2022; Guerzoni and Raiteri, 2015).

Startups, often conduits of disruptive innovation, contribute significantly to innovation

outcomes and overall economic progress (Guzman and Stern, 2020; Adelino et al., 2017; Haltiwanger et al., 2013; Hicks and Hegde, 2005). While existing literature extensively documents the positive effects of federal-level innovation policies on firm innovation and commercialization outcomes, far fewer studies examine interactions between federal and state-level incentives (Lanahan et al., 2021; Mulligan et al., 2022). This study contributes by specifically investigating how these two tiers of policy interact and identifying potential unintended substitution effects that could impact decisions of startup founders.

Innovation policies span a variety of approaches, including direct financial incentives such as grants, tax incentives, and public venture capital, as well as regulatory frameworks designed to stimulate entrepreneurial and innovative activity. The innovation policy mix framework emphasizes the interaction and collective impact of these diverse policies in shaping innovation outcomes (Flanagan et al., 2011). Previous research underscores the effectiveness of state-level R&D tax credits in promoting high-tech enterprises and entrepreneurial growth (Fazio et al., 2020; Wu, 2008). Smaller firms, frequently serving as sources of disruptive innovation, are crucial to innovation outcomes and economic progress (Adelino et al., 2017; Haltiwanger et al., 2013; Hicks and Hegde, 2005).

However, existing scholarship predominantly focuses on federal-level policies (Lanahan, 2016), neglecting the increasingly influential role of state-level interventions since the 1980s. The growing prominence of state-level innovation policies warrants a deeper investigation of how state-level interventions interact with federal policy goals, particularly in influencing startups' strategic engagement with public funding opportunities. This study contributes to the evolving discourse by underscoring the role of state-level policies in shaping innovation outcomes. This contextual shift underscores how state-level policies influence innovation outcomes, access to public support, and the commercialization process.

2.1 Substitution Effect

State-level R&D tax credits are fiscal incentives designed to lower the effective cost of innovation by allowing firms to reduce their state tax liabilities proportionally to qualified research expenditures. These credits typically encourage increased private-sector investment in R&D by lowering its after-tax cost, thus incentivizing higher overall R&D expenditures by firms Melnik and Smyth (2024). Entrepreneurs face substantial strategic uncertainty when choosing among alternative funding opportunities and evaluating policy incentives. When the market for startup financing functions well, founders efficiently pursue the most advantageous funding opportunities, and, moreover, they do so without delay Arora et al. (2023). Founders navigate various strategic decisions when assessing their resource options,

adjusting their choices to the relative attractiveness of available alternatives. This section considers how state-level R&D tax credits might substitute firms' interest in pursuing federal funding opportunities, particularly for new high-tech startups, based on the substitution effect.

The substitution effect describes how firms and individuals alter their choices when faced with shifting incentives or constraints. Entrepreneurs may adjust their behaviors by substituting one resource or activity for another depending on changes in policy incentives, perceived uncertainty, or institutional environments Guzman et al. (2024); Dechezleprêtre et al. (2023). In this context, startups may delay or forgo interest in SAM registration if state R&D tax credits provide sufficient financial relief or are more accessible.

Zellweger and Zenger (2023) conceptualize entrepreneurs as scientists who manage uncertainty systematically by forming beliefs, testing these beliefs in the market, and updating strategies based on received feedback. Agrawal et al. (2021) argue that entrepreneurs frequently encounter situations where it is difficult to disentangle whether an outcome results from the underlying quality of an idea or the effectiveness of a specific strategic choice. Given that startups have to make critical decisions with the constraints of time and resources, R&D tax credits at the state level may be more obtainable than interest in federal procurement which is a multi-step process.

This paper investigates how policy instruments may unintentionally shift founders' incentives, potentially shaping the broader effectiveness of public efforts to stimulate high-tech entrepreneurship.

3 Data

My analysis uses a sample of 8,443 high-tech startup firms observed between 2000 and 2021. To specifically focus on startups, I limit the sample to firms within six years of their establishment date. Furthermore, following the Small Business Administration (SBA), I define small firms as those employing 500 or fewer individuals. The treatment group includes firms located in states that implemented an R&D tax credit between 2003 and 2016, which were still active at the end of the sample period (2021). This group comprises Arkansas, Florida, Louisiana, Michigan, Nebraska, New Mexico, New York, Ohio, and Vermont. The control group consists of firms from states that never enacted R&D tax credits before or during the 2000–2021 period: Alabama, Alaska, Kentucky, Mississippi, Nevada, South Dakota, Tennessee, and Wyoming. Virginia and Colorado, which implemented R&D tax credits but lacked owner demographic data, were excluded from the analysis. The treatment and control groups can be found in Figure 1.

Active startup information was collected from Data Axle, (formerly known as Reference Solutions), is a database that provides state-level information on active businesses. I focus on for-profit small businesses, defined by the SBA, that are registered as a corporation, LLC, or partnership and have their primary location within the state. The data gathered include key information such as the year the firm was established, location, primary NAICS industry, number of employees, owners' names, and demographic information.

I utilize the System for Award Management (SAM) database to measure domestic small firms interested in federal funding. SAM is a public database that includes businesses seeking federal contracts and grants. Businesses must register with SAM to apply for federal grants, loans, and contracts, and their registration must be renewed annually. Firms must answer various questions, including topics such as Core Business Questions, Representation and Certification, and Financial Information. The information is then verified by the General Services Administration (GSA), and once approved, startups can apply for federal procurement opportunities. To gather data on annual active SAM-registered businesses from 2000 to 2021, I use the entity management API. This API provides unclassified data, including key variables such as business name, primary location, initial SAM registration date, and primary NAICS code.

To creae the dataset I linked the state business registration data with SAM business registration records. To specifically focus on high-tech startups, I follow the definition by Heckler (2005), identifying industries that (1) employ a significant proportion of scientists, engineers, and technicians; (2) have substantial R&D activities; (3) produce high-tech products; or (4) use advanced technological production methods. This definition is commonly used in similar literature (Atkins and Burrage, 2025; Qian and Haynes, 2014; Azoulay et al., 2009). The specific 12 NAICS industries included are listed in Table 1.

I used Python's record linkage module for fuzzy matching based on legal names and locations to combine the datasets, employing manual verification of matches (see Appendix A for a detailed description of the matching process). Key variables in the final dataset include the year the firm was established, location, primary NAICS industry, employee count, owners' names, SAM registration dates, and self-identified owner demographics.

To measure startup activity accurately, only firms within their first six years of operation are included. Furthermore, I define small firms according to the SBA as those with 500 or fewer employees. I cross-reference the sample from Data Axle with the Systems for Award Management database to identify high-tech small firms interested in federal grants. I identified 1,318 firms that expressed interest in federal grants, which is 15 percent of firms identified in the sample.

Figure 2 displays the sample construction process.

3.1 R&D Tax Credits and Panel Database on Incentives and Taxes

The R&D Tax Credit information derives from the publicly available Panel Database on Incentives and Taxes (PDIT) database compiled by the Upjohn Institute (Bartik, 2017). Data from PDIT span 33 states and 45 industries, covering over 90 percent of U.S. output and labor compensation. The database provides yearly information on taxes paid and incentives received by a business for a new hypothetical facility started in that year. For the seventeen states not included in the dataset, existing research on state R&D was used to verify if the state had an R&D tax credit (Wu, 2008; Wilson, 2009).

3.2 Summary Statistics

In Table **??**, I report the means, standard deviations, and observations for the identified high-tech firms, highlighting their industry composition and geographic distribution. Among high-technology industries, the most represented sectors are pharmaceutical and medicine manufacturing (40.2%), scientific research and development (29.1%), and semiconductor and electronic manufacturing (19.3%). In contrast, industries such as aerospace product manufacturing, architectural engineering, and computer manufacturing have a much smaller share of firms. This variation in industry representation reflects differences in firm formation patterns within the high-tech sector. The highest concentration is in Florida (43.3%) and New York (15.1%), while states such as Alaska (1.2%), Mississippi (1.1%), and Wyoming (0.4%) have relatively few firms in the sample. The geographic spread of firms enhances the external validity of the analysis, ensuring that findings are not driven by any single region or economic structure. 1.7% of starts up in the dataset registered in System of Award Management which indicates interest in federal procurement opportunities.

In Table 3, I present the average capital expenditure for different sectors. Following Lofstrom and Wang (2009), I classify an industry as capital-intensive if its average startup costs place it in the top one-third of all sectors. The information sector has the highest average startup costs at $1.45 million, followed by components and parts manufacturing ($932,160) and general manufacturing ($807,992). In contrast, science and technology (S&T) services have significantly lower startup costs, averaging $24,684. This variation in capital requirements highlights differences in the financial constraints firms may face upon entry and the role of capital intensity in shaping industry dynamics.

3.3 Hypothesis

I anticipate that the implementation of a state R&D tax credits will decrease a startups interest in federal procurement opportunities

I hypothesize that U.S. state research and development (R&D) tax credits serve as substitutes, rather than complements, to federal funding initiatives because firms use these financial mechanisms interchangeably to support eligible expenses. The availability of state R&D tax credits may discourage firms from seeking federal funding by providing a less burdensome alternative. Unlike federal grants, which are highly competitive and require extensive application processes, state R&D tax credits are non-competitive, widely accessible, and impose fewer administrative and time constraints. As a result, firms that can offset R&D costs through state tax incentives may have less incentive to invest time and resources in pursuing uncertain federal funding opportunities.

This substitution effect is particularly relevant because state R&D tax credits operate independently of federal funding initiatives. In contrast to Pless (2022), who find that R&D tax incentives in the UK complement federal grants due to their alignment within the same level of government, state R&D tax credits in the U.S. function at a different jurisdictional level. Because the state tax credit is not designed to enhance federal R&D initiatives, it is unlikely to increase firms' interest in federal funding. Instead, the presence of a state tax credit may reduce firms' need to pursue competitive federal grants, further reinforcing the substitution effect.

Prior research supports the idea that tax incentives and direct funding may not always complement each other. Studies show that startups exhibit only temporary increases in R&D spending following the adoption of federal R&D tax credits, while state R&D tax credits do not significantly boost firm innovation or patenting activity in the U.S. (Rao, 2016; Melnik and Smyth, 2024). Similarly, in Canada, small firms that lacked tax liabilities increased R&D spending only when tax incentives were refundable, meaning they provided immediate financial relief (Agrawal et al., 2020). However, these studies do not examine whether firms shifted away from grant applications after adopting tax incentives, leaving open the question of whether the availability of state tax credits reduces firms' reliance on competitive grants.

Given these factors, I propose that the introduction of state R&D tax credits does not simply leave firms' federal funding behavior unchanged—it actively discourages firms from engaging with competitive federal grant programs. If firms perceive state tax credits as a reliable and less complex alternative, they are likely to substitute tax incentives for federal funding, reducing overall demand for grants. Future research should examine whether this shift leads to long-term changes in firms' innovation strategies and the composition of federal grant applicants.

4 Empirical Strategy

My objective is to examine how state policies affect the timing of startup interest in federal funding. The primary empirical strategy exploits variation in the timing of when startups first register in the System for Award Management (SAM) relative to the implementation of state-level research and development (R&D) tax credits. For each startup, I observe annual data from the firm's establishment year up to six years following its founding (including the founding year), covering a total of 8,443 firms in the dataset. A key feature of the dataset is the distinction between states with and without research and development (R&D) tax credits, which serves as a natural treatment and control framework for analyzing the impact of these incentives on firm behavior. This variation in state tax policy allows for a comparison of firms operating under different incentive structures, providing a more rigorous assessment of how R&D tax credits influence firm registration and participation in high-tech industries.

The failure event in the study is the registration of firms in the System for Award Management (SAM), which is necessary for bidding on federal contracts. Our primary independent variable is *Post R&D Tax Credit*, indicating whether a firm's state has implemented an R&D tax credit, regardless of whether the firm actually utilizes the tax credit. This allows us to assess the impact of state-level R&D tax credit implementation on firms' likelihood of registering in SAM.

I define $register_{it}$ as equal to 0 until the year in which the startup first registers with SAM (a unique, absorbing event). I also define a time-varying regressor, $PostR\&DTaxCredit$, equal to zero from the year the firm is established until the year when the firm's state implements a R&D tax credit, and equal to one thereafter. Some firms may have registered in SAM prior to their state implementing a R&D tax credit. For example, consider two hypothetical startups, Company X and Company Y. Company X was founded in 2005 in a state that introduced an R&D tax credit in 2008. Thus, $PostR\&DTaxCredit$ equals zero from 2005 to 2007, then becomes one from 2008 onward. Company X registers in SAM in 2009, making $register_{it}$ equal to 0 until 2008 and 1 from 2009 onward. Company Y was founded in 2000 in a state that implemented an R&D tax credit in 2001. Hence, $PostR\&DTaxCredit$ equals 0 in 2000 and 1 starting in 2001. Company Y registers in SAM in 2002, resulting in $register_{it}$ being 0 until 2001 and 1 from 2002 onward.

I use a Cox proportional hazards model with time-varying explanatory variables. This continuous-time model defines the hazard rate by combining a non-parametric baseline hazard rate with a multiplicative term. This term allows the regressors to proportionally influence the hazard rate relative to the baseline Lancaster (1990). Let equal the hazard rate of

firm registering in SAM from zero to one, allowing for stratification by industry and including controls for observable factors.

$$h(t \mid Z_i, X^t_{\text{RD},i}) = h_0(t) \exp(\beta_0 + \beta_Z Z_i + \beta_{\text{RD}} X^t_{\text{RD},i}) \tag{1}$$

I model the hazard $h(t \mid Z_i, X^t_{\text{RD}i})$ of firm i registering in the System for Award Management (SAM) at time t using a Cox proportional hazards framework with time-varying covariates. The hazard function represents the instantaneous risk of registration given firm-specific characteristics Z_i and the time-varying effect $X^t_{\text{RD}i}$ of state-level R&D tax credits on the firm's decision to register. The baseline hazard $h_0(t)$, which may be stratified by factors such as industry or geographic location, captures the underlying risk over time absent the influence of the covariates. Firm characteristics Z_i, including ownership type and sector, account for inherent differences between firms that may affect their propensity to register. The inclusion of the time-varying covariate $X^t_{\text{RD}i}$ allows us to assess how changes in state-level R&D tax credits influence the hazard of registration over time.

To accurately assess the effect of state-level R&D tax credits—the treatment effect in our study—while accounting for unobserved heterogeneity, it is important to recognize that firm-specific characteristics Z_i influence the hazard rate continuously over time. In contrast, the time-varying covariate $X^t_{\text{RD}i}$ affects the hazard rate only after the implementation of the R&D tax credits (as per Abbring and van den Berg 2003). The dataset includes information on the timing of R&D tax credit enactments for all states—including those where firms registered before the credits were introduced—I include the lag between tax credit implementation and firm registration as an additional regressor in our hazard model. This inclusion allows us to directly control for potential spurious correlations between the implementation lag and unobserved firm-specific factors, resulting in a more precise estimation of the treatment effect.

I model the hazard function for firm i registering in the System for Award Management (SAM) at time t using the Cox proportional hazards model with time-varying covariates:

$$h_{\text{REGISTER}}(t \mid X^t_{\text{RD}i}, Z_i) = h_0(t) \cdot \exp\left\{\beta_0 + \beta_Z Z_i + \beta_{\text{CREDIT_LAG}} \,\text{CREDIT_LAG}_i + \beta_{\text{POST_CREDIT}} \, X^t_{\text{RD}i} + \epsilon_i\right\} \tag{2}$$

In this equation:

- $h_{\text{REGISTER}}(t \mid X^t_{\text{RD}i}, Z_i)$ is the hazard rate of firm i registering at time t.

- $h_0(t)$ represents the baseline hazard function at time t, which may vary over time and can be stratified by factors such as industry.
- Z_i includes firm-specific characteristics like ownership type and sector.
- CREDIT_LAG_i denotes the lag time between the enactment of state-level R&D tax credits and the firm's registration decision.
- $X^t_{\text{RD}i}$ is a time-varying covariate indicating the presence of R&D tax credits affecting the firm at time t.
- $\beta_0, \beta_Z, \beta_{\text{CREDIT_LAG}}, \beta_{\text{POST_CREDIT}}$ are coefficients to be estimated.
- ϵ_i is the error term capturing unobserved heterogeneity.

By incorporating CREDIT_LAG_i into the model, I account for the potential influence of the time delay between the implementation of R&D tax credits and the firm's decision to register. This helps control for any spurious correlations that might arise due to unobserved factors affecting both the lag and the hazard rate.

Provided that the timing of R&D tax credit implementation is conditionally independent of the error term ϵ_i—after controlling for industry stratification, firm characteristics Z_i, and the lag CREDIT_LAG_i—the coefficient $\beta_{\text{POST_CREDIT}}$ associated with the time-varying covariate $X^t_{\text{RD}i}$ can be interpreted as the causal effect of the R&D tax credits on the hazard rate of firm registration.

5 Empirical Results

5.1 Cox Hazard Baseline Results

Table ?? presents our baseline Cox hazard regression results based on monthly data, examining the impact of the R&D tax credit on firms' likelihood of registering in SAM. The event of interest in these regressions is a firm's first instance of registration.

The first specification (Model 1) estimates the effect of the R&D tax credit without additional controls. The estimate is statistically significant at the 1% level and implies that the introduction of the tax credit is associated with a 46.9% reduction in the hazard of SAM registration. This suggests that, following the implementation of the R&D tax credit, firms are significantly less likely to register, potentially reflecting a shift in priorities away from federal contracting and toward leveraging the new tax incentives for private-sector R&D investment.

Model 2, includes state fixed effects and industry stratification. The inclusion of state fixed effects accounts for time-invariant differences across states that may influence firms' registration decisions, such as state-level economic conditions, procurement culture, or pre-existing business incentives. Additionally, stratification by industry ensures that firms are only compared within their respective sectors, allowing the baseline hazard rate to vary across industries. This is important given that industries differ significantly in their reliance on federal contracts and their responsiveness to R&D incentives.

With these controls, the estimated effect of the R&D tax credit strengthens, implying a 50.4% reduction startups having a SAM registration. The consistency of the findings across both models reinforces the conclusion that the tax credit significantly decreases the likelihood of firms engaging in federal procurement.

These results indicate that the introduction of the R&D tax credit has a substantial and sustained impact on firm behavior. The reduction in registration likelihood persists across different model specifications, highlighting the robustness of the effect. The findings suggest that firms may be reallocating resources toward private-sector R&D efforts rather than seeking government contracts, although further investigation is needed to confirm the underlying mechanisms driving this shift.

Temporal Effects: 3, 5, and 8 Years Post-Implementation

The baseline results establish that the R&D tax credit significantly reduces firms' likelihood of registering in SAM. To assess how this effect evolves over time, Table 5 presents hazard rate estimates at three, five, and eight years after a state implements an R&D tax credit.

In the first three years, the estimated effect is small and not statistically significant, suggesting that firms' registration behavior remains largely unchanged in the short run. However, after five years, the estimated hazard ratio implies a 34.1% reduction in the likelihood of SAM registration, statistically significant at the 5% level. By year eight, the effect becomes even more pronounced, with a 41.1% reduction in the hazard rate, significant at the 1% level.

These results suggest that the impact of the R&D tax credit on firms' procurement behavior intensifies over time, rather than exerting an immediate effect. One possible explanation is that firms initially take time to assess the benefits of the tax credit before shifting their focus away from federal procurement. Alternatively, firms that would have otherwise registered may instead reinvest in private-sector R&D, delaying or forgoing SAM registration in later years.

Across all three specifications, state fixed effects and industry stratification are included to control for unobserved heterogeneity, ensuring that the findings reflect within-state, within-industry variation. The increasing magnitude of the effect over time reinforces the conclusion that the tax credit significantly influences firms' strategic decisions, with a growing deterrent effect on federal procurement interest as firms adjust to the new incentive structure.

5.2 Interaction Model: R&D Tax Credit and High Capital Expenditures

Next, I examine whether this effect varies based on firms' capital expenditure levels, as startups in high-capital expenditure sectors may face different constraints and strategic considerations when responding to tax incentives. Capital-intensive industries often require significant upfront investment, which could influence firms' reliance on federal procurement opportunities and their responsiveness to R&D incentives. Following the methodology outlined by Lofstrom and Bates (2013), I compute the average capital expenditures per industry to identify high- and low-cost industries. By distinguishing between these sectors, I assess whether firms with greater capital intensity exhibit a different likelihood of SAM registration in response to the tax credit. Table ?? presents hazard rate estimates for firms in high capital expenditure sectors.

The results indicate that firms with high capital expenditures do not experience a significantly different response to the tax credit. The interaction effect is small and not statistically significant, suggesting that the tax credit leads to a 51.2% reduction in SAM registration likelihood regardless of a firm's capital expenditure level. This implies that firms' investment intensity does not substantially alter their response to the tax credit.

These findings suggest that the tax credit's impact on procurement behavior is broad-based, affecting firms across different investment levels. Unlike other firm characteristics that may shape responsiveness to tax incentives, capital expenditure does not appear to be a determining factor in whether firms reduce their likelihood of engaging in federal contracting.

5.3 Placebo Timing Test

As a robusntess check to examine if the observed effect of the R&D tax credit is not driven by broader time trends or unobserved factors, I conduct a placebo test using a fictitious implementation date. This allows us to assess whether the estimated reduction in SAM registration likelihood is genuinely attributable to the tax credit or simply reflects the underlying economic patterns.

Table 7 presents the results of this robustness check. The placebo variable for *Post R&D Tax Credit* is not significantly associated with a change in hazard rates, confirming that firms' likelihood of registration remains unaffected when the tax credit is artificially assigned. The estimated hazard ratios suggest that the placebo event leads to a negligible and statistically insignificant change in SAM registration likelihood, reinforcing that the actual tax credit implementation is responsible for the previously observed 50.4% reduction in firms' likelihood of registration.

These results provide strong evidence that the main findings are not driven by spurious correlations or broader shifts in firms' contracting behavior. By demonstrating that no similar effect emerges when the tax credit is artificially introduced, this placebo test enhances confidence in the causal interpretation of the tax credit's impact on procurement participation.

Taken together, these findings provide compelling evidence that the implementation of the R&D tax credit significantly reduces firms' likelihood of registering in SAM, with the effect strengthening over time. The temporal analysis shows that while the impact is modest in the short term, it grows more pronounced in later years, suggesting that firms gradually adjust their strategic priorities in response to the tax incentive. Furthermore, the analysis of capital expenditure levels reveals that this effect is consistent across firms, regardless of investment intensity, indicating that the tax credit broadly influences firms' procurement decisions rather than being confined to capital-intensive sectors. The placebo test confirms that the observed reductions in registration likelihood are not driven by broader economic trends or unobserved time-varying factors.

6 Conclusion

This study examines the impact of state-level R&D tax credits on firms' likelihood of registering in the System for Award Management (SAM), contributing to literature on how tax incentives influence firms' engagement with federal procurement. Using a Cox hazard model and annual registration data for the System for Award Management (SAM), the results consistently show that the introduction of the R&D tax credit is associated with a substantial and sustained reduction in firms' likelihood of registering in SAM.

The baseline findings indicate that the tax credit reduces the probability of SAM registration by approximately 50%, suggesting that firms are less inclined to pursue federal contracts in the presence of R&D incentives. This effect becomes more pronounced over time, with the most significant reductions occurring five to eight years post-implementation. These results imply that firms gradually adjust their strategic priorities, possibly reallo-

cating resources toward private-sector R&D rather than government contracting. Further analysis demonstrates that this effect is consistent across industries, regardless of capital expenditure levels, indicating that the tax credit influences firms broadly rather than being limited to capital-intensive sectors. The robustness check using a placebo test confirms that the observed reductions are not driven by broader economic trends, reinforcing the causal interpretation of the findings.

These findings have important policy implications. While R&D tax credits are designed to stimulate innovation by reducing the cost of private investment in research and development, they may also have unintended consequences by disincentivizing firms from engaging with federal procurement programs. Given that government contracts often provide a critical funding source for small businesses and early-stage firms, policymakers should consider whether adjustments to tax incentives or complementary policies are needed to prevent a decline in firms' participation in public-sector innovation initiatives.

However, several limitations should be acknowledged. First, the study is limited to 18 states due to data constraints in the SAM API, which only includes active registration data beginning in the year 2000. While the states included in the sample vary in economic output, extending this analysis to additional states would help assess whether the observed effects hold at a national level. Second, this study focuses on SAM registration as a proxy for federal procurement engagement, but does not measure whether firms ultimately secure contracts or experience changes in innovation output. Examining long-term firm performance, including revenue growth and patenting activity, could provide deeper insights into the broader implications of the tax credit.

Furthermore, this study does not differentiate between firm types beyond capital expenditure levels. Given that small firms, minority- and women-owned businesses, and high-tech startups may respond differently to tax incentives, future research should explore whether these groups are disproportionately shifting away from federal procurement opportunities. Finally, while this study leverages a quasi-experimental approach, incorporating difference-in-differences models or synthetic control methods could strengthen causal identification and rule out potential confounding factors.

Based on these findings, future research could expand the geographic scope by incorporating additional states or alternative datasets to assess the broader applicability of these effects. Examining the long-term consequences of reduced federal procurement participation, including its impact on firm survival, innovation output, and market competitiveness, would provide valuable insights into whether the tax credit leads to unintended trade-offs. Further studies could also investigate how firm characteristics, such as size, ownership demographics, or prior procurement experience, influence firms' responsiveness to R&D incentives.

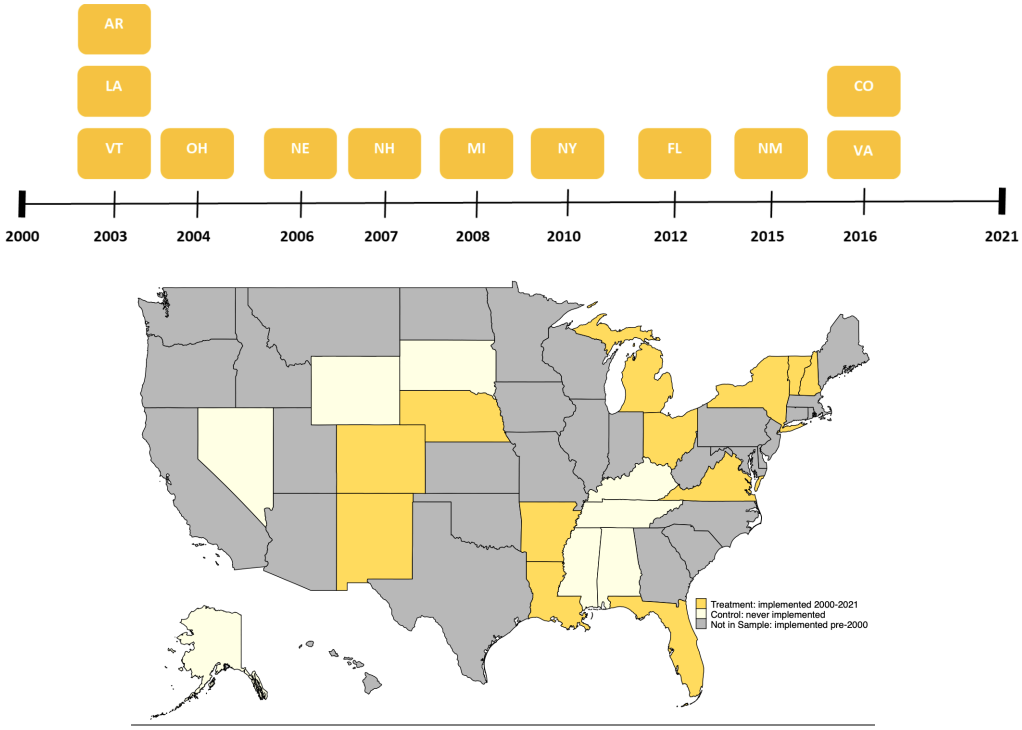
Another important avenue for future research is assessing the interaction between state-level tax incentives and federal R&D funding to determine whether these policies complement or compete with each other. Finally, refining causal identification strategies through difference-in-differences models or synthetic control methods would enhance the robustness of findings and help isolate the precise mechanisms through which tax credits shape firm behavior.

This study highlights that the R&D tax credit reduces firms' likelihood of registering in SAM by approximately 50%, with the effect intensifying over time. This suggests that tax incentives not only influence firms' short-term decisions but may also lead to structural changes in how firms allocate resources between public-sector and private-sector innovation opportunities. A key next step for research is to examine whether this decline in federal procurement participation has long-term consequences for firm growth and innovation outcomes. Are firms that shift away from government contracting due to the tax credit more likely to experience sustained R&D investment, or do they face greater financial constraints without federal support? Understanding these trade-offs will be essential for designing policies that effectively balance private-sector innovation incentives with sustained engagement in public-sector opportunities.

7 Figures and Tables

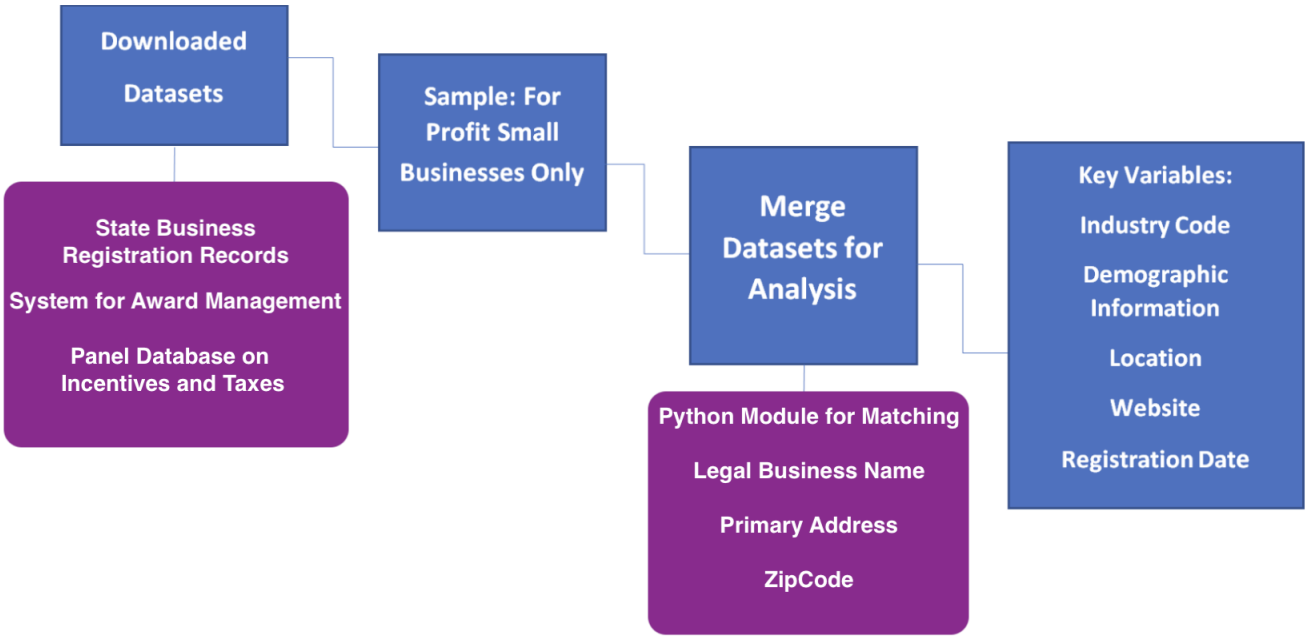
7.1 Figures

Figure 1: Timeline and Map of State Research and Development Tax Credits



This figure presents a timeline and map of states that implemented research and development tax credits between 2000 and 2021. For the treatment group, I only included states that implemented an R&D tax credit from 2003 to 2016 and were still active at the end of the sample period in 2021, in order to facilitate pre- and post-trend analysis for the estimators and causal analysis. I list the state R&D tax credits by year on the timeline during the sample period. The map includes the treatment and control states in the sample.

Figure 2: Data Construction



This figures describes the data construction process for this study. I had three main data sources for this analysis: Data Axle, System for Award Management, and the Small Business Innovation Research program awardee database. I used Python fuzzy matching to develop the dataset for analysis. The final dataset provides demographic information of the firms.

7.2 Tables

Table 1: List of High Technology Industries

Primary NAICS Code	Description	Sector
3254	Pharmaceutical Medicine Manufacturing	Manufacturing
3341	Computer Peripheral Equipment Manufacturing	Manufacturing
3342	Communications Equipment Manufacturing	Manufacturing
3364	Semiconductor and Other Electronic Component Manufacturing	Manufacturing
3345	Navigational, Measuring, Electromedical, Control Instruments Manufacturing	Manufacturing
3364	Aerospace Product Parts Manufacturing	Manufacturing
5171	Wired Telecommunications	Telecommunications and IT Services
5179	Other Telecommunications	Telecommunications and IT Services
5182	Data Processing, Hosting, Related Services	Telecommunications and IT Services
5413	Architectural, Engineering, Related Services	Research Services
5415	Computer Systems Design, Related Services	Telecommunications and IT Services
5417	Scientific Research, Development Services	Research Services

These are the 12 NAICS codes listed as high-tech industries from (Heckler, 2005). The businesses, when registering on the System for Award Management, self-select the NAICS code that describes their business. Heckler defines 12 NAICS industries as "High-Technology Industries" since these industries: (1) employ a high proportion of scientists, engineers, and technicians; (2) employ a high proportion of R&D workers; (3) produce high-tech products; or (4) use high-tech production methods.

Table 2: Summary Statistics for State Business Registration Records

Variable	N	Mean	Std. Dev.
Registered in SAM	8443	0.017	0.100
High Technology Category			
Aerospace Product and Parts	8443	0.006	0.074
Architectural Engineering	8443	0.004	0.063
Communications Equipment Manufacturing	8443	0.004	0.060
Computer and Peripheral Equipment Manufacturing	8443	0.006	0.079
Computer Systems Design	8443	0.016	0.126
Data Processing, Hosting	8443	0.003	0.056
Navigational, Measuring, Electromedical	8443	0.074	0.262
Pharmaceutical and Medicine Manufacturing	8443	0.402	0.490
Scientific Research and Development	8443	0.291	0.454
Semiconductor and Other Electronic Manufacturing	8443	0.193	0.395
States with Research and Development Tax Credits			
Arkansas	8443	0.016	0.126
Florida	8443	0.433	0.495
Louisiana	8443	0.051	0.220
Michigan	8443	0.068	0.252
Nebraska	8443	0.017	0.131
New Hampshire	8443	0.018	0.132
New Mexico	8443	0.010	0.099
New York	8443	0.151	0.358
Ohio	8443	0.058	0.234
Vermont	8443	0.007	0.084
States without Research and Development Tax Credits			
Alabama	8443	0.030	0.172
Alaska	8443	0.012	0.109
Kentucky	8443	0.026	0.159
Mississippi	8443	0.011	0.104
Nevada	8443	0.030	0.171
South Dakota	8443	0.007	0.086
Tennessee	8443	0.049	0.216
Wyoming	8443	0.004	0.066

This table displays the summary statistics for the state business registration records included in the sample. The mean, standard deviation, and observation count are showcased. The dataset covers the timeframe from 2000 to 2021.

Table 3: Cox Hazard Interaction with High Capital Expense Sector

Sector	Average Startup Cost	High or Low
Components and Parts	$932,160	High
Manufacturing	$807,992	High
Information	$1,449,877	High
S&T Services	$24,684	Low

The annual capital expenditures by sector were calculated using data from the U.S. Census Bureau's publicly available 2019 Annual Capital Expenditures Survey and the 2019 County Business Patterns, specifically the "Number of Firms and Establishments, Employment, and Annual Payroll by State, Industry, and Enterprise Employment Size" table. Following the methodology of Lofstrom and Wang (2009), sectors were classified as having high capital expenditures if they fell within the top one-third quantile. In 2019, this threshold was defined as sectors with estimated annual capital expenditures per firm of $690,083.16 or higher.

Table 4: Cox Hazard Baseline Results

Independent Variable	Hazard Ratio	Coefficient
Post R&D Tax Credit	0.634** (0.202)	0.035 (0.029)
Post R&D Tax Credit (Adjusted)	0.703*** (0.128)	0.036 (0.035)
State Fixed Effects	No	Yes
Stratified by Industry	No	Yes

Cox proportional hazards model results for the effect of post-R&D tax credits on firm registration. Hazard ratios and coefficients are presented for two models: one without state fixed effects and industry stratification, and one with both adjustments. *** p <0.01, ** p <0.05, * p <0.10.

Table 5: Cox Hazard Model: 3, 5, and 8 Years Post-Implementation

Independent Variable	3 Years	5 Years	8 Years
Hazard Ratio	-0.617 (0.637)	-0.417* (0.207)	-0.530** (0.192)
Coefficient	0.023 (0.131)	-0.042 (0.043)	-0.023 (0.038)
State Fixed Effects	Yes	Yes	Yes
Stratified by Industry	Yes	Yes	Yes
N	21,371	28,646	44,131

Cox proportional hazards model results across different time horizons (3, 5, and 8 years). The table presents hazard ratios and coefficients for each time horizon, with state fixed effects and industry stratification applied in all models. *** p <0.01, ** p <0.05, * p <0.10.

Table 6: Cox Hazard Interaction with High Capital Expense Sector

Independent Variable	Hazard Ratio	Coefficient
Post R&D Tax Credit	-0.719* (0.357)	0.034 (0.034)
High CapEx	0.431 (0.275)	0.431 (0.275)
Post R&D Tax Credit X High CapEx	0.046 (0.347)	0.046 (0.347)
State Fixed Effects	No	Yes
Stratified by Industry	No	Yes
N	70,310	70,310

Cox proportional hazards model showing the interaction between post-R&D tax credits and high capital expenditures (CapEx). Hazard ratios and coefficients are displayed for models with and without state fixed effects and industry stratification. *** p <0.01, ** p <0.05, * p <0.10.

Table 7: Cox Hazard Rate Placebo Timing Effect

Independent Variable	Hazard Ratio	Coefficient
Placebo Post-Tax Credit	-0.713** (0.248)	0.089 (0.087)
Placebo Post-Tax Credit	-0.589* (0.259)	0.068 (0.085)
State Fixed Effects	No	Yes
Stratified by Industry	No	Yes

Placebo analysis results for the effect of post-tax credits on firm registration. Hazard ratios and coefficients are presented for two models: one without state fixed effects and industry stratification, and one with both adjustments. *** p <0.01, ** p <0.05, * p <0.10.

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A Appendix A

A.1 Fuzzy Matching Process

I used Python module recordlinkage to match firms from the Data Axle dataset, System for Award Management database, and Small Business Innovation Research awardee list. In order to use the dataset, pandas has to be installed in python. I split each file by state based on the primary location of the firm in order to block locations by state. Prior to matching, I removed common strings in business names in order to have a higher match rate for the firms. I also made the variable in each dataset that listed the legal business name to all uppercase to account for fuzzy match module missing a match due to different strings being used. I trimmed leading and trailing spaces in the name variables and the zipcode variables. The threshold for matching was 92% or higher. Matched firms were exported to a .csv file and I manually reviewed the files to catch any errors or potential duplication, the Unique Entity Identification number was also exported in the file in order to merge this information in the constructed dataset with the additional variables. Recordlinkage classifies matches and non-matches using a built in algorithm. The matched Data Axle files were matched to System for Award Management on the legal business name of the firm and the zipcode.

A.2 Variable Definitions

Table A1: Strings Removed to Prepare for Fuzzy Matching

Strings Removed
Corp
Corporation
Domestic
L.L.C.
L.L.P.
Limited
Limited Liability
LLC
LLLP
LLP
Partnership
Profit

This table lists the strings removed from the company names to assist with the fuzzy matching process. The words were selected based on common abbreviations in firms.

A.2.1 Sample Python Code

```
import pandas as pd
import recordlinkage

# Specify the file names
files = ['al_reference_state.csv', 'al_final.csv']

print("Processing file set 1")

reference = pd.read_csv(files[0], index_col='id')
oc_data = pd.read_csv(files[1], index_col='uei', low_memory=False)

indexer = recordlinkage.Index()
indexer.full()
candidates = indexer.index(reference, oc_data)
print(len(candidates))

compare = recordlinkage.Compare()
compare.string('name',
               'business_name',
               threshold=0.92,
               label='business')
compare.string('zipcode',
               'zipcode',
               threshold=1,
               label='postal code')

features = compare.compute(candidates, reference, oc_data)

match_counts = features.sum(axis=1).value_counts().sort_index(ascending=False)
print(match_counts)

# Sort the features DataFrame by match score in descending order
sorted_features = features.sort_values(by='business', ascending=False)

# Filter the sorted_features DataFrame to include only the matched records
matched_results = sorted_features[sorted_features['business'] > 0].copy()

# Add company_name, zipcode, and threshold columns to matched_results
matched_results['name'] = reference.loc[matched_results.index.get_level_values(0),
'name'].values
matched_results['business_name'] = oc_data.loc[matched_results.index.get_level_values(1),
 'business_name'].values

 matched_results['zipcode'] = reference.loc[matched_results.index.get_level_values(0),
 'zipcode'].values
matched_results['threshold'] = matched_results['business']

# Specify the output file path
oc_file = 'oc_results_1.xlsx'

# Save the matched results to an Excel file
matched_results.to_excel(oc_file, index=True)
```

```
print(f"Output saved to: {oc_file}")
print("-----------------------------------")
\end{mintedbox}
```

A.3 State R&D Tax Credit and the Panel for Database Incentives on Taxes

There are 31 states that offer a tax credit for company-based R&D, with Minnesota being the first to implement a state credit in 1982.

The effective credit rate is determined by the statutory credit rate, the base definition, and whether the credit itself is subject to taxation. The median credit rate among the treatment group stands at 15%, and the median number of years for which unused credit can be carried forward is 6 years. Further details can be found in Table A2 for the treatment group.

Companies figure out the taxable income they owe to a state. Companies either pay corporate income or franchise taxes to states based on an apportionment of their total federal taxable income. Typically the tax is based on the revenue generated in the state. States tend to follow the federal definition of qualified R&D in their tax codes.

Policymakers have increasingly deployed focused supply-side incentives such as R&D tax credits (1) to spur investment in innovation by larger and more established companies (their original intended purpose); (2) and to encourage the formation and growth of small firms (Fazio et al., 2020). 35 states have implemented R&D tax credits to encourage participation in innovation, draw high-growth businesses to their state, and for local economic growth and development.

Research finds that R&D tax credits may be driven not by state-to-state diffusion but rather by similar economic, education, and structural conditions rather than by similar geographic conditions. It is more about competition than geography (Mulligan et al., 2022; Hearn et al., 2014).

Table A2: Summary of State-Level R&D Tax Credits

State	Year RD Tax Adopted	Credit Rate	Base Definition	Carry Forward Period (Years)
Arkansas	2003	20.00%	Federal (fixed-period)	9 years
Colorado	2016	3.00%	Federal (fixed-period)	Indefinite
Florida	2012	10.00%	Average past 4 years	5 years
Louisiana	2003	30.00%	Federal (fixed-period)	5 years
Michigan	2008	2.00%	Federal (fixed-period)	None
Nebraska	2006	15.00%	Federal (fixed-period)	20 years
New Mexico	2015	5.00%	Federal (fixed-period)	3 years
New York	2010	15.00%	Federal (fixed-period)	None
Ohio	2004	20.00%	Federal (fixed-period)	7 years
Vermont	2003	27.00%	Average past 4 years	10 years
Virginia	2016	15.00%	Federal (fixed-period)	10 years
Median	N/A	15.00%	N/A	6 years

This table displays the statutory R&D tax credit rate for each treatment state in the sample. All of these states had active R&D tax credit rates in 2021. For states with different rates, the highest credit rate was selected for small firms. The information was derived from the following sources, https://www.bdo.com/insights/tax/state-r-d-tax-credits and https://www.mossadams.com/services/accounting/tax/credits-and-incentives/research-and-development/tax-credits-by-state/new-york.