Government R&D Contracts as Platforms for Experimentation*

Larisa Cioaca†

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Abstract

Startups experiment with technologies and markets to reduce uncertainty. Although experimentation leads to learning, it is costly, raising questions about funding. High-tech startups operating outside the narrow range of technologies that receive venture capital can turn to government R&D contracts to fund experimentation. I examine the effect of experimenting with technologies and markets on startup performance. Using data on $42 billion in government R&D contracts awarded to American high-tech startups between 1989 and 2019, I analyze the impact of experimentation on employment, sales, and exit through initial public offerings or mergers and acquisitions. I identify the effect through industry-specific exposure to (i) size standards used by federal agencies to determine which firms can compete for small business programs and (ii) increased government spending before the fiscal year's end. The results show that experimentation with markets, rather than technologies, drives startup performance. However, the effect is heterogeneous: Market experimentation benefits low-growth startups more than high-growth startups. This finding underscores the role of government R&D contracts as platforms for experimentation, with significant implications for the level and trajectory of experimentation in the U.S. economy.

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†Duke University, Fuqua School of Business; larisa.cioaca@duke.edu

1 Introduction

Reducing uncertainty is central to innovation and entrepreneurship (Kline & Rosenberg, 1986; Knight, 1921; McMullen & Shepherd, 2006). Prior research has identified various dimensions of uncertainty. For instance, *technology uncertainty* involves questions like "What is technically feasible?" and "Can we build this prototype?" In contrast, *market uncertainty* raises questions such as "What do customers need?" and "Which market will adopt this innovation?" Startups can reduce both technology and market uncertainty through *purposeful experimentation* (Murray & Tripsas, 2004), which involves identifying problems, hypothesizing, testing, and analyzing to gain insights.[1] Experimentation includes both classical hypothesis testing to determine causal relationships (answering "Does X cause Y?") and free-play experimentation (answering "What happens if I do X?").

Traditionally, the experimentation literature has focused on either technology or market experimentation (Murray & Tripsas, 2004). Similarly, the innovation and entrepreneurship literature has emphasized the sequential nature and different funding sources for technology development and market commercialization. Initially, the U.S. government supports research and development (R&D), allowing startups to reduce technology uncertainty (David, Hall, & Toole, 2000; B. H. Hall & Lerner, 2010). Subsequently, venture capital (VC) supports commercialization, enabling startups to reduce market uncertainty (Hellmann & Puri, 2000; Samila & Sorenson, 2010).

However, some startups must conduct technology and market experimentation simultaneously rather than sequentially. For example, "deep tech" startups face high levels of both technology and market uncertainty at the same time. These are young science-based firms working on technologies with lengthy, costly, and uncertain R&D cycles (de Apodaca, Murray, & Frolund, 2023), such as clean energy or new materials. As a result, their hypotheses about technical feasibility and commercial application must be tested together. Yet, deep

[1] Startups can also reduce uncertainty through routine-based local search (Nelson & Winter, 1982) and unplanned, opportunistic adaptation (Bhide, 2000).

tech startups are unlikely to secure venture capital to fund their technology experimentation (Arora, Fosfuri, & Rønde, 2024; Ewens, Nanda, & Rhodes-Kropf, 2018; Kerr, Nanda, & Rhodes-Kropf, 2014), despite developing solutions to societal challenges. Instead, they may leverage government R&D support to perform market experimentation.

The U.S. government has a long tradition of funding technology experimentation in both intramural and extramural labs. For instance, after creating the Los Alamos National Laboratory in 1943 to design nuclear weapons for the Manhattan Project, the government established a second lab, Lawrence Livermore National Laboratory, in 1952 to enhance national security by offering competing designs (Bartman, 2023). In 2019, the government obligated $142.4 billion for R&D activities conducted by industry (35.5%), intramural labs (27.6%), universities (27.6%), and other organizations (9.3%) (NCSES, 2021).[2] Of the $50.5 billion obligated to industry, $47.7 billion (94.5%) was awarded as R&D contracts (USAspending.gov, 2023). High-tech startups received approximately $2.1 billion (4.4%) of those R&D contracts, along with $7.7 billion in VC funding and $2 billion in federal grants. These figures show that government R&D contracts are an important funding source for technology experimentation in startups.[3]

Although government R&D contracts are often overlooked in the innovation and entrepreneurship literature (Belenzon & Cioaca, 2024; De Rassenfosse, Jaffe, & Raiteri, 2019), they offer opportunities for market experimentation. Contrary to the misconception that the federal government is a monolithic entity with homogeneous demand, in 2019, 734 different contracting offices from 33 distinct agencies awarded R&D contracts. Those offices had specific requirements aligned with their respective agency missions, satisfied by unique combinations of upstream industries. They acted as sophisticated lead users, capable of making large purchases, defining product specifications and standards, and establishing markets for

[2]The industry, university, and nonprofit shares also include R&D performed in industry-, university-, and nonprofit-administered Federally Funded Research and Development Centers, respectively.

[3]The government also sponsors challenges and prize competitions that represent a tiny fraction of the federal investment in R&D. For example, the combined prize purse for 814 competitions conducted from 2010 to 2020 across the U.S. government and listed on Challenge.gov reached $243 million, compared to the total federal R&D outlays of $1.3 trillion over the same period (Crawford & Wulkan, 2021).

new technologies (Edquist & Hommen, 2000). Historical examples include the development of semiconductors and the Internet. Given the scale and scope of public investment in startup experimentation, understanding its performance implications is essential.

This paper examines the effect of experimenting with technologies and markets on startup performance outcomes, including employment, sales, and exit through initial public offerings (IPOs) or mergers and acquisitions (M&A). The context is startups performing contract R&D for the U.S. government. I also explore how the effect varies by firm, industry, agency, and contract characteristics. I test two potential mechanisms: (i) startups *certify* their commercialization capabilities to potential investors, and (ii) startups *develop* commercialization capabilities they later leverage in private-sector markets.

I collect detailed government procurement data on 64 million transactions related to $1.2 trillion in R&D contracts and $9.6 trillion in production contracts awarded from 1989 to 2019 from SAM.gov and USAspending.gov. I add data on 43 million transactions involving $27.3 trillion in project grants, cooperative grants, insurance, and direct payments awarded between 2001 and 2019. I combine these government awards with firm performance data on over 5.9 million American startups from 1989 to 2019 from the National Establishment Time Series (NETS) HiTech database. I define startups as independent firms with 1-499 employees at founding, established in 1989 or later, in one of 46 four-digit 2002 NAICS industries classified as high-tech based on their occupational mix (Hecker, 2005).[4]

I focus on startups that successfully engage with the U.S. government (i.e., firms that win federal procurement contracts or grants during their first ten years). My analysis sample includes an unbalanced firm-year panel of 106,462 startups, of which 16,983 receive government R&D contracts. In total, sample firms receive $42 billion in R&D contracts and $416 billion in production contracts between 1989 and 2019, as well as $27 billion in grants from 2001 to 2019. For each startup and year, I measure *technology experimentation* by the dollar value of R&D contracts awarded, and *market experimentation* by the number of

[4]In robustness checks, I use independent firms with just 1-49 employees at founding.

distinct contracting offices that awarded those R&D contracts.[5] The performance outcomes include employment, sales, and exit via IPO or M&A. Firms are classified as large if they have above-median annual sales compared to other startups in the same four-digit industry (SIC4). Additionally, firms are categorized into five main industries based on their SIC4 and industry definitions from Fama and French (1993).

Using the dollar value of R&D contracts (i.e., the depth of a startup's government R&D work) to measure technology experimentation is reasonable because many R&D contracts involve early-stage, conceptual work to turn ideas into working prototypes. That work requires search, hypothesis development, testing, and iterative analysis—hallmarks of purposeful experimentation. Indeed, Allen (1984) found that teams funded by government R&D contracts spent over 77% of their project time on analysis and experimentation. Similarly, using the number of distinct contracting offices that awarded R&D contracts (i.e., the breadth of a startup's government R&D work) to measure market experimentation is reasonable because many R&D contracts go through competitive solicitation processes. That means a startup must purposefully search for a federal opportunity, form a hypothesis about the value of its technology, assemble a customized proposal, and negotiate the proposal with the contracting office *before* an R&D contract can be awarded.

A major challenge in identifying the effect of experimentation on performance is the endogeneity of contracts (David et al., 2000). Common technology or demand shocks can affect both federal R&D contracting and startup performance. If R&D contracts are systematically awarded to startups experiencing positive (negative) technology or demand shocks, estimates of the effect of R&D contracts on performance will be upward (downward) biased. To address this, I use two plausibly exogenous instruments in an instrumental variables framework.

[5]In robustness checks, I also measure technology experimentation using: (i) the dollar value of contracts awarded for basic research, applied research and exploratory development, or advanced development; (ii) an indicator variable equal to 1 if the startup received an R&D contract and 0 otherwise; and (iii) the number of R&D contracts awarded to the startup. I measure market experimentation using: (i) the number of distinct *agencies* that awarded R&D contracts; (ii) an indicator variable equal to 1 if the startup received R&D contracts from two or more contracting offices and 0 otherwise; and (iii) the diversity of procurement portfolios (across NAICS4 industries) for the contracting offices awarding R&D contracts.

First, I use size standards set by the Small Business Administration, which determine eligibility for small business programs. Using a "fuzzy" regression discontinuity design (RDD), I show that startups just below the relevant employee size standard (treated startups) obtain R&D contracts from more offices compared to those just above the size threshold (control startups). Therefore, I use a treatment indicator variable as an instrument for the number of R&D contracting offices.

Second, I exploit increases in federal R&D funding driven by the "use it or lose it" budgeting policy of federal agencies. Federal agencies spend their leftover funds before the fiscal year-end, September 30, bumping up R&D contract value. I instrument the value of R&D contracts with an indicator equal to 1 if the firm received any R&D contracts during September of the focal year. I then employ two-stage least squares (2SLS) regressions to estimate the causal effect of technology and market experimentation on startup performance.

I present two sets of results. First, the dollar value of R&D contracts, my empirical proxy for *technology* experimentation, is not significantly related to startup performance. However, the number of distinct contracting offices awarding R&D contracts, my proxy for *market* experimentation, significantly increases employment, sales, and the likelihood of an exit via IPO or M&A. This relationship is robust across industries, agencies, and contract characteristics. The key takeaway is that for startups contracting with the government, it is not the amount of funding that matters but the diversity of their engagements.

Second, I observe substantial heterogeneity in the effect of market experimentation based on firm characteristics. The number of contracting offices that award R&D contracts increases performance for large startups and decreases it for small startups. This aligns with the idea that large startups possess more resources and capabilities to assess and pursue diverse market opportunities. More importantly, the number of contracting offices that award R&D contracts boosts performance more for low-growth startups than high-growth ones. This reflects a tradeoff startups face: Innovating for the government provides funding for joint testing of technical feasibility and commercial application but also requires time and

attention that might otherwise be directed toward testing private markets. For ambitious startups, time is scarce due to patent expiration and competing innovations.

With these results, I make two contributions. First, my research contributes to the empirical literature on entrepreneurial experimentation. Prior studies have focused on single aspects of experimentation, such as technologies (e.g., Koning, Hasan, & Chatterji, 2022) or markets (e.g., Gruber, MacMillan, & Thompson, 2008). In contrast, my research examines both technologies and markets simultaneously. Prior studies have focused on individual experiments or on startups' capacity to experiment (e.g., Camuffo, Cordova, Gambardella, & Spina, 2020). In contrast, my research measures the extent of experimentation performed in startups. My findings suggest that market experimentation, rather than technology experimentation, drives high-tech startup performance. The managerial implication is that low-growth startups should prioritize increasing the diversity of contracting offices (not the size of contracts) to benefit from government R&D work.

Second, my research contributes to policy debates on the government's role in funding innovation, particularly innovation aimed at addressing major societal challenges. Deep tech startups face significant entry barriers—such as high levels of information asymmetry and capital intensity (de Apodaca et al., 2023), and a lower ability to appropriate the value they create (Arora et al., 2024)—leading to market failures and underinvestment by the private sector (Kerr et al., 2014). As a result, promising technologies with potential societal benefits may go unfunded if startups rely solely on venture capital or incumbents. This could cause us to miss breakthroughs in clean energy, advanced materials, and robotics. My findings suggest that contract R&D work for the federal government could be a viable alternative for developing promising technologies.

The paper proceeds as follows. Section 2 offers an overview of the institutional background on startups and government procurement. Section 3 reviews the related literature. Section 4 summarizes the data, while Section 5 provides nonparametric evidence supporting the validity of the proposed measures for market and technology experimentation. Sec-

tion 6 outlines the econometric specifications, and Section 7 presents the results. Section 8 concludes with suggestions for future research.

2 Institutional Background

2.1 Startups

What are startups, and why study them? In this paper, startups are defined as new employer firms (whether founded *de novo* or spun off from existing firms), tracked over their first ten years of activity (unless the firm exits earlier). While most startups are small (90% have fewer than 20 employees) and exit within this period (Decker, Haltiwanger, Jarmin, & Miranda, 2014), they play a crucial role in the U.S. economy by contributing to job creation (Haltiwanger, Jarmin, & Miranda, 2013) and economic growth (Aghion, Akcigit, & Howitt, 2014). From 1980 to 2010, startups created an average of 2.9 million jobs annually, accounting for about 18% of all new private-sector jobs.

The startup rate is a key indicator of economic dynamism (Decker et al., 2014). In 2019, the U.S. had over 6.1 million employer firms operating 8 million establishments (U.S. Census Bureau, 2022).[6] That year, about 1 million new establishments (13%) were launched, while 0.9 million (11%) closed (BLS, 2022). Between 1994 and 2019, an average of 67.6% of new establishments survived at least two years, 48.9% at least five years, 33.6% at least ten years, and 25.7% at least 15 years (SBA, 2021). A small fraction of startups, however, scale to become giants. For instance, Google, founded in 1998, was valued at over $23 billion when it went public six years later, in 2004.

An analysis of 111 startup failures between 2018 and 2021 by CBInsights (2021) identified the top three reasons for failure as: (i) running out of cash or failing to raise capital (38%), (ii) solving problems that didn't meet market needs (38%), and (iii) being out-competed

[6] An establishment is a physical location where one predominant activity occurs. A firm may consist of one or more establishments.

(20%). Startups face significant financing constraints, with only a few thousand securing traditional VC funding each year (Lerner & Nanda, 2020). Even among startups that file patents, only 7% go on to raise VC investments (Farre-Mensa, Hegde, & Ljungqvist, 2020). Corporate VC funds, similarly, focus on technologies that benefit their parent companies, particularly in sectors like software, telecommunications, semiconductors, and biotechnology (Dushnitsky, 2012).

Research by Ewens et al. (2018) and Nanda (2020) suggests that startups with long timelines to exit (via IPO or M&D) and costly, less-informative early experiments struggle to secure VC funding. Additionally, Arora et al. (2024) show that startups facing both technology and market uncertainty may be less attractive to investors due to their weakened bargaining position compared to incumbents in future acquisitions.

In summary, startups are vital to the U.S. economy. To survive and grow, they need funding to develop products and services that meet market needs. This often requires experimenting with technologies and markets under high uncertainty, but venture capital is frequently unavailable for such experimentation.

2.2 Government Contracts

Federal procurement is an important yet understudied context for technology and market experimentation, characterized by monopsonistic and oligopolistic traits. A few federal agencies allocate a large portion of contract dollars to a few major contractors specializing in government work. However, there is also considerable fragmentation on both the buyer and supplier sides. On the buyer side, federal procurement involves thousands of contracting offices working for dozens of agencies. Unlike branches of a parent corporation, federal contracting offices do not share a single mission (e.g., maximizing profit). Instead, they align with the diverse missions of their parent agencies (e.g., national security vs. space exploration), as detailed in Appendix Table B3. On the supplier side, the U.S. Congress established a goal of awarding 20% of prime contracting dollars to small businesses in 1988,

increased it to 23% in 1997, and extended it to include subcontracting and disadvantaged small businesses. Contracting offices' diverse technology needs enable startups to explore technology-market fit.

Federal Acquisition Regulation (FAR) acknowledges that R&D contracts involve substantial technology uncertainty:

> The primary purpose of contracted R&D programs is to advance scientific and technical knowledge and apply that knowledge to the extent necessary to achieve agency and national goals. Unlike contracts for supplies and services, most R&D contracts are directed toward objectives for which *the work or methods cannot be precisely described in advance* [emphasis added]. It is difficult to judge the probabilities of success or required effort for technical approaches, some of which *offer little or no early assurance of full success* [emphasis added]. (FAR § 35.002)

At the same time, R&D contracts reflect future government demand:

> [R&D] contracts shall be used only when *the principal purpose is the acquisition of supplies or services* [emphasis added] for the direct benefit or use of the Federal Government. Grants or cooperative agreements should be used when the principal purpose of the transaction is to stimulate or support research and development for another public purpose. (FAR § 35.002)

From 2017 to 2021, federal agencies awarded $224 billion for R&D services and $2,582 billion for products and other services, reflecting diverse government demand. DoD ($139.4 billion), NASA ($46.2 billion), and HHS ($16.5 billion) led R&D awards, with seven agencies exceeding $1 billion each (see Appendix Table B4).

These R&D contracts were awarded by various contracting offices, which function as the "business units" of federal agencies.[7] Their primary role is to acquire products and

[7] As of March 31, 2016, the Federal Acquisition Regulation (FAR) requires the use of a six-character code, the Activity Address Code (AAC), to identify each contracting office across all federal agencies uniquely.

services to fulfill the agency's mission while managing budgets, contracts, and procedures in accordance with Federal Acquisition Regulation. For example, 13 of the Department of Energy's 27 contracting offices awarded R&D contracts (see Appendix Table B5). While most federal contracting offices awarded relatively small amounts in R&D contracts, 47 offices awarded over $1 billion each (see Appendix Figure B1). These 47 offices provided significant opportunities for technology and market experimentation.

Most industries received contracts from multiple agencies and contracting offices (see Appendix Figure B2). On average, a NAICS6 industry received contracts from 15 agencies and 207 contracting offices.[8] Figure 1 displays the value of contracts (in constant 2012 $ billion) awarded by each of the top 24 contracting offices (ranked by total contract value during 2017-2021) to industries within each of the 24 NAICS2 sectors. In the heat map, a deeper purple color indicates higher spending by the contracting office in that sector. For example, contracting office N00019 (Naval Air Systems Command Headquarters in Patuxent River, MD) spent $202 billion from 2017 to 2021, including $196 billion in Sector 33 Manufacturing and $4 billion in Sector 54 Professional, Scientific, and Technical Services. In contrast, contracting office 892332 (Department of Energy's National Nuclear Security Administration M&O Contracting facility in Albuquerque, NM) spent $66 billion, including $54 billion in Sector 56 Administrative and Support and Waste Management and Remediation Services, and $10 billion in Sector 54 Professional, Scientific, and Technical Services.

The heat map reveals two key insights. First, most industrial sectors experience a relatively low concentration of government demand at the contracting office level.[9] Second, each contracting office's needs are met by a unique combination of upstream industries. Consequently, when a startup performs R&D work for a particular contracting office, it gains insights into that government customer's needs and those of private-market customers with similar demand profiles (i.e., located downstream from the same industries). Furthermore,

[8]NAICS6 is a very granular industry classification scheme. I obtained similar results using the less-granular NAICS4 classification scheme (see Appendix Table B3).

[9]The notable exception is sector 33 Manufacturing, which received most of its contracts from offices N00019 and N00024.

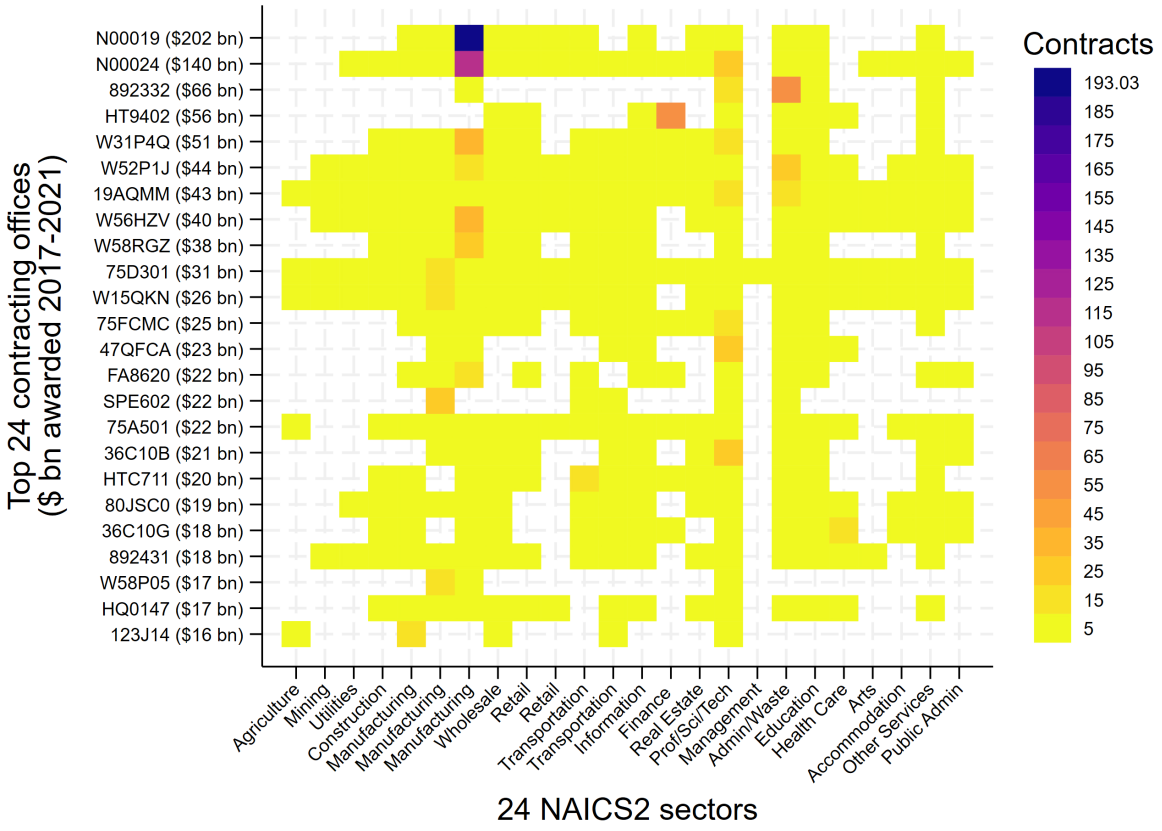


Figure 1: Heat Map of the Value of Contracts Awarded During 2017-2021

This figure plots the value of contracts (in constant 2012 $ billion) awarded by each of the top 24 contracting offices to each of the 24 NAICS2 sectors during 2017-2021.

performing R&D work for various contracting offices allows a startup to explore different potential market applications for its technology.

In summary, government demand for new technologies is large and heterogeneous. Federal procurement provides a valuable context for firms to develop new technologies while learning about both government and private-market demand.

3 Related Literature

This paper integrates two literature streams to examine the intersection of entrepreneurial experimentation and the role of government in firm innovation.[10] The first stream investigates why firms engage in entrepreneurial experimentation, what they experiment with, and how they conduct these experiments. The second stream explores why firms seek government contracts and grants and the effects of these awards on firm performance. Key studies are discussed below.

3.1 Entrepreneurial Experimentation

The literature on entrepreneurial experimentation examines *why* entrepreneurs experiment, *what* they experiment with, and *how* they experiment.[11] Entrepreneurs experiment—by forming beliefs, testing them, and responding to feedback—to understand cause-and-effect relationships between their actions and value creation and capture under uncertainty (Zellweger & Zenger, 2023).

Entrepreneurs experiment with various business aspects, including strategies and organizational forms (Pillai, Goldfarb, & Kirsch, 2020; Rosenberg, 1994), technologies and product features (Brown & Eisenhardt, 1997; T. A. Hall & Hasan, 2022; Koning et al., 2022; Thomke, 2003), markets (Contigiani & Young-Hyman, 2022; Gruber et al., 2008; Savage & Ziedonis, 2024), and business models (Andries & Debackere, 2007; Andries, Debackere, & Van Looy, 2013; Blank, 2020; Burnell, Stevenson, & Fisher, 2023; Ries, 2011). Appendix Table B6 summarizes the measures of experimentation used in the empirical literature.

Different experimentation approaches have been proposed and tested. For instance, technology and product feature experimentation can involve A/B testing (Koning et al., 2022)

[10] It is also related to the literature on uncertainty in entrepreneurial action (e.g., McMullen & Shepherd, 2006; Townsend, Hunt, McMullen, & Sarasvathy, 2018) and frictions in entrepreneurial financing (e.g., Arora et al., 2024; Nanda, 2020).

[11] Scholarly debates also address whether entrepreneurship involves causation (e.g., Delmar & Shane, 2003), effectuation (Sarasvathy, 2001), or bricolage (Baker & Nelson, 2005). See Fisher (2012) for a discussion of these theories. See Ott, Eisenhardt, and Bingham (2017) for a discussion of entrepreneurial strategizing by "doing" vs. "thinking."

or the design-build-test-analyze cycle (Thomke, 2003). Business model experimentation can follow the *theory-based view*, emphasizing theory development and hypothesis testing, or the *lean startup method*, which focuses on rapid iterative testing (Agarwal et al., 2023; Camuffo et al., 2020). Recent research aims to integrate and differentiate these methods and define their boundary conditions (e.g., Blank & Eckhardt, 2023; Felin, Gambardella, Novelli, & Zenger, 2024). For instance, Teece, Peteraf, and Leih (2016) argue that the lean startup method is effective when product development costs are low, adjustments are inexpensive, and customer feedback can be obtained early and frequently, as seen in the software industry.

The optimal level of startup experimentation remains unclear. Experimentation fosters learning (Murray & Tripsas, 2004; Thomke, 2003), enabling cost-effective adaptation of technology and commercialization. However, excessive experimentation and frequent pivoting may hinder learning from individual experiments (Chen, Elfenbein, Posen, & Wang, 2024). Moreover, experimentation takes time, which is a scarce resource as patents may expire and competing innovations may emerge.

Another cost of experimentation is the risk of expropriation. Increased exposure to the startup's technology raises the risk of imitation or intellectual property theft. Contigiani (2023) demonstrates that the degree of (1) uncertainty faced by startups and (2) competition from other startups and incumbents influences the tension between learning and appropriability in startup experimentation. In the context of government R&D contracts, the risk of expropriation is exacerbated by the government's non-exclusive license and march-in rights (though the latter are rarely exercised). Since the likelihood of granting a nonexclusive license increases with the number of distinct R&D contracting offices a startup engages with, the optimal amount of experimentation with government R&D contracts is likely bounded.

3.2 Role of Government in Innovation

There is extensive literature on the role of the U.S. government in firm innovation (Howell, 2024). Previous studies have primarily focused on the Small Business Innovation Research

(SBIR) program, which funds small businesses to help them commercialize early-stage research, either in the private sector or for government use. The program has three phases, but only Phase I and Phase II receive SBIR funding through grants or R&D contracts (depending on the participating agency). Phase III focuses on commercialization and may involve non-SBIR funded R&D or production contracts.

Bhattacharya (2020) examines the incentives for small businesses to participate in the Department of Defense (DoD) SBIR program. Conceptually, incentives may be internal, such as succeeding in early phases to qualify for larger awards, or external, such as gaining knowledge useful for other projects or becoming more attractive to potential acquirers. Bhattacharya uses contract-level data and finds strong internal but weak external incentives. Additionally, he finds that small businesses often use SBIR contracts as substitutes for other government contracts rather than as precursors to them.

The effect of SBIR awards on firm performance has been the subject of various studies over the past three decades. Initial research by Wallsten (2000) indicates that SBIR awards reduce firms' R&D expenditures but do not affect employment. Conversely, Lerner (2000) finds that firms receiving Phase II awards experience greater growth in employment and sales compared to a set of matched firms, but only if located in ZIP codes with substantial VC funding. Such recipients are more likely to secure subsequent venture capital, suggesting that SBIR awards may serve as a certification to investors. Similarly, Howell (2017) finds that Phase I grants from the Department of Energy (DoE) double the chance of receiving venture capital and increase firm patenting and sales, especially for financially constrained young firms. However, larger Phase II grants, which account for most of the SBIR budget, have no significant effect. Howell also finds no evidence that SBIR grants certify firm quality.

In a study of SBIR contracts from the Department of Defense (DoD), Rathje (2019) finds a positive effect on patenting, survival, and employment but a negative effect on sales (especially if the firms are younger or in high-growth industries). In contrast, Lanahan, Joshi, and Johnson (2021) show that participation in the SBIR program reduces firm employment.

In a recent study, Howell, Rathje, Van Reenen, and Wong (2021) find that winning an open-topic Phase I R&D contract (as opposed to a conventional Phase I R&D contract awarded in response to a specific solicitation) from the U.S. Air Force SBIR program increases the likelihood of venture capital funding, patenting, and the chances of winning a subsequent non-SBIR contract from the DoD. Despite ongoing scholarly interest, the effect of the SBIR program on small businesses remains unclear.

There is an opportunity to connect the literature on uncertainty reduction in entrepreneurial experimentation with government support for innovation. To my knowledge, only one previous study has done this. Fini, Perkmann, Kenney, and Maki (2023) investigate whether SBIR awards are more effective in supporting firms in industries with higher technology uncertainty compared to those with higher market uncertainty. Using data on 531 University of California spinoffs established between 2000 and 2013 and a propensity score matched pair design, they find that SBIR awards have heterogeneous effects on startup fundraising and performance outcomes. On average, SBIR awards reduce the likelihood of failure but do not significantly affect VC funding, first sale, or successful exit. However, for startups with high market uncertainty (i.e., information and communication technology firms), SBIR awards decrease VC funding. For the remaining startups—including firms in biotechnology, energy, etc.—SBIR awards increase VC funding and performance outcomes.

What about the startups that face high levels of both technology and market uncertainty? Prior literature has shown that accumulated product-market knowledge may complement technology knowledge in new product introductions (Nerkar & Roberts, 2004). Yet, as far as I know, no prior research has assessed the effect of simultaneous experimentation with both technologies and markets or explored the impact of government R&D contracts on American high-tech startups at scale. In this paper, I address this gap by examining all high-tech startups (not just small businesses) that receive financial support (including R&D contracts, grants, and production contracts) from any federal agency (whether through the SBIR program or not).

I rely on insights from Allen (1984) to argue that the dollar value of government R&D contracts is a good measure of technology experimentation. He studied 35 R&D project teams working on two scientific research projects and 17 technology development projects funded by government R&D contracts. The projects included research studies aimed at understanding phenomena, preliminary design studies, and feasibility studies leading to, at most, a prototype. They were primarily from the aerospace and electronics industries. The engineers involved in the 17 development projects reported that 31% of the technical idea-generating messages (e.g., solutions to problems or reasons for discarding solutions) came from analysis and experimentation. In contrast, 19% originated from the government customer (p. 45). Project teams spent, on average, 77.3% of the total project time on analysis and experimentation (p. 60). Allen's study thus revealed that technology experimentation and government feedback accounted for half of the technical ideas considered and more than three-quarters of the time spent by contractor firms on government R&D projects.

3.3 Predicted Effect on Startup Performance

Startups can reduce uncertainty by undertaking scientific experiments, such as performing one or more R&D projects for a specific R&D contracting office. Prior research has suggested several ways in which experimenting with technologies and markets can increase startup performance. Government R&D contracts may provide funding for prototype development (Howell, 2017), certify quality to investors (Lerner, 2000) or private market customers, reduce costs until the new technology is competitive with existing technologies (Mowery, 2012), and create pathways to substantial government demand (Belenzon & Cioaca, 2024). Failed R&D projects may also improve R&D quality (Khanna, Guler, & Nerkar, 2016). Additionally, working with multiple R&D contracting offices may help identify more valuable markets (Gruber et al., 2008), facilitate learning (Agrawal, Gans, & Stern, 2021), or reduce the risk of hold-up by a single government customer (Williamson, 1985).

Conversely, experimenting with technologies and markets may decrease startup perfor-

mance due to unreimbursed costs, such as bid and proposal or R&D expenditures (e.g., deferred costs, production engineering costs); the need to apply for government funding signaling a "lemon" to investors (Fini et al., 2023); the risk of expropriation (Contigiani, 2023); lengthy iteration time (Thomke, 2003); and the stigma of failure (Landier, 2005). Alternatively, experimentation may not affect startup performance if, for example, the government's needs differ from private-market needs (Laffont & Tirole, 1993) or if the government captures all potential rents from startups.

In Online Appendix A, I adapt the framework from Agrawal et al. (2021) to my context, where startups conduct R&D work for the government. I empirically test whether the value of R&D contracts and the number of distinct contracting offices that awarded them affect startup employment, sales, and the likelihood of a successful exit.

4 Data and Measures

I combine data from several sources: (i) high-tech startups from the 2020 National Establishment Time-Series (NETS) HiTech Database; (ii) venture capital investments from PitchBook Venture Capital Global; (iii) Delaware-registered legal entities from OpenCorporates; (iv) federal procurement contracts from the Federal Procurement Data System (FPDS); (v) federal grants and other assistance from the Financial Assistance Broker Submission (FABS); and (vi) industry sales and R&D expenditures from Compustat.

4.1 High-Tech Startups

The 2020 NETS HiTech Database provides annual time-series information for 6.869 million unique establishments that reported their primary market (SIC8) in one of the High Technology Levels (I, II, or III) between January 1990 and January 2020.[12] The database

[12] Hecker (2005) identified 46 four-digit 2002 NAICS industries as high-tech based on occupational mix. In the 2017 NAICS, the original 46 NAICS4s were updated to 43 NAICS4s plus 24 SIC8s. The 2020 NETS HiTech Database includes 2.627 million establishments in Level I (where high-tech occupations are at least five times the average), over 3.202 million in Level II (3-4.9 times the average), and over 1.111 million in

includes 9-digit Dun & Bradstreet (DUNS) numbers, business names, addresses, contact information, headquarters linkages, industry classifications, employment, sales, and Dun & Bradstreet ratings. An "establishment" refers to a unique primary market (SIC8) at a specific location. Thus, firms serving multiple markets or having multiple locations are classified as multi-establishment firms.

The 2020 NETS HiTech Database is based on 31 annual snapshots (taken every January) of the full Dun & Bradstreet DUNS Marketing Information file. Since the median report date for establishments in these snapshots ranges from June to August of the prior year, I treat data from snapshot years 1990-2020 as referring to calendar years 1989-2019, respectively.

Starting with 6,868,513 establishments, I identified high-tech startups through a multi-step process. First, I removed 14,139 establishments that were delisted between 1989 and 2019 (typically due to administrative errors). Next, I used headquarters linkages to determine the ultimate owner of each establishment, going up to four levels in the ownership hierarchy. This process yielded 6,543,607 firms. To focus on independent firms, I excluded 858 subsidiaries, 12 branches, 1,945 foreign-owned firms, 1,665 nonprofits, and 12,794 government entities. To identify startups, I removed 498,469 firms established before 1989, 77,209 firms not operating in high-tech industries, and 5,301 firms with more than 1-499 employees in their establishment year. The resulting dataset included 5,945,354 high-tech startups.

My analysis sample comprises an unbalanced firm-year panel of 106,462 startups that did business with the government (i.e., won at least one federal procurement contract or grant), tracked for up to ten years of activity. To calculate employees (sales) at the firm-year level, I summed the number of employees (value of sales) reported by the focal startup and all its owned establishments in the focal year. Using total sales figures, I created the variable *Large* as an indicator equal to 1 if the focal firm-year had above-median sales compared to other high-tech startups in the same SIC4 industry and 0 otherwise.

Level III (2-2.9 times the average). Approximately 11.1% of establishments fall into more than one level over the 31 years.

4.2 Venture Capital Investments

PitchBook is a venture capital, private equity, and M&A database that includes public and private companies, investments, funds, investors, exits, and people. PitchBook data include several common identifiers for linking to other datasets (e.g., Central Index Key or CIK codes used by the Securities and Exchange Commission). However, the DUNS numbers used by the NETS HiTech Database are not included. Therefore, I used headquarters country and name matching to link companies from PitchBook Venture Capital Global to my panel of high-tech startups.

From the initial set of 367,700 PitchBook companies, I removed 223,605 headquartered outside the U.S. and 21,453 with founding dates before 1987 or after 2021. For the remaining 122,642 companies, I identified 141,374 (current and former) company names. From the initial set of 6,868,513 NETS HiTech establishments, I removed 14,139 that were delisted. For the remaining 6,854,374 establishments, I identified 7,993,750 (current and former) business names. I then compared these lists of names and identified 70,329 exact matches and 13,979 "fuzzy" matches corresponding to 51,887 PitchBook companies and 84,172 NETS HiTech establishments.[13] From 1989 to 2019, 3,525 panel startups (3.3%) received 9,204 investments included in the PitchBook Venture Capital Global deals database, totaling $105.9 billion.

To calculate the venture capital raised at the firm-year level, I summed the value of completed VC deals involving the focal startup (and its establishments) in the focal year. The variable *Raised any venture capital* is an indicator equal to 1 if the focal firm raised venture capital in the focal year, and 0 otherwise. *High VC industry* is an indicator equal to

[13] After excluding exact matches, I identified additional potential matches using the *matchit* command in Stata. I used vector decomposition of names into 5-grams (sequences of five adjacent letters or spaces), simple weights (to reduce false positives from common grams like " Tech" and "Corp"), and Jaccard similarity scoring. For each PitchBook company name, I retained the top five potential matches for further processing. I discarded all potential matches with a Levenshtein distance (edit distance) greater than 15 and a Jaccard similarity score below 0.90. I cleaned the name stings by removing legal suffixes, conjunctions, and other high-frequency terms, then reapplied the *matchit* command to the resulting "core" and "nongeneric" names. I retained the best match with both a core *and* a nongeneric Jaccard similarity score ≥ 0.99 as a match. I manually checked the best matches with either a core *or* a nongeneric similarity score ≥ 0.99 and identified additional matches.

1 if the focal firm's main industry—defined using the 10-industry classification from Fama and French (1993)—received above-median VC funding compared to other industries that year, and 0 otherwise. *Successful exit* is an indicator equal to 1 if the startup went public or was acquired within ten years, and 0 otherwise. *IPO exit* is an indicator equal to 1 if the startup went public via IPO or reverse merger within ten years, and 0 otherwise. *M&A exit* is an indicator equal to 1 if the startup experienced an acquisition, buyout, or merger of equals within ten years, and 0 otherwise.

4.3 Delaware Entities

Startups seeking outside capital often register in Delaware due to that state's business-friendly legal system.[14] OpenCorporates is a database of legal entities registered in official sources. Each record includes the company name, type, current status, date of incorporation and dissolution, etc. I used exact name matching to link the 4,873,369 legal entities registered in Delaware to my panel of startups. This process identified 264,359 exact matches corresponding to 178,739 legal entities and 246,827 NETS HiTech establishments. From 1989 to 2019, 9,751 panel startups (9.2%) were registered in Delaware or owned establishments registered there. I created the variable *High growth* as an indicator equal to 1 if the focal firm was *initially* registered in Delaware, and 0 otherwise.

4.4 Federal Procurement Contracts

The Federal Procurement Data System (FPDS) is the authoritative source for U.S. government procurement contracts with an estimated value above the micro-purchase threshold.[15] FPDS data are accessible via SAM.gov (for fiscal years before 2001) and USAspending.gov

[14] According to the Delaware Division of Corporations, "more than 55% of all U.S. publicly traded companies and 65% of the Fortune 500" are registered in Delaware (https://icis.corp.delaware.gov/eCorp/).

[15] The micro-purchase threshold is defined under Federal Acquisition Regulation. For supplies and services (except construction and a few other specific exclusions), the micro-purchase threshold was $2,000 effective December 15, 1994; $3,000 effective September 28, 2006; $3,500 effective October 1, 2015; and $10,000 effective August 31, 2020. Note that every modification to a reported contract, regardless of dollar value, must also be reported to FPDS.

(for fiscal years since 2001). I focus on "prime" contracts awarded to firms working directly with the government. I exclude subcontracts due to inconsistent availability over the sample period. Data include information on contract transaction value and description, transaction date, awarding agency and office, recipient, industry (NAICS6), product or service code (PSC), extent competed, and type of set-aside, among other details.[16]

From 1989 to 2019, federal agencies awarded $10,707 billion in procurement contracts, including $1,152 billion for R&D services and $9,555 billion for products and other services (in nominal dollars). Each contract transaction included (i) the recipient DUNS number, (ii) the recipient's parent DUNS number, or (iii) both. When the recipient's DUNS number was missing, I used the recipient's parent DUNS number. I then linked these DUNS numbers to the NETS HiTech establishments. During 1989-2019, 96,873 panel startups (91%) were awarded $472 billion in procurement contracts, including $42 billion for R&D services and $416 billion for products and other services.

I used the PSC to classify each contract transaction as either R&D (involving R&D services) or production (involving products and other services).[17] I measured *technology experimentation* using the dollar value of R&D contracts awarded to the focal firm (and its establishments) in the focal year. This is reasonable because work on government R&D contracts involves substantial efforts to identify problems, develop hypotheses, conduct specific tests, and analyze results (i.e., purposeful experimentation). Empirically, Allen (1984) showed that technology experimentation and government feedback account for half of the technical ideas considered and more than three-quarters of the time spent by contractors on R&D projects.

Receiving an R&D contract does not guarantee project success. The *Value of R&D contracts* is the sum of *Value of R&D obligations* and *Value of R&D deobligations*. Obligations

[16] A single procurement contract may have numerous transactions over time, some with $0 values. Observations in FPDS are at the transaction level, not the contract level.

[17] The PSC is a 4-digit code used to describe the service(s) or product(s) acquired in each procurement contract. Appendix Tables B7 and B9 present the 24 letter codes used to classify services and the 78 two-digit numerical codes used to classify product groups, respectively.

are the funds initially promised to the contractor for agreed-upon work (Datalab, 2018). Deobligations are any funds not spent by the end of the project. That could be due to small accounting adjustments but also due to project delays and performance issues. For example, if DoE awarded $250,000 for an R&D contract but the contractor was only able to perform $200,000 worth of work, the last transaction associated with the R&D contract would be a deobligation of -$50,000. Because federal agencies generally operate under a "use it or lose it" policy (Liebman & Mahoney, 2017), they have an incentive to minimize deobligations.[18] Correspondingly, I use the *Value of R&D deobligations* as an empirical proxy for incomplete project success or even failure.

For robustness checks, I created three alternative measures of technology experimentation. First, I divided the dollar value of R&D contracts into (i) the first three stages (i.e., basic research, applied research and exploratory development, and advanced development) and (ii) the last four stages (i.e., engineering development, operational systems development, management and support, and commercialization).[19] Second, I created an indicator variable equal to 1 if the startup received any R&D contracts and 0 otherwise. Third, I used the number of R&D contracts awarded to the focal firm (and its establishments) in the focal year.

I used the variable *Awarding office code* to identify the federal contracting office that awarded each contract. I measured *market experimentation* using the number of distinct contracting offices that awarded R&D contracts to the focal firm (and its establishments) in the focal year. For robustness checks, I created three alternative measures of market experimentation: the number of distinct *agencies* that awarded R&D contracts to the startup, an indicator variable equal to 1 if the startup received R&D contracts from two or more distinct

[18]"If an agency fails to obligate its annual funds by the end of the fiscal year for which they were appropriated, they cease to be available for incurring and recording new obligations and are said to have 'expired'." (U.S. Government Accountability Office, 2004, pp. 5-4 to 5-6).

[19]For R&D contracts, the PSC contains two alphabetic and two numeric digits. The first digit is always the letter "A" to identify R&D, the second digit is an alphabetic character ("A to Z") for the major category, the third digit is numeric (1 to 9) for the subdivision, and the fourth digit is numeric (1 to 7) for the R&D stage, as shown in Appendix Table B8.

contracting offices and 0 otherwise, and a measure of the diversity of contracting offices that awarded R&D contracts to the startup (equal to 1 minus the Herfindahl-Hirschman Index of contracting offices' procurement portfolios across NAICS4 industries).

In general, federal agencies must use full and open competition in procurement. However, there are several exceptions to this rule. I used the variable *Extent competed* to distinguish contracts awarded competitively (following sealed bidding, a competitive proposal, or another competitive method that did not exclude sources) from those awarded noncompetitively. Federal agencies must also strive to meet their contracting goals with small businesses (including those with specific designations, such as veteran-owned or small disadvantaged businesses). I used the variable *Type of set aside* to identify contracts where a socioeconomic program set-aside was used.

Firms report total sales to Dun & Bradstreet; those data are aggregated into the NETS HiTech database. The U.S. government reports the R&D and production contracts obligated to each firm (i.e., its government sales). Therefore, I calculated the private sales as total sales minus government sales.

4.5 Federal Grants

The Financial Assistance Broker Submission (FABS) is the authoritative source for U.S. government financial assistance awards, including project grants, cooperative agreements, insurance, and direct payments. FABS data are available via USAspending.gov (for fiscal years since 2001). Like with contracts, I focus on "prime" financial assistance awards, as sub-awards are not consistently available over the sample period. Data include information about the award transaction value and description, transaction date, awarding agency and office, recipient, and assistance listing (or CFDA program), among other details. I used the same procedure described for procurement contracts to link grant recipients to the NETS HiTech establishments. From 2001 to 2019, 13,348 panel startups (11.6%) received $27.1 billion in federal grants and other financial assistance awards.

To calculate grants at the firm-year level, I summed the value of grants and other forms of financial assistance awarded to the focal startup (and all its owned establishments) in the focal year. Grant data were not available at scale before 2001, so the panel has missing grant data for 1989 through 2000.

4.6 Industry Sales and R&D Expenditures

Compustat provides a database of financial and market data for publicly traded companies, including balance sheet items, income statements, cash flow data, and industry-specific metrics. I downloaded the Compustat North American Fundamentals Annual database, covering June 1950 to July 2024, from Wharton Research Data Services. Financial services firms and those listed on Canadian stock exchanges were excluded. I aggregated deflated annual sales and R&D expenditures at the historical NAICS4-year level. For each industry j and year t, I calculated two measures: $\textit{Annual R\&D intensity}_{jt} = \textit{R\&D expenditures}_{jt}/\textit{Sales}_{jt}$ and $\textit{Annual Sales Growth}_{jt} = (\textit{Sales}_{jt} - \textit{Sales}_{jt-1})/\textit{Sales}_{jt-1} \times 100$. I averaged *Annual R&D intensity* over a ten-year window, $[t-9, t]$, to derive a historical measure of technology uncertainty, $\textit{Industry R\&D intensity}_{jt}$. I used the standard deviation of *Annual Sales Growth* over the same window to calculate $\textit{Industry revenue volatility}_{jt}$, a historical measure of market uncertainty. I divided the distributions of these measures into tertiles for the entire 1950-2024 period.

Figure 2 plots technology and market uncertainty for industry-years between 1989 and 2019 (on logarithmic scales). The lines labeled "T1" and "T2" mark the first and second tertiles. Examples of industries with low technology and market uncertainty include rail transportation (4821) and depository credit intermediation (5221); those with medium levels include oil and gas extraction (2111) and iron and steel mills and ferroalloy manufacturing (3311); those with high levels include other nonmetallic mineral product manufacturing (3279) and other electrical equipment and component manufacturing (3353).

A summary of the main variables used in the econometric analyses is provided in Ap-

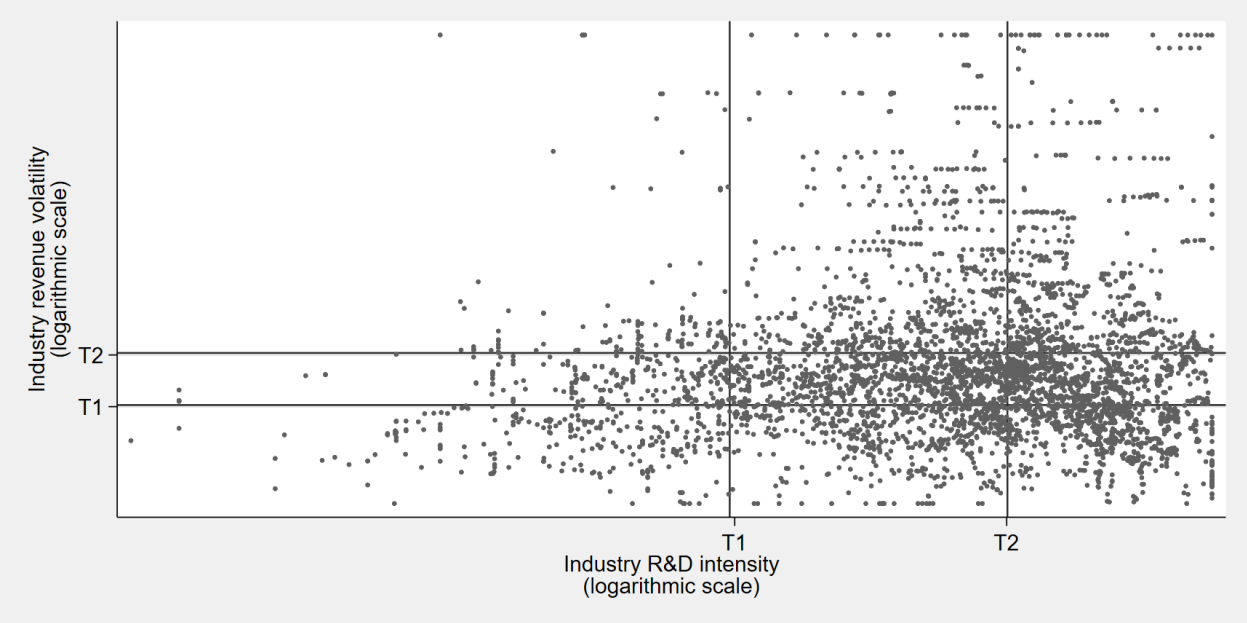


Figure 2: TECHNOLOGY AND MARKET UNCERTAINTY AT NAICS4-YEAR LEVEL

This figure plots industry R&D intensity (a measure of technology uncertainty) and industry revenue volatility (a measure of market uncertainty) for NAICS4-years during 1989-2019 on logarithmic scales. The lines labeled "T1" and "T2" mark the first and second tertiles, respectively.

pendix Table B10.

4.7 Descriptive Statistics

My estimation sample is restricted to the 106,462 startups that successfully engaged with the government. Of these, 96,873 (91%) received at least one federal procurement contract during 1989-2019 (hereafter, "contractors"), 16,983 (16%) received at least one federal R&D contract during 1989-2019 (henceforth, "R&D contractors"), and 13,348 (13%) received at least one federal grant or other assistance during 2001-2019 (hereafter, "grantees"). Overall, government sales represented a significant share of total sales. Collectively, the startups received $42 billion in R&D contracts and $416 billion in production contracts in their first ten years of operation, accounting for approximately 19% of their $2,376 billion in total sales.

The $42 billion in R&D contracts covered various R&D services, as detailed in Appendix Table B11. The top areas by R&D contract value were defense ($26.2 billion), other research and development ($6 billion), medical ($3.7 billion), general science and technology ($2.5

billion), and space ($2 billion). The share of (basic and applied) research in total R&D ranged from 1% (housing R&D) to 88% (natural resource R&D). Overall, $22.9 billion (54%) were awarded for upstream research and $19.3 billion (46%) for downstream development and commercialization.

Firms operated in various high-tech industries, representing 871 different NAICS6 codes. The top three SIC3 industries were Management and Public Relations Services (28,082 startups, 27% of sample), Computer and Data Processing Services (15,483 startups, 15%), and Research and Testing Services (11,877 startups, 11%). By NAICS2 industrial sector, a combined 81% of startups operated in Professional, Scientific, and Technical Services (66,707 startups), Manufacturing (12,579 startups), or Wholesale Trade (6,420 startups).

Table 1 provides summary statistics for the main variables used in the econometric analyses.[20] On average, panel startups had 13 employees (with headcount ranging from 1 in the 5th percentile to 40 in the 95th) and $2.68 million in annual sales (with sales ranging from $0.03 million in the 5th percentile to $6.81 million in the 95th). Compared to the entire sample, R&D contractors were larger (employing 18 people and generating $3.41 million in annual sales) and raised more venture capital ($0.22 million versus $0.12 million per year). On average, R&D contractors received $0.29 million in R&D contracts from 0.42 distinct contracting offices annually (see Appendix Table B4 for frequency distributions).

Table 2 presents mean comparison tests for the 16,983 R&D contractors based on specific firm characteristics. As expected, *Large* startups raise more VC funds and secure more government contracts and grants. *High growth* startups (those initially registered in Delaware) are larger (in terms of both employees and sales), raise more venture capital, and win more government contracts and grants. Startups in industries with above-median VC funding relative to other industries in the same year are smaller and secure more R&D contracts from a greater number of distinct contracting offices, but they win fewer production contracts.

[20] Correlations are reported in Appendix Tables B14 and B15.

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Distribution				
	Obs.	Mean	Std. dev.	min	5th	50th	95th	max
A. All startups								
Employees (#)	885,188	13.11	111.13	1.00	1.00	3.00	40.00	21,312.00
Sales ($ mm)	885,188	2.68	42.44	0.00	0.03	0.26	6.81	8,085.91
Venture capital raised ($ mm)	885,188	0.12	3.57	0.00	0.00	0.00	0.00	1,281.71
Raised any venture capital	885,188	0.01	0.10	0.00	0.00	0.00	0.00	1.00
Large	885,188	0.56	0.50	0.00	0.00	1.00	1.00	1.00
High growth	885,188	0.05	0.21	0.00	0.00	0.00	0.00	1.00
High VC industry	885,188	0.87	0.33	0.00	0.00	1.00	1.00	1.00
Number of R&D contracts (#)	885,188	0.10	1.96	0.00	0.00	0.00	0.00	1,213.00
Number of production contracts (#)	885,188	1.83	39.29	0.00	0.00	0.00	4.00	13,045.00
B. Only R&D contractors								
Employees (#)	146,207	17.96	148.27	1.00	1.00	4.00	50.00	11,207.00
Sales ($ mm)	146,207	3.41	51.68	0.00	0.04	0.34	7.89	7,879.65
Venture capital raised ($ mm)	146,207	0.22	5.04	0.00	0.00	0.00	0.00	872.80
Raised any capital	146,207	0.02	0.13	0.00	0.00	0.00	0.00	1.00
Number of R&D contracts (#)	146,207	0.63	4.79	0.00	0.00	0.00	2.00	1,213.00
Number of production contracts (#)	146,207	3.05	54.20	0.00	0.00	0.00	8.00	13,045.00
Number of R&D contracting offices	146,207	0.42	0.94	0.00	0.00	0.00	2.00	35.00
Value of R&D contracts ($ mm)	146,207	0.29	2.88	0.00	0.00	0.00	0.99	377.57
Value of R&D obligations ($ mm)	146,207	0.30	2.99	0.00	0.00	0.00	1.00	404.00
Value of R&D deobligations ($ mm)	146,207	-0.01	0.38	-84.05	0.00	0.00	0.00	0.00
Value of production contracts ($ mm)	146,207	1.18	23.85	0.00	0.00	0.00	2.22	3,856.07
Value of grants ($ mm)	114,767	0.05	1.49	0.00	0.00	0.00	0.00	264.41

Notes: This table provides summary statistics for the main variables used in the econometric analyses. The unit of analysis is a firm-year. Panel A summarizes the full analysis sample, while Panel B summarizes the subsample of 16,983 R&D contractors. The grant value is only available for the years 2001-2019.

5 Nonparametric Evidence of Experimentation

I investigate how experimentation affects startup performance by measuring firms' simultaneous experimentation with technologies and markets. While direct measures from interviews or surveys would be ideal, they are impractical for a sample of 106,462 startups. Instead, I use administrative data as proxies and validate them by comparing theoretical expectations about what patterns would emerge if firms were experimenting with observed empirical patterns.

Experimentation entails both higher variability in outcomes and changes in strategic behavior over time. Due to the nature of experimentation—which inherently involves trying

Table 2: Difference in Means for R&D Contractors by Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Large vs. not		High growth vs. not		High VC industry vs. not	
	Diff.	t	Diff.	t	Diff.	t
Employees (#)	25.70	32.38	12.38	8.26	-8.56	-4.98
Sales ($ mm)	5.35	19.29	1.40	2.67	-5.19	-8.66
Venture capital raised ($ mm)	0.27	10.10	1.18	23.28	-0.02	-0.42
Number of R&D contracting offices	0.20	39.01	0.12	13.02	0.06	5.57
Value of R&D contracts ($ mm)	0.32	20.66	0.16	5.52	0.13	4.04
Value of production contracts ($ mm)	1.73	13.52	2.30	9.54	-1.44	-5.20
Value of grants ($ mm)	0.06	6.25	0.06	3.86	0.01	0.53

Notes: This table displays mean comparison tests for the 16,983 R&D contractors by specific firm characteristics. Columns 1 and 2 compare *Large* startups (i.e., firm-years with above-median sales compared to other startups operating in the same SIC4 industry) with *Small* startups (i.e., firm-years with below-median sales compared to other startups operating in the same SIC4 industry). Columns 3 and 4 compare *High growth* startups that initially registered in Delaware with those that registered in other states. Columns 5 and 6 compare startups operating in *High VC industries* (i.e., industries with above-median funding relative to other industries in the same year) with startups operating in *Low VC industries* (i.e., industries with below-median funding relative to other industries in the same year). The two-sample t-tests use unequal variances. The grant value is only available for the years 2001-2019.

untested ideas or entering uncertain markets—I expect firms receiving larger R&D contracts to have higher variance in contract returns, with some contracts yielding breakthrough innovations and others resulting in little to no value. I also expect firms receiving R&D contracts from two or more contracting offices to have higher exposure to unsuccessful attempts (e.g., prototypes that don't work, markets that lack demand). As a result, such firms should experience higher project failure rates (e.g., abandoned projects or R&D contracts terminated early) compared to other R&D contractors.

Firms often experiment more aggressively in their formative stages to identify viable technologies and markets. Over time, firms refine their focus as they learn what works. In the early years, I expect a rapid increase in the number of R&D contracting offices as firms explore multiple markets (both government and private). In later years, the number should stabilize or decline as surviving firms achieve technology-market fit.

The nonparametric evidence is consistent with these theoretical expectations. Table 3 shows a cross-tabulation of market experimentation and project failure for the subsample of 16,983 R&D contractors. Among them, 2,951 (17%) experienced at least one R&D deobli-

gation, suggesting their technology experimentation ended in incomplete project success or even failure. 3,623 (21%) received R&D contracts from two or more contracting offices in the same year, suggesting they engaged in simultaneous market experimentation. As expected, the share of startups that had at least one R&D deobligation was much higher among those that received R&D contracts from two or more contracting offices in the same year (32%) compared to those that did not (14%).

Table 3: Market Experimentation and Project Failure

	(1) No R&D deobligations		(2) R&D deobligations		(3) Total	
Received R&D contracts from 2+ offices	Count	%	Count	%	Count	%
No	11,551	86%	1,809	14%	13,360	100%
Yes	2,481	68%	1,142	32%	3,623	100%
Total	14,032	83%	2,951	17%	16,983	100%

Notes: This table provides a cross-tabulation of market experimentation (receiving R&D contracts from two or more distinct contracting offices in the same year) and project failure (having R&D deobligations) for the subsample of 16,983 R&D contractors. The unit of analysis is a firm.

One potential concern is that startups with a high volume of R&D contracts—whether measured by total dollars or the number of contracts—may have higher chances of (i) working with multiple R&D contracting offices and (ii) experiencing R&D deobligations. This could create a mechanical correlation unrelated to market experimentation. To address this, I normalized the R&D deobligations by either (i) the value of R&D obligations or (ii) the total number of R&D contracts won. Startups were classified as having *High* project failure if their normalized R&D deobligations were in the first decile within their four-digit SIC industry. As shown in Appendix Table B16, regardless of the normalization approach, the share of *High* project failure startups was higher among the group engaging in market experimentation than among the group that did not. This pattern underscores the inherent risks of market experimentation, where startups exploring different market applications for their nascent technology face increased chances of project failure.

Another potential concern is that startups working with multiple R&D contracting offices may primarily specialize in providing R&D services to the government, treating it as their

main product rather than a pathway to develop technology-market fit. To address this, Table 4 presents a cross-tabulation of market experimentation and product sales to the government. Encouragingly, startups that received R&D contracts from two or more contracting offices in the same year were more likely to sell products (or non-R&D services) to the government (52%) compared to those that did not (46%). This supports the idea that firms engage in market experimentation as a strategy to sell innovative products.

Table 4: Market Experimentation and Product Sales to the Government

	(1) No product sales		(2) Product sales		(3) Total	
Received R&D contracts from 2+ offices	Count	%	Count	%	Count	%
No	7,225	54%	6,135	46%	13,360	100%
Yes	1,740	48%	1,883	52%	3,623	100%
Total	8,965	53%	8,018	47%	16,983	100%

Notes: This table provides a cross-tabulation of market experimentation (receiving R&D contracts from two or more distinct contracting offices in the same year) and product sales to the government for the subsample of 16,983 R&D contractors. The unit of analysis is a firm.

Figure 3 shows changes in headcount, sales, and experimentation over time. Conditional on survival, R&D contractors grow as they age, as shown in Panel A. As they grow, they also receive more R&D contracts from a greater number of distinct R&D contracting offices (Panel B). To analyze how market and technology experimentation change over the life cycle, I normalize the *Number of R&D contracting offices* and *Value of R&D contracts* by headcount and sales, respectively. Two trends emerge. First, the normalized value of R&D contracts (a proxy for technology experimentation) rises in the first 3-4 years, then declines slowly. This pattern aligns with firms eventually achieving product sales to the government or private markets (as shown in Panel D of Appendix Figure B5). Second, the normalized number of R&D contracting offices (a proxy for market experimentation) increases in the first 1-2 years and then declines rapidly. This pattern reflects the experimentation process: early on, firms explore the applicability of their technology to various government customers and potential private markets. Subsequently, they focus on the most promising applications,

reducing the number of distinct R&D contracting offices relative to the size of the firm.

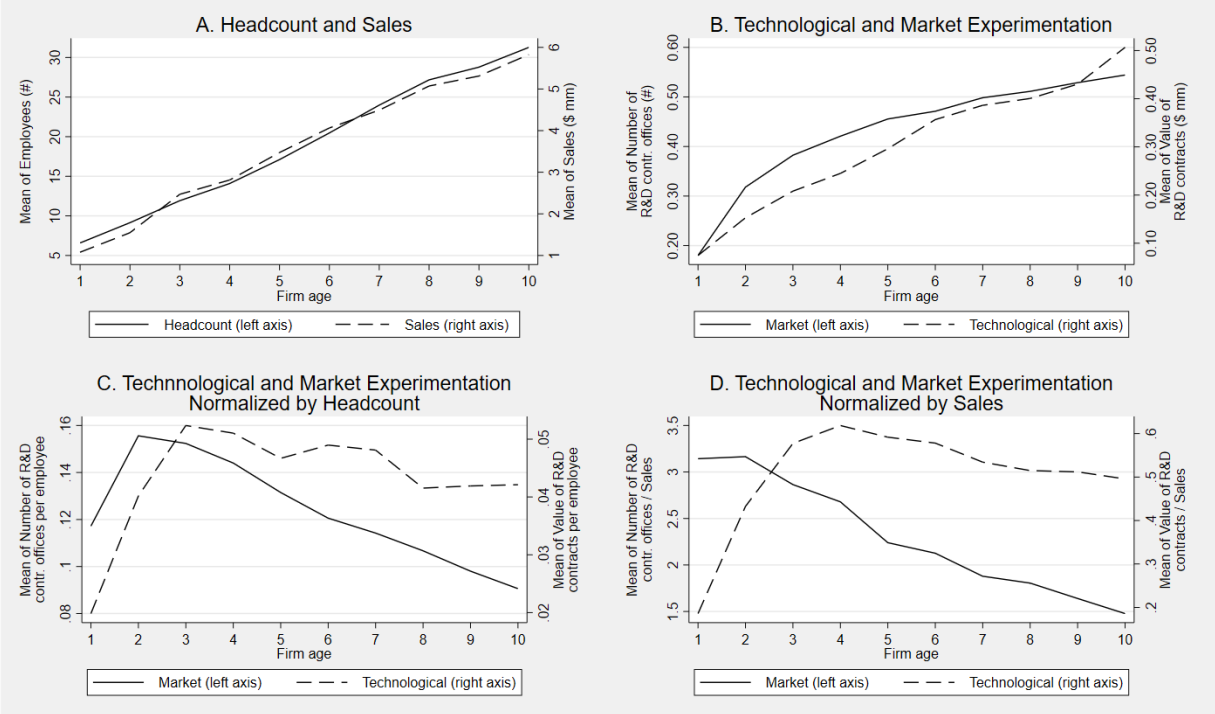


Figure 3: Changes in Headcount, Sales, and Experimentation Over Time

This figure plots the mean number of employees and sales as a function of firm age for the 16,983 R&D contractors (Panel A). It also plots the mean number of R&D contracting offices and the value of R&D contracts awarded in levels (Panel B) and normalized by headcount (Panel C) or sales (Panel D) at different firm ages.

In summary, the nonparametric evidence supports the validity of the proposed proxies for market and technology experimentation. Firms with R&D contracts from multiple contracting offices show higher rates of project failure rates and product sales, reflecting the risks and rewards of market experimentation. Similarly, the normalized value of R&D contracts aligns with patterns of early exploration and later focus, validating its use as a measure of technology experimentation. These results confirm that the proxies effectively capture experimentation, enabling an analysis of its impact on startup performance.

6 Econometric Specifications

6.1 The Relationship Between Experimentation and Performance

Most analyses are conducted at the firm-year level. The relationship between experimentation and performance is estimated as follows:

$$\begin{aligned} ln(Y)_{i,t} = \alpha_0 &+ \alpha_1 Number\ of\ R\&D\ contracting\ offices_{i,t-1} \\ &+ \alpha_2 Value\ of\ R\&D\ contracts_{i,t-1} \\ &+ \alpha_3 Value\ of\ production\ contracts_{i,t-1} \\ &+ \alpha_4 Value\ of\ grants_{i,t-1} + \boldsymbol{Z}'_{i,t-1}\boldsymbol{\omega} + \boldsymbol{\eta_i} + \boldsymbol{\tau_t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

$Y_{i,t}$ represents the number of employees or value of sales. $Number\ of\ R\&D\ contracting\ offices_{i,t-1}$, the count of *distinct* contracting offices awardeding R&D contracts to firm i in year $t-1$, proxies for *market* experimentation. $Value\ of\ R\&D\ contracts_{i,t-1}$, the dollar value of R&D contracts awarded to firm i in year $t-1$, proxies for *technology* experimentation. $Value\ of\ production\ contracts_{i,t-1}$ is the dollar value of all production contracts awarded to firm i in year $t-1$. $Value\ of\ grants_{i,t-1}$ is the dollar value of all federal grants and other assistance awarded to firm i in year $t-1$. (This variable is only available during 2001-2019.) The vector $\boldsymbol{Z}$ includes time-varying indicator variables that are equal to 1 when the value of R&D contracts, production contracts, and grants, respectively, was changed from negative to zero, and 0 otherwise. They account for the practice of federal agencies recording negative transactions when initial awards are partially or fully "deobligated." The vectors $\boldsymbol{\eta}$ and $\boldsymbol{\tau}$ represent firm fixed effects and year fixed effects, respectively, and ϵ is an *iid* error term. All monetary values are adjusted to constant 2012 dollars using the GDP Implicit Price Deflator (U.S. Bureau of Economic Analysis, 2021). Standard errors are clustered at the firm level.

The coefficients of interest are α_1 and α_2. I expect $\hat{\alpha_1} > 0$ because firms benefit from learning about the applicability of their technology to various markets, with the effect varying

based on firm characteristics. I anticipate $\hat{\alpha_2} \geq 0$, as R&D contracts should not negatively impact startup performance outcomes. This expectation is reasonable because most government R&D projects use cost-reimbursement contracts, where the risk of cost overruns is borne by the awarding agency rather than the R&D contractor.[21] Additionally, I examine heterogeneity by analyzing differences across industry, agency, and contract characteristics.

One concern with these econometric specifications is that *Employees* is an overdispersed count variable. To address this, I supplement OLS regression estimates with Poisson fixed effects regression estimates. I report Poisson estimates for both employment and sales, as Poisson regression produces valid semi-elasticity estimates and standard errors even when the outcome variable is continuous (Cohn, Liu, & Wardlaw, 2022).

6.2 Instrumental Variable Strategy

Contract endogeneity (David et al., 2000) poses a key challenge, as technology or demand shocks may influence both federal R&D contracting and startup performance. If R&D contracts systematically target startups experiencing positive technology or demand shocks, then $\hat{\alpha_1}$ and $\hat{\alpha_2}$ may be upward biased. Conversely, if R&D contracts target startups facing negative shocks, then $\hat{\alpha_1}$ and $\hat{\alpha_2}$ may be downward biased. To address this challenge, I use an instrumental variable strategy with two instruments for two endogenous regressors.

First, I use the size standards set by the Small Business Administration (SBA) to determine which firms can compete for government programs reserved for small businesses. I apply a "fuzzy" regression discontinuity design (RDD) to estimate a local average treatment effect (LATE) around the known cutoff points in the "assignment" variable.

In this context, the assignment variable can be either the number of employees or the value of sales of a firm. The cutoff points are the size standards, which define the maximum size a firm can be (in terms of employees or sales, but not both) while still being considered

[21] The federal government uses two primary types of contracts: fixed-price and cost-reimbursement. Fixed-price contracts impose the greatest risk on the contractor (to cover cost overruns). In contrast, cost-reimbursement contracts shift most of the risk to the government (which covers cost overruns).

a small business for federal contracting purposes.[22] Importantly, size standards vary by industry (NAICS6) and over time.[23] Between 2001 and 2019, I identify 767 industries with employee size standards and 593 industries with sales size standards (in one or more years). The employee size standards range from 50 to 1,500, with a mean of 588. The sales size standards range from \$0.5 million to \$38.5 million, with a mean of \$11.79 million (in nominal dollars). Figure 4 displays the frequency distributions of employee and sales size standards at the industry-year level from 2001 to 2019.

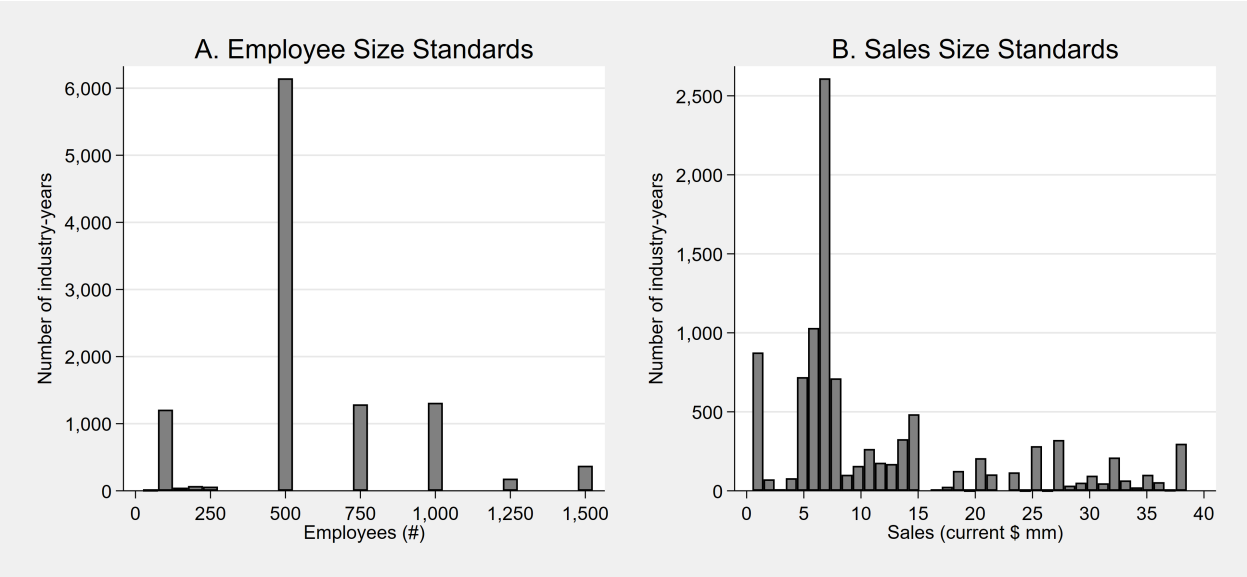


Figure 4: Frequency Distributions of Employee and Sales Size Standards
This figure plots the frequency distributions of small business size standards in terms of employees (Panel A) and sales (Panel B), at the industry-year level, between 2001 and 2019.

The basic idea is that startups with employees (or sales) just below the size standard for their industry that year (and thus eligible for small business set-aside contracts) provide good comparisons to those just above the size standard (who are ineligible for set-aside contracts). The former should be more likely to receive R&D contracts from multiple contracting offices

[22] To qualify for contracts set aside for small businesses, firms must also be for-profit, independently owned and operated, not nationally dominant in their field, and physically located and operated in the U.S. or its territories (U.S. Small Business Administration, 2024).

[23] The SBA revises size standards based on changes in industries (e.g., competition, firm size distribution, start-up costs, entry barriers) and the overall economy (e.g., technology changes, competition from other industries, growth trends). The SBA reviews the impact of inflation on monetary size standards at least once every five years, adjusting the standards as necessary.

compared to the latter.

The key identifying assumption is that firms cannot *precisely* manipulate their assignment variable (D. S. Lee & Lemieux, 2010). I use the number of employees as the assignment variable and *center* it by subtracting the applicable size standard from the firm's headcount. For example, a firm with 135 employees in a year when its industry's size standard is 150 would have a centered assignment variable of $135 - 150 = -15$. A firm with 515 employees in a year when its industry's size standard is 500 would have a centered assignment variable of $515 - 500 = +15$.

Figure 5 plots the density of the centered assignment variable within the [-50,+50] interval. It shows the number of firm-year observations with a headcount of up to 50 employees smaller or larger than the applicable size standard, using a bandwidth of 2 employees and grouping observations into 50 bins (25 on each side of the cutoff). A discontinuity in the density at the cutoff would suggest manipulation. Reassuringly, there is no jump in the number of observations just before the cutoff, indicating that firms do not artificially reduce their headcount to qualify for small business set-asides.

Figure 6 illustrates a "fuzzy" discontinuity: startups with a headcount just below the applicable employee size standard (i.e., treated startups) receive R&D contracts from more contracting offices compared to those just above the size standard (i.e., control startups). Therefore, I use a treatment indicator variable, equal to 1 for firm-years with a centered assignment variable in the [-50,0] interval, as an instrument for the number of distinct R&D contracting offices.

Second, I use the fact that federal agencies spend their leftover funds before the end of the fiscal year, September 30, bumping up R&D contract value. This is not driven by technology or demand shocks that also affect startup employment or sales. Rather, it is driven by the "use it or lose it" budgeting policy of the federal government.

Figure 7 uses data for all R&D contracts awarded during 2000-2019 (not restricted to the analysis sample). The red dots mark the months of September. The number of R&D

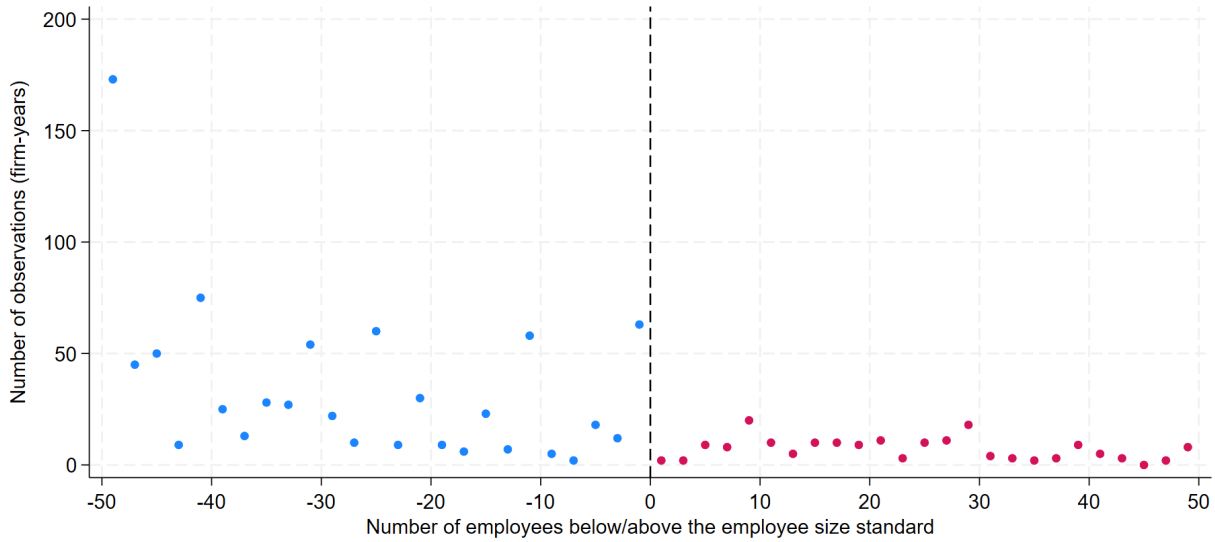


Figure 5: Density of the Assignment Variable

This figure plots the density of the centered assignment variable in the [-50,+50] interval. It shows the number of firm-year observations with a headcount of up to 50 employees smaller or larger than the applicable employee size standard. Data are plotted in 50 bins (25 on each side of the cutoff) using a bandwidth of 2 employees. There is more density overall to the left of the size standard because there are more small firms than large firms.

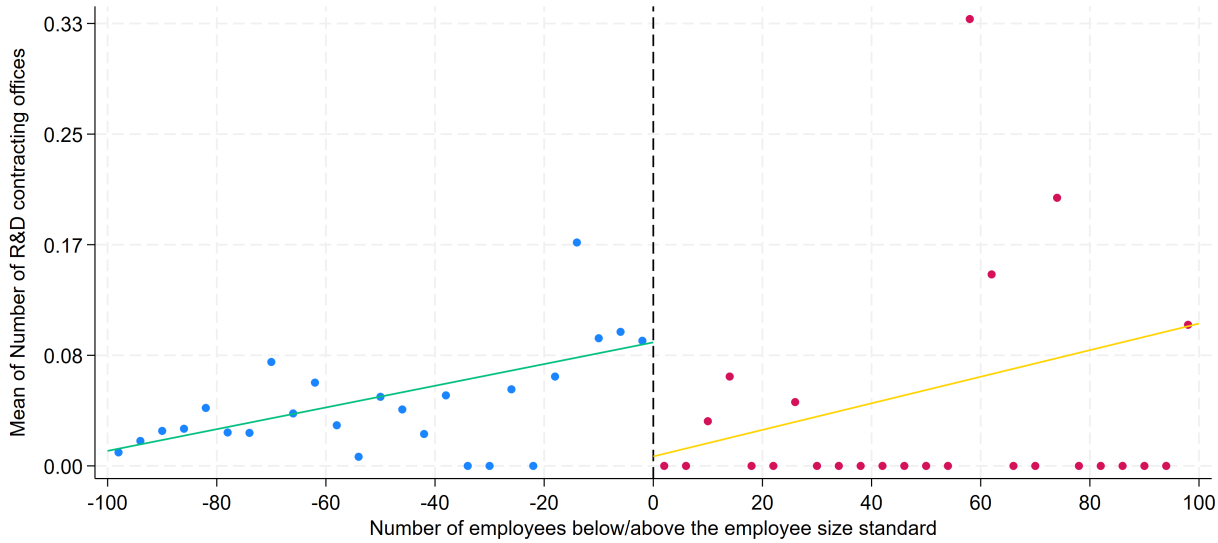


Figure 6: Number of R&D Contracting Offices

This figure plots the conditional mean number of R&D contracting offices for observations with centered assignment variables in the [-100,+100] interval. It uses firm-years with a headcount up to 100 employees smaller or larger than the applicable employee size standard. Data are plotted in 50 bins (25 on each side of the cutoff) using a bandwidth of 4 employees.

contract transactions spikes each September (Panel A), consistent with agencies modifying more contracts toward the end of the fiscal year. The dollar value of R&D obligations also spikes (Panel B). The dollar value of R&D deobligations (i.e., funds no longer spent, so potentially available for reallocation to more promising projects) also spikes (Panel C). On average, over 2000-2019, $5.5 billion in R&D contracts were awarded during September, compared to just $2.6 billion during July (Panel D).

Therefore, I instrument the value of R&D contracts with an indicator variable equal to 1 if the firm received any R&D contracts during September of the focal year. I then estimate the causal effect of experimenting with technologies and markets on startup performance using two-stage least squares (2SLS) regressions. In the second stage of 2SLS, I use only the variation in the *Number of R&D contracting offices* explained by being below the size standard and the variation in the *Value of R&D contracts* explained by receiving funding during September.

7 Estimation Results

The estimation results suggest a strong effect of the number of R&D contracting offices (i.e., *market experimentation*) on startup performance. I present the detailed analyses below.

7.1 Employment and Sales Equations

Table 5 presents the results of within-firm estimations for startup employment. The OLS estimates in Columns 1, 3, and 4 show that the *Number of R&D contracting offices* is positively related to headcount (p-values < 0.01).[24] At the sample means, the coefficient estimate in Column 4 suggests that winning R&D contracts from one additional contracting office is associated with a 10.6% increase in headcount. Because *Employees* is an overdispersed count variable, Column 5 reports Poisson regression estimates. Additional robustness checks are

[24] Adding a control for startup age or venture capital funds raised does not change the results.

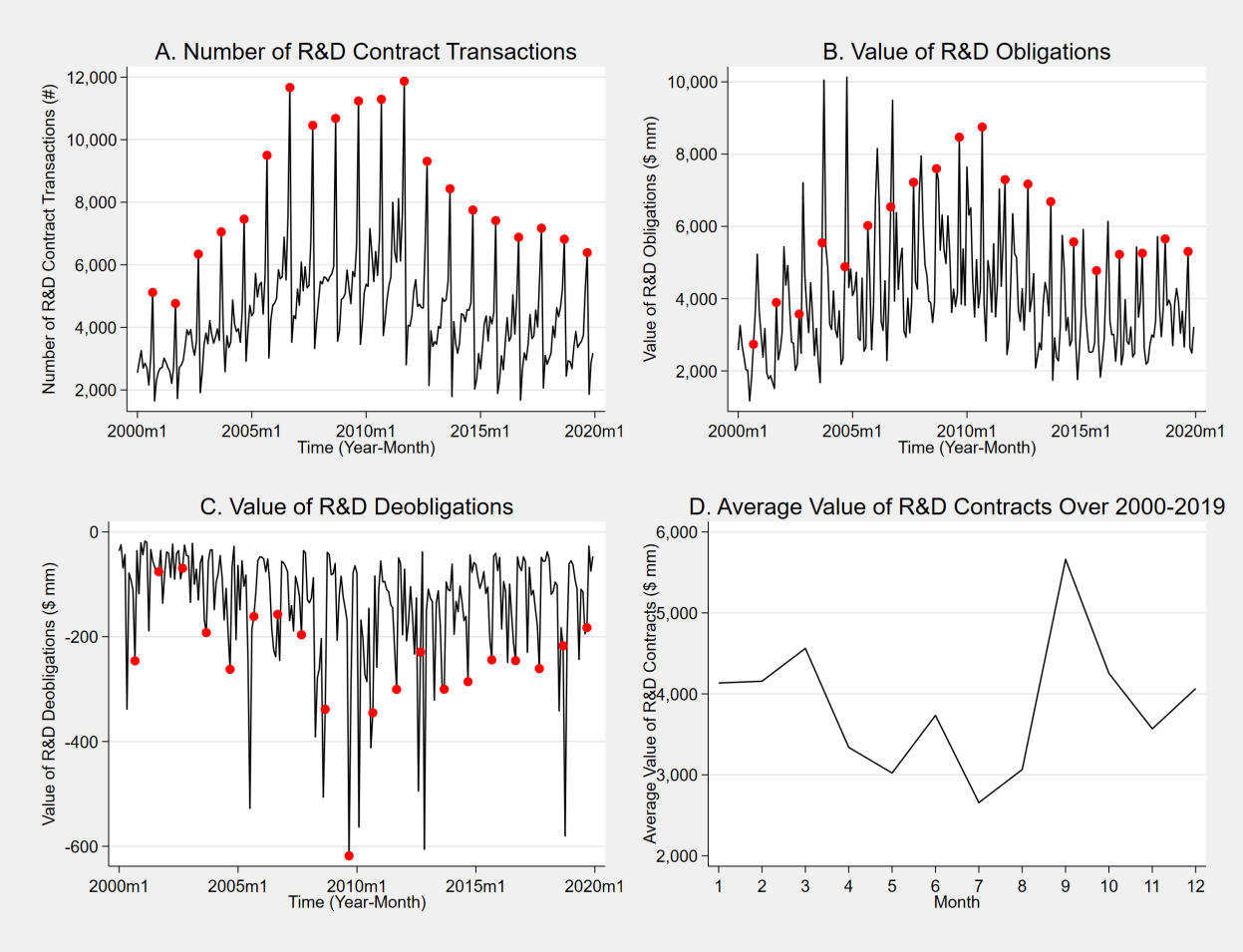


Figure 7: Timing of R&D Contracts

This figure summarizes R&D contracts over 2000-2019. Panel A plots the number of R&D contract transactions by month. The red dots identify the month of September. Panels B and C plot the dollar value of R&D obligations and R&D deobligations by month, respectively. Panel D plots the average value of R&D contracts awarded each calendar month.

provided in Appendix Table B17. Since larger firms may be better positioned to work with more R&D contracting offices, I use *Employee growth* (i.e., the percentage change in headcount year-over-year) as the dependent variable. Since older firms may be better positioned to work with more R&D contracting offices, I add a control for *Firm age* (measured in years since founding). And, since specialist firms may be better positioned to work with more R&D contracting offices, I restrict the analysis sample to the 16,983 R&D contractors. Across all these specifications, the results remain qualitatively similar.

Conversely, the *Value of R&D contracts* does not consistently relate to startup employ-

Table 5: Relationship Between Experimentation and Startup Employment

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(Employees)$_t$				Employees$_t$	ln(Employees)$_t$	
	Number (OLS)	Value (OLS)	Both (OLS)	Additional controls (OLS)	Additional controls (Poisson)	Narrow window (OLS)	Narrow window (2SLS)
Number of R&D contr. offices$_{t-1}$	0.116***		0.108***	0.106***	0.067***	0.246***	118.725***
	(0.004)		(0.005)	(0.005)	(0.015)	(0.047)	(41.970)
Value of R&D contracts$_{t-1}$		0.021***	0.010***	0.011**	-0.009**	0.030	-156.958***
		(0.005)	(0.003)	(0.004)	(0.004)	(0.039)	(58.001)
Value of production contracts$_{t-1}$				0.001***	0.001**	0.021***	-0.021
				(0.000)	(0.000)	(0.002)	(0.208)
Value of grants$_{t-1}$				0.002**	0.002	0.026	-1.001
				(0.001)	(0.001)	(0.017)	(1.033)
Year FE	Yes	Yes	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	No	No
Industry-year FE	No	No	No	No	No	Yes	Yes
Mean DV	14.03	14.03	14.03	12.01	12.01	9.55	9.55
Firms	102,958	102,958	102,958	91,708	91,708	6,146	6,146
Observations	780,976	780,976	780,976	630,409	630,409	31,946	31,946
Weak identif. (Kleibergen-Paap)							4.01
Adjusted/pseudo R-squared	0.88	0.88	0.88	0.89	0.88	0.07	-560.94

Notes: This table presents the effect of experimentation on startup employment. The analysis samples in Columns 4 and 5 include only the years 2001-2019 when grant data are available. The analysis samples in Columns 6 and 7 are restricted to firm-years between 2001 and 2019 with a headcount of up to 100 employees smaller or larger than the applicable employee size standard. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms (Columns 1-5) or industry-years (Columns 6 and 7). * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

ment. OLS estimates in Columns 2, 3, and 4 are small and positive. The coefficient in Column 4 indicates that an additional $1 million in R&D contracts is associated with a 1.1% increase in headcount. Given the average R&D contractor receives $0.29 million in R&D contracts per year, a $1 million increase represents a substantial change associated with a negligible increase in headcount. Moreover, the Poisson estimate in Column 5 is small and negative, raising concerns about the relationship between R&D contracts and startup employment. The robustness checks in Appendix Table B17 are similarly inconclusive. These results align with the idea that government R&D contracts may fund projects that startups would undertake regardless.[25]

These coefficient estimates may be biased due to endogeneity. I address this using the

[25]Previous studies on SBIR awards and small firm employment have yielded mixed results: Wallsten (2000) found no effect, Lerner (2000) found a positive effect, while Lanahan et al. (2021) found a negative effect.

instrumental variables described in Section 6.2. Specifically, I estimate a *local* average treatment effect (LATE) within a narrow window around the employee size standards used to define treatment and control groups in the regression discontinuity design. For comparison, new baseline OLS estimates are included in Column 6. The sample includes only firm-years between 2001 and 2019 with a headcount of up to 100 employees smaller or larger than the applicable size standard. Firm and year fixed effects are replaced with NAICS6 industry-year fixed effects, and standard errors are clustered by industry-years rather than by firm.

In the first stage of 2SLS, I regress the *Number of R&D contracting offices* on an indicator variable, *Treated*, which equals 1 for firm-years with headcount up to 50 employees *below* the applicable size standard and 0 otherwise (plus controls).[26] To test the relevance of the second instrument, I regress the *Value of R&D contracts* on an indicator variable, *September*, which equals 1 for firm-years that received any R&D contracts during September and 0 otherwise (plus controls).[27] In the second stage, I regress startup employment on the predicted *Number of R&D contracting offices* and *Value of R&D contracts* from the first stage (plus controls). Column 7 shows a strong positive effect of the number of R&D contracting offices (proxy for *market experimentation*) and a strong negative effect of the value of R&D contracts (proxy for *technology experimentation*) on headcount.

The 2SLS estimates represent local average treatment effects. Startups that receive R&D contracts from one additional contracting office *only because* they are small businesses grow their headcount next year. In contrast, startups that secure additional R&D contract dollars *only because* it is the end of the federal fiscal year shrink their headcount next year. The 2SLS results suggest that the government systematically "broadens" R&D contracting to startups experiencing negative technology or demand shocks, while at the same time "deepening" R&D contracting with the most promising startups. The downward bias on the measure of

[26] First-stage results in Column 7 of Appendix Table B17 show an F-statistic of 71.23 and a positive and significant coefficient estimate on *Treated* (p-value < 0.01), indicating the first instrument is valid. Similar results are obtained using thresholds of 25 or 75 employees below the size standard to define the treated group.

[27] First-stage results in Column 8 of Appendix Table B17 show an F-statistic of 15.49 and a positive and significant coefficient estimate on *September* (p-value < 0.01), indicating the second instrument is valid.

contracting breadth is expected, given the government's focus on small and disadvantaged businesses in procurement. The upward bias on the measure of contracting depth is also expected, given the government's focus on developing the most promising technologies to achieve its agencies' missions.

Table 6 presents the results of within-firm estimations for startup sales. Similar to the headcount equation, the *Number of R&D contracting offices* is positively related to sales in both OLS and Poisson regressions (p-values < 0.01). As shown in Appendix Table B18, this relationship also holds for *Sales growth* and remains robust when controlling for firm age and restricting the sample to R&D contractors. The 2SLS results further suggest a positive effect of market experimentation and a negative effect of technology experimentation on startup sales. The latter result is not surprising when considering that prior studies on the impact of SBIR awards on small firm sales have yielded mixed results. Lerner (2000) found a positive effect for Phase II awards, while Howell (2017) found a positive effect for Phase I awards but a negative effect for the larger Phase II awards.

A concern may be that the *Treated* instrument (i.e., headcount up to 50 employees below the size standard) could affect startup performance through other pathways than its direct effect on the *Number of R&D contracting offices*.[28] For example, small businesses may receive additional guidance and mentorship on how to win government awards. To address it, I use the *Value of private sales* (i.e., total sales minus government sales) as the dependent variable. I reason that a firm's headcount relative to the government standard should have little direct effect on private-sector sales. In unreported specifications, I estimate second-stage coefficients on the *Number of R&D contracting offices* and *Value of R&D contracts* that are similar to those reported in Column 7 (112.179 and -285.056, respectively).

In summary, experimenting with markets while conducting contract R&D work for the federal government increases startup employment and sales. However, it is important to note that I do not observe the firm's decision to bid on government R&D contracts. Conditional

[28] I am grateful to Timothy Simcoe for raising this point.

Table 6: Relationship Between Experimentation and Startup Sales

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(\text{Sales})_t$				Sales_t	$\ln(\text{Sales})_t$	
	Number (OLS)	Value (OLS)	Both (OLS)	Additional controls (OLS)	Additional controls (Poisson)	Narrow window (OLS)	Narrow window (2SLS)
Number of R&D contr. offices$_{t-1}$	0.133***		0.124***	0.120***	0.055***	0.183***	128.205***
	(0.005)		(0.005)	(0.005)	(0.015)	(0.066)	(45.608)
Value of R&D contracts$_{t-1}$		0.024***	0.011***	0.014***	-0.007*	-0.026	-169.561***
		(0.006)	(0.004)	(0.005)	(0.004)	(0.034)	(63.049)
Value of production contracts$_{t-1}$				0.001*	0.001***	0.040***	-0.006
				(0.001)	(0.000)	(0.005)	(0.225)
Value of grants$_{t-1}$				0.002**	0.003	0.031*	-1.080
				(0.001)	(0.004)	(0.016)	(1.119)
Year FE	Yes	Yes	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	No	No
Industry-year FE	No	No	No	No	No	Yes	Yes
Mean DV	2.90	2.90	2.90	2.35	2.35	2.65	2.65
Firms	102,930	102,930	102,930	91,682	91,684	6,146	6,146
Observations	780,774	780,774	780,774	630,250	630,285	31,946	31,946
Weak identif. (Kleibergen-Paap)							4.01
Adjusted/pseudo R-squared	0.92	0.91	0.92	0.93	0.87	0.09	-328.39

Notes: This table presents the effect of experimentation on startup sales. The analysis samples in Columns 4 and 5 include only the years 2001-2019 when grant data are available. The analysis samples in Columns 6 and 7 are restricted to firm-years between 2001 and 2019 with a headcount of up to 100 employees smaller or larger than the applicable employee size standard. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms (Columns 1-5) or industry-years (Columns 6 and 7). * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

on bidding, winning R&D contracts from multiple distinct R&D contracting offices boosts startup employment and sales. In contrast, doing more and more contract R&D work for the government decreases startup growth. Next, I analyze the effect of experimentation on another set of startup performance outcomes: successful exit via IPO or M&A.

7.2 Exit Equations

Table 7 presents the relationship between experimentation and startup exit outcomes. I aggregate the panel data at the firm level and conduct cross-sectional analyses with establishment year (cohort) and industry fixed effects. I use three indicator variables as the dependent variables: *Successful exit* is equal to 1 if the startup went public or was acquired within the first ten years, and 0 otherwise; *IPO exit* is equal to 1 if the startup went public

via IPO or reverse merger within the first ten years, and 0 otherwise; *M&A exit* is equal to 1 if the startup experienced an acquisition, buyout, or merger of equals within the first ten years, and 0 otherwise. I report estimates from both OLS and logistic regression. I use three indicators as independent and control variables. *Received R&D contracts from 2+ offices* identifies firms that engaged in simultaneous market experimentation at least once before their successful exit. *Received R&D contracts* identifies firms that engaged in technology experimentation at least once before their successful exit. *Received production contracts* identifies firms that won production contracts at least once before their successful exit.

Across most specifications, market experimentation is positively related to a successful exit, while technology experimentation is negatively related. The odds ratios reported in Columns 2, 4, and 6 suggest that startups working with two or more R&D contracting offices simultaneously have a 102% higher chance of a successful exit, with this effect observed via both IPO and M&A. Conversely, startups doing R&D work for the government have an 83% lower chance of a successful exit, driven by a lower chance of both IPO (98% lower) and M&A (72% lower).

7.3 Heterogeneity Analyses

The positive relationship between market experimentation and startup performance is not confined to a single industry (see Appendix Table B19). It also extends beyond a single federal agency (see Appendix Tables B20 and B21). Additionally, the results remain consistent for R&D contracts awarded with or without competition and for R&D contracts set aside for small/disadvantaged businesses or not (see Appendix Table B22).

7.3.1 Variation by Industry Uncertainty

However, industries face different levels of market and technology uncertainty—which are not captured by standard industrial classifications, such as SIC or NAICS. Prior literature suggests that biotech firms face low market uncertainty but high technology uncertainty

Table 7: Relationship Between Experimentation and Startup Exit Outcomes, Firm Level

Dependent variable:	(1) Successful exit	(2) Successful exit	(3) IPO exit	(4) IPO exit	(5) M&A exit	(6) M&A exit
	(OLS)	Odds ratio (Logit)	(OLS)	Odds ratio (Logit)	(OLS)	Odds ratio (Logit)
Received R&D contracts from 2+ offices before exit	0.006***	2.019***	0.002***	2.388***	0.004***	1.876**
	(0.002)	(0.376)	(0.001)	(0.768)	(0.001)	(0.463)
Received R&D contracts before exit	-0.013***	0.170***	-0.007***	0.024***	-0.007***	0.278***
	(0.003)	(0.053)	(0.002)	(0.017)	(0.002)	(0.081)
Received production contracts before exit	-0.023***	0.075***	-0.011***	0.014***	-0.014***	0.124***
	(0.005)	(0.015)	(0.002)	(0.008)	(0.003)	(0.021)
Establishment year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.0066	0.0076	0.0023	0.0032	0.0047	0.0056
Firms	105,661	92,008	105,677	76,612	105,663	89,011
Observations	105,661	92,008	105,677	76,612	105,663	89,011
Adjusted R-squared	0.02	.	0.01	.	0.02	.

Notes: This table presents the relationship between experimentation and startup exit outcomes. The unit of analysis is a firm. *Successful exit* is an indicator variable equal to 1 if the startup went public or was acquired, and 0 otherwise. *IPO exit* is an indicator variable equal to 1 if the startup went public via IPO or reverse merger, and 0 otherwise. *M&A exit* is an indicator variable equal to 1 if the startup experienced an acquisition, buyout, or merger of equals, and 0 otherwise. *Received R&D contracts from 2+ offices* identifies firms that engaged in simultaneous market experimentation at least once before their exit. *Received R&D contracts* identifies firms that engaged in technology experimentation at least once before their exit. *Received production contracts* identifies firms that won production contracts at least once before their exit. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by NAICS6 industries. * p-value $<$ 0.10 ** p-value $<$ 0.05 *** p-value $<$ 0.01

while information and communication technology (ICT) firms face high market uncertainty but low technology uncertainty (e.g., BCG, 2021; Kerr et al., 2014). In Appendix Table B23, I present results using two subsamples: (i) 1,353 startups in the pharmaceutical product industries (henceforth, "pharma startups") and (ii) 18,775 startups in communication, computer hardware, software, and electronic equipment industries (henceforth, "ICT startups"). Consistent with the idea that market (technology) experimentation is more beneficial for firms with high market (technology) uncertainty, the number of distinct R&D contracting offices is unrelated to headcount and sales for pharma startups but positively and significantly related for ICT startups. Conversely, the value of R&D contracts has a positive and significant relationship with headcount and sales for pharma startups but shows no relationship for ICT startups.

7.3.2 Variation by Firm Characteristics

Table 8 shows how the relationship between market experimentation and startup performance varies by firm characteristics. In Columns 1, 3, 5, and 7, the variable *Large* is an indicator equal to 1 for firm-years with above-median sales compared to other startups in the same SIC4 industry. The OLS and Poisson coefficient estimates indicate that market experimentation benefits large startups but harms small startups (p-values < 0.01). This result is consistent with the idea that large startups have more resources and capabilities to pursue various market opportunities simultaneously. In contrast, for smaller startups, the costs of market experimentation outweigh the benefits.

In Columns 2, 4, 6, and 8, the variable *High growth* is an indicator equal to 1 if the startup was initially registered in Delaware and 0 otherwise. Registering in Delaware often indicates the company is seeking outside capital. Overall, the OLS and Poisson coefficient estimates suggest that market experimentation benefits low-growth startups more than high-growth startups. To further explore this heterogeneity, I report results with an interaction term measuring industry munificence in Appendix Table B24. Specifically, *High VC industry* is an indicator equal to 1 if the firm's industry receives above-median VC funding compared to other industries that year, and 0 otherwise. The Poisson estimates suggest that startups in munificent environments (whether high-growth or not) benefit less from market experimentation using government R&D contracts compared to other startups. These results support the idea that government funding may be the second-best option for startups (i) seeking venture capital and (ii) having ample access to it.

This finding highlights a tradeoff: while innovating for the government provides non-dilutive funding for joint testing of technical feasibility and commercial application, it also diverts time and attention from testing the private market. Time is often the scarcest resource for ambitious startups as patents expire and competing innovations emerge.

Table 8: Variation by Firm Characteristics

Dependent variable:	(1) ln(Employees)$_t$	(2) ln(Employees)$_t$	(3) ln(Sales)$_t$	(4) ln(Sales)$_t$	(5) Employees$_t$	(6) Employees$_t$	(7) Sales$_t$	(8) Sales$_t$
	Firm size (OLS)	Firm registration (OLS)	Firm size (OLS)	Firm registration (OLS)	Firm size (Poisson)	Firm registration (Poisson)	Firm size (Poisson)	Firm registration (Poisson)
Number of R&D contr. offices$_{t-1}$	-0.046***	0.110***	-0.080***	0.123***	-0.147***	0.072***	-0.326***	0.059***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.017)	(0.017)	(0.025)	(0.015)
× *Large*	0.208***		0.273***		0.217***		0.383***	
	(0.009)		(0.010)		(0.020)		(0.027)	
× *High growth*		-0.036**		-0.032*		-0.059*		-0.055
		(0.016)		(0.018)		(0.031)		(0.034)
Value of R&D contracts$_{t-1}$	0.007	0.011**	0.009*	0.014***	-0.010***	-0.010***	-0.007*	-0.007*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001*	0.001*	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002**	0.002**	0.002**	0.002	0.002	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.00	12.00	2.34	2.34	12.00	12.00	2.34	2.34
Firms	91,145	91,145	91,119	91,119	91,145	91,145	91,121	91,121
Observations	626,855	626,855	626,696	626,696	626,855	626,855	626,731	626,731
Adjusted/pseudo R-squared	0.89	0.89	0.93	0.93	0.88	0.88	0.87	0.87

Notes: This table presents the variation in the relationship between market experimentation and startup employment and sales by firm characteristics. *Large* firm-years have above-median sales compared to other startups operating in the same SIC4 industry. *High growth* is an indicator variable equal to 1 if the firm initially registered in Delaware, and 0 otherwise. The analysis samples in all columns include only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value $<$ 0.10 ** p-value $<$ 0.05 *** p-value $<$ 0.01

7.4 Potential Mechanisms

The SBIR literature examines two mechanisms by which government R&D contracts and grants may impact small firm performance: a certification/signaling effect and a funding effect. The certification mechanism suggests that receiving an SBIR award signals the quality of the technology or firm to investors (Lerner, 2000). The funding mechanism posits that the SBIR award's value enables the firm to develop a prototype and de-risk the technology (Fini et al., 2023; Howell, 2017). In this paper, only the number of R&D contracting offices increases startup performance, ruling out a funding mechanism.

Market experimentation may drive startup performance via two mechanisms that are not mutually exclusive. First, winning government R&D contracts from multiple agencies

may *certify* the startup's commercialization capabilities to investors, customers, and acquirers. In this case, experimenting startups should attract more venture capital funding, gain more customers, and have a higher likelihood of exiting via M&A. Second, the diversity of customer feedback across multiple government markets may help startups *develop* commercialization capabilities they can later apply in both public and private sectors. In this case, experimenting startups should see increased sales, particularly in unrelated markets.

Table 9 tests these mechanisms. Columns 1-3 examine whether market experimentation certifies the startup to VC investors. If this is the case, I would expect the *Number of R&D contracting offices* to be positively associated to future venture capital raised. However, the number of distinct R&D contracting offices is not significantly related to either the likelihood of raising venture capital or the amount raised.[29] This casts doubt on the certification mechanism, at least in terms of VC investors.

Columns 4-7 test whether market experimentation builds commercialization capabilities. If this mechanism holds, I would expect the *Number of R&D contracting offices* to be positively related to future government and private sales. Government sales are the sum of R&D and production contracts from the federal government, while private sales are total sales minus government sales. Empirically, the number of R&D contracting offices is positively associated with future government sales (Columns 4 and 5), which is expected: startups working with many different offices on R&D projects will secure more government contracts in the future. Notably, the number of R&D contracting offices is also positively related to future private sales (Columns 6 and 7), supporting the commercialization capabilities mechanism.

Firms with strong commercialization capabilities are better equipped to turn innovations into successful products. Appendix Table B26 examines how firms' experimentation relates to the breadth of products sold to the government, measured by the number of distinct

[29] If venture capital predicted the number of R&D contracting offices, it would suggest that VC investors are steering startups toward public funding (Lerner, 2000). Fortunately, this is not the case, as shown in Appendix Table B25.

Table 9: Relationship Between Experimentation and Future Venture Capital Raised and Sales

Dependent variable:	(1) Raised any VC$_t$	(2)	(3) Value of VC raised$_t$	(4)	(5) Value of govt. sales$_t$	(6)	(7) Value of private sales$_t$
	(Logit)	(OLS)	(Poisson)	(OLS)	(Poisson)	(OLS)	(Poisson)
Number of R&D contr. offices$_{t-1}$	0.067	0.016	0.065	0.544**	0.049**	0.394*	0.037*
	(0.051)	(0.012)	(0.048)	(0.272)	(0.024)	(0.230)	(0.021)
Value of R&D contracts$_{t-1}$	-0.058*	-0.009	-0.048*	1.255***	0.001	-0.014	-0.007
	(0.034)	(0.006)	(0.025)	(0.366)	(0.004)	(0.305)	(0.009)
Value of production contracts$_{t-1}$	0.010	-0.000	-0.007	0.364**	0.000	0.102	0.001**
	(0.022)	(0.000)	(0.017)	(0.166)	(0.000)	(0.110)	(0.000)
Value of grants$_{t-1}$	0.008	0.000	0.003	-0.011	-0.046	0.027	0.004
	(0.011)	(0.002)	(0.017)	(0.011)	(0.046)	(0.026)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.32	0.14	4.13	0.61	0.76	2.14	2.16
Firms	3,087	91,142	2,998	91,142	70,826	91,142	90,116
Observations	21,716	626,834	20,914	626,834	501,460	626,834	621,941
Adjusted/pseudo R-squared	.	0.24	0.49	0.72	0.87	0.70	0.87

Notes: This table presents the relationship between experimentation and future venture capital raised, public sector sales, and private sector sales. *Value of government sales* is the sum of R&D contracts and production contracts from the federal government. *Value of private sales* is total sales minus government sales. The analysis sample includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms (except in Column 1, where standard errors are calculated using bootstrapping). * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

product and service codes (PSC) linked to procurement contracts. The results show that the number of R&D contracting offices has a positive effect, indicating that firms engaged in market experimentation tend to diversify their offerings to government agencies. This provides additional indirect support for the commercialization mechanism. Conversely, the value of R&D contracts has a negative effect, suggesting that firms focused on technology experimentation prioritize fewer but more complex products.

7.5 Robustness Checks

The following robustness checks address an alternative explanation for the empirical results—learning by doing—and concerns regarding the definition of startups, the measures of technology and market experimentation, and the assumed lag structure in the main specifications.

7.5.1 Alternative Explanation: Learning by Doing

An alternative to purposeful experimentation is *learning by doing* (Arrow, 1962; Pisano, 1994), which emphasizes hands-on experience over the controlled testing characteristic of the scientific method. By engaging in activities such as bidding on and negotiating R&D contracts, interacting with government customers, and fulfilling contractual obligations, startups may iteratively refine their technology offerings based on real-world experience rather than purposeful experimentation.

To test this alternative, I rerun the OLS and Poisson analyses from Tables 5 and 6 using a measure of learning by doing: the stock of the number of R&D contracts won. As shown in Appendix Table B27, the results do not support the learning-by-doing explanation. There is no statistically significant relationship between the stock of R&D contracts won and startup employment or sales. Moreover, controlling for the stock of the number of R&D contracts won leaves the coefficient estimates for market and technology experimentation largely unchanged.

7.5.2 Alternative Definitions of Startups

Most startups are small; 90% have fewer than 20 employees at founding Decker et al. (2014). However, my panel includes startups with 1-499 employees in their founding year. To ensure the reliability of my findings, I rerun the main OLS and Poisson analyses on a sample of startups with 1-49 employees at establishment. The results remain largely unchanged after lowering the maximum employee threshold from 499 to 49 (see Appendix Table B28).

Most startups fail quickly; only 33.6% of new establishments survive at least ten years (SBA, 2021). However, my panel considers up to ten years of activity. To check if the findings are driven by the most "established" startups, I rerun the main analyses on just the first seven years of activity. The results again remain largely unchanged (see Appendix Table B29).

7.5.3 Alternative Measures of Experimentation

I construct three alternative measures of technology experimentation. First, I use the fourth digit of the product or service code (PCS) associated with each government R&D contract to more narrowly identify the extent of technology experimentation. The government's Product and Service Codes Manual defines seven stages of R&D, ranging from basic research to commercialization. Based on these definitions (see Appendix Table B8), I reason that contracts for work in the first three stages of R&D (i.e., basic research, applied research and exploratory development, and advanced development) likely include substantial technology experimentation, whereas contracts for work in the last four stages of R&D (i.e., engineering development, operational systems development, management and support, and commercialization) likely do not.[30] Accordingly, I split the dollar value of R&D contracts into the first three stages and the last four stages. Second, I construct an indicator variable equal to 1 if the startup receives an R&D contract and 0 otherwise. Third, I count the number of R&D contracts awarded to the startup.

Appendix Table B30 reports the results. Splitting the value of R&D contracts by stage of R&D does not substantially change the results (Columns 1, 4, 7, and 10). Nor does using the number of R&D contracts won (Columns 3, 6, 9, and 12). However, the coefficient estimate for the indicator variable *Received an R&D contract* is positive and significant (Columns 2, 5, 8, and 11), indicating that engaging in government R&D work is important for startup performance, even if the dollar value of R&D contracts or the number of R&D contracts won are not.

I also create three alternative measures for market experimentation. First, I use the number of distinct *agencies* that award R&D contracts to the startup, a broader measure that captures government demand heterogeneity. Second, I use an indicator variable equal to 1 if the startup receives R&D contracts from two or more distinct contracting offices

[30] I consider stage 3 work experimental because the result of "advanced development" is just a proof of concept or prototype in the government's conceptualization of R&D stages. Any subsequent engineering work is captured in stages 4 and 5.

and 0 otherwise. Third, I assume that contracting offices that purchase from different industries provide diverse feedback to startups on the applicability of their technology across various private markets.To quantify this, I calculate the Herfindahl-Hirschman Index (HHI) of contracting offices' procurement portfolios across industries and measure the diversity of contracting offices as 1 - HHI.[31]

As shown in Appendix Table B31, the results remain consistent. At the sample means, the OLS coefficient estimates in Columns 1 and 7 suggest that winning R&D contracts from one additional agency is associated with a 14.1% increase in headcount and a 15.7% increase in sales. These estimates are higher than before, consistent with the idea that demand heterogeneity is greater across different agencies than within the same agency.

7.5.4 Longer Time Lags

The lag structure between receiving an R&D contract and firm outcomes is unclear. The Federal Procurement Data System records contractual *obligations*, not *outlays*, and multi-year projects may delay outlays for months or years. Even if R&D begins immediately after the contract award, headcount or sales changes may lag. To ensure my findings are robust, I rerun the main analyses from Tables 5 and 6 using longer lags. The results remain qualitatively similar, as shown in Appendix Table B32. The positive relationship between the number of R&D contracting offices (i.e., market experimentation) and firm headcount/sales weakens slightly with two- and three-year lags. Still, the value of R&D contracts (i.e., technology experimentation) continues to show no consistent and significant relationship with firm outcomes over longer lags.

[31]Suppose there are two startups (1 and 2), two contracting offices (A and B), three NAICS4 industries (a, b, and c), and one year of data. Suppose startup 1 received one R&D contract from office A and one R&D contract from office B, while Startup 2 received three R&D contracts from office A. Suppose office A procured \$1 million in products and services from industry a and \$2 million from industry b, while office B procured \$2 million from industry a and \$2 million from industry c. The *Diversity of contracting offices* would be $1 - HHI = 1 - [(3/7)^2 + (2/7)^2 + (2/7)^2] = 0.6531$ for startup 1 and $1 - [(1/3)^2 + (2/3)^2] = 0.4445$ for startup 2. This measure is consistent with the idea that startup 1 was exposed to a more diverse set of government customers than startup 2.

8 Discussion and Conclusion

Startups often face significant challenges on the path to success. A survey of over 400 hard-tech startups identified lengthy time-to-market (27%), high capital intensity (25%), technology risk and complexity (17%), and yet-to-be-developed commercial applications (14%) as key challenges (De la Tour, Soussan, Harlé, Chevalier, & Duportet, 2017). High-tech startups generally require sufficient funding to develop the new *technology* to a point where it can compete in a specific *market* (Malerba, Nelson, Orsenigo, & Winter, 2007). However, attracting venture capital is often difficult. This paper proposes a viable alternative for high-tech startups: experimenting by performing contract R&D for the federal government.

The key insight of this study is that market experimentation, rather than technology experimentation, drives firm performance. Specifically, market experimentation increases startup employment and sales levels, growth, and the likelihood of an exit via IPO or M&A. Heterogeneity analyses show that market experimentation benefits low-growth startups more than high-growth startups, the latter defined as those initially registered in Delaware. The findings suggest actionable strategies for startup leaders. First, they should diversify their engagements with the government. Working with multiple contracting offices can provide valuable opportunities to learn. Second, they should focus on market experimentation. Rather than pursuing large R&D budgets, startups should prioritize testing their technology in diverse market settings.

Previous research has shown that governmental interventions to spur entrepreneurship often fail (and waste billions in taxpayer dollars) due to poor design, misunderstanding of the entrepreneurial process, and implementation problems (Lerner, 2009). This paper highlights a previously unexplored impact of government procurement on entrepreneurial growth. The government's large and diverse demand for innovative products and services provides high-tech startups with opportunities to experiment with markets, driving growth.

The policy implication is that efforts to cut costs by consolidating government procurement into fewer contracting offices, while efficient for the government, may stunt en-

trepreneurial growth. In recent years, federal agencies have sought to pool spending, which can lower prices and reduce duplication and administrative costs. Pooling can be achieved by centralizing contracting decisions or using "contract vehicles" such as the Multiple Award Schedule (MAS), multi-agency contracts (MACs), and government-wide acquisition contracts (GWACs).[32] For example, under MAS, the General Services Administration establishes long-term, government-wide contracts with firms offering commercial supplies and services. The value of MAS procurement increased from $33.16 billion in fiscal year 2019 to $45.52 billion in fiscal year 2023, a 37% increase in four years.

This study suggests that cost/benefit analyses of procurement consolidation should consider the potential impact on the level and trajectory of market experimentation performed in the U.S. economy. Future research should explore whether pooling federal procurement reduces the number and diversity of contracting offices, thereby limiting the heterogeneity of government demand and reducing opportunities for high-tech startups to experiment with market applications of their technologies.

This study has several limitations. First, it does not account for other forms of purposeful experimentation (e.g., with entrepreneurial strategies or business models). Second, it does not capture the firm's decision to engage with the government, only the outcome of winning contracts and grants after the government's selection process. As a result, this study does not assess the impact of unsuccessful bidding on startup performance. Third, the estimated causal effects of market (technology) experimentation represents a local average treatment effect among firms that were induced to win R&D contracts from additional offices (larger R&D contracts) by the employee size standard ("use it or lose it" budget policy).

Future research can overcome these limitations while exploring *how* and *where* government funding and procurement impact entrepreneurship. For example, by leveraging entity registration data from the System for Acquisition Management (SAM.gov), future studies

[32] According to the General Services Administration, "a contract vehicle is a contract, or group of contracts, that provides a streamlined process for government agencies to place multiple orders for certain products and services with a pre-selected vendor or group of vendors. Government agencies will look to satisfy their requirements for supplies through existing contract vehicles before looking elsewhere."

can identify which types of startups decide to engage in government procurement and are more likely to win. By analyzing startups that receive either VC funding or government funding, future studies can unpack the relative contributions of private and public investments in innovation. By leveraging the rich location data available in the NETS HiTech dataset, future studies can also explore the geography of public procurement of innovative products and services. Such analyses would deepen our understanding of the government's role in the U.S. innovation ecosystem.

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Online Appendces

Appendix A Conceptual Framework

I seek to understand when high-tech startups bid on government R&D contracts and how many R&D contracts they bid on. Empirically, I don't observe the identity of bidders in government procurement. Therefore, I infer startups' bidding activity *ex-post* based on the observed contract awards. Prior work has shown heterogeneity in the objectives of the firms that bid on government R&D contracts (e.g., Bhattacharya, 2020). Some firms focus on providing R&D services to the government, while others use government funding to develop new technologies for commercialization in private sector markets. This conceptual framework generates testable predictions about the latter.

I focus on the choices facing a startup that can commercialize a single technology. Based on the assumption that it is easier for the startup to change its target market rather than its technology, I hold the technology fixed. The startup chooses which private market to attempt to commercialize its technology in. When making that choice, the startup faces significant uncertainty about the applicability of its technology to a particular private market (which can be either good or bad). Fortunately, the startup can engage in market experimentation to reveal more information about the technology's applicability. Such experimentation can be funded using the startup's own resources, public or private grants, debt, or dilutive venture capital funding. Alternatively, it can be funded using government R&D contracts.

A.1 Setup

Consider the following setup, with notation summarized in Table A1. A startup's technology has two possible private markets, A and B. The technology is applicabile to market A with probability p_a. If the technology is applicable to market A, the gross payoff from commercialization is V_a. The cost to commercialize the technology in market A is C_a. An analogous setup applies to market B. However, due to resource limitations (e.g., managerial time and attention), the startup can attempt to commercialize its technology in at most one private market. The startup can reduce uncertainty about the applicability of its technology by conducting a market experiment at a cost of c.

A market experiment results in a signal that can take values $\{Yes, No\}$. Let the probability of getting a Yes signal when the technology is applicable to the market be $Pr(Yes|Good) = \alpha$ (i.e., the true positive rate). Let the probability of getting a Yes signal when the technology is not applicable to the market be $Pr(Yes|Bad) = \beta$ (i.e., the false positive rate).[33] Using Bayes' Rule, I calculate the following conditional and marginal probabilities:

$$Pr(Good|Yes) = \frac{Pr(Yes|Good)Pr(Good)}{Pr(Yes|Good)Pr(Good) + Pr(Yes|Bad)Pr(Bad)} = \frac{\alpha p}{\alpha p + \beta(1-p)}$$

$$Pr(Good|No) = \frac{Pr(No|Good)Pr(Good)}{Pr(No|Good)Pr(Good) + Pr(No|Bad)Pr(Bad)} = \frac{(1-\alpha)p}{(1-\alpha)p + (1-\beta)(1-p)}$$

$$Pr(Yes) = Pr(Yes|Good)Pr(Good) + Pr(Yes|Bad)Pr(Bad) = \alpha p + \beta(1-p)$$

[33] Because $Pr(Good) = p$, $Pr(Bad) = 1 - p$.

Table A1: NOTATION

Concept	Notation
Private markets	$\{A, B\}$
Federal contracting offices	$\{a, b\}$
Probability the technology's applicability is good	$Pr(Good) = p$
Probability the technology's applicability is bad	$Pr(Bad) = 1 - p$
Gross payoff from commercialization	V
Cost of commercialization	C
Cost of a market experiment	c, where $c < C$
Private cost of a government R&D contract	g, where $g < c < C$
Signal from a market experiment or R&D contract	$\{Yes, No\}$

The startup's expected payoff from conducting a market experiment is:

$$Pr(Yes)(\max\{Pr(Good|Yes)V - C, 0\}) + (1 - Pr(Yes))(\max\{Pr(Good|No)V - C, 0\}) - c \tag{2}$$

I assume that $Pr(Good|No)V \leq C \leq Pr(Good|Yes)V$, so that the startup does not attempt to commercialize its technology when it receives a No signal. This implies:

$$\frac{(1-\alpha)p}{(1-\alpha)p + (1-\beta)(1-p)}V \leq C \leq \frac{\alpha p}{\alpha p + \beta(1-p)}V \tag{3}$$

After taking the reciprocal and rearranging, I obtain:

$$\frac{(1-\beta)(1-p)}{(1-\alpha)p} \geq \frac{V - C}{C} \geq \frac{\beta(1-p)}{\alpha p} \tag{4}$$

The middle term is the rate of return at the commercialization stage. Therefore, compound Inequality 4 imposes bounds on the rate of return. The first inequality indicates that there is little value in conducting market experiments for technologies that are almost certainly applicable (i.e., when p is very high, the first term is very small, and the inequality cannot be satisfied).

The second inequality indicates that markets with a very low rate of return will not benefit from experimentation (as long as there is a cost). In addition, as $\alpha \to 1$ (i.e., there are few false negatives), the first inequality is more likely to be satisfied. As $\beta \to 0$ (i.e., there are few false positives), the second inequality is more likely to be satisfied.

A.2 A Government R&D Contract

Instead of paying c to conduct the market experiment, the startup can pursue a government R&D contract that provides a signal at a private cost g, where $g < c < C$. This cost may include the loss of time in approaching the private market, leakage of proprietary know-how, and any direct costs not reimbursed by the government. Federal contracting offices have heterogeneous demand, as shown in Figure 1. Assume there are two federal contracting

offices, a and b. An R&D contract from office a will reveal more information about the applicability of the technology to market A, while an R&D contract from office b will reveal more information about the applicability of the technology to market B.

It is reasonable to believe that a successful R&D contract is akin to a Yes signal, while an unsuccessful R&D contract is akin to an No signal. Realistically, a No signal does not mean that the technology isn't applicable to the private market, as government requirements may differ from those of the private market. However, for now, I assume that $\alpha = 1$ so that there are no false negatives. I also assume that the cost of bidding on the government R&D contract is 0. Then, the payoff from conducting a market experiment using a government R&D contract is positive when:

$$p(V-C)-(1-p)\beta C-g\geq 0 \iff \frac{V-C}{C}\geq \frac{g}{pC}+\frac{\beta(1-p)}{p} \tag{5}$$

I assume the return of a "sure thing" is high enough so that Inequality 5 holds.

A.3 Who Will Seek a Government R&D Contract

The expected payoff without an R&D contract is $\max\{pV-C,0\}$. Comparing it with Inequality 5 suggests that startups with low probabilities the technology is applicable will benefit from experimenting, but startups with high probabilities may not.

In what follows, I assume that:

$$p(V-C)-(1-p)\beta C-g>pV-C \iff (1-p)(1-\beta)C>g \tag{6}$$

This condition requires that the commercialization cost, C, be sufficiently high compared to the cost of using the R&D contract to experiment, g.

A.4 Two Government R&D Contracts

If the startup can only commercialize in one private market, why would the startup bid on a second government R&D contract that relates to a different private market? One possible reason is that even a technology with good applicability might return a No signal. In other words, there are false negatives in reality. By conducting two market experiments, the startup reduces the chance of missing out, as the probability of two false negatives is always smaller than the probability of one false negative.

Note that the benefit from a second experiment is smaller than the benefit from the first experiment. Moreover, there are costs in terms of managerial time and attention. This diminishing return limits the number of experiments (i.e., R&D contracts) the startup may seek.

To save on notation, suppose both markets had the same gross payoffs, $V_a = V_b = V$, commercialization costs, $C_a = C_b = C$, and probabilities that the technology is applicable, $p_a = p_b = p$.

Because the markets are otherwise identical, and the experiments are independent, as long as at least one experiment is successful, the startup will get a gross expected payoff of $p(V-C)-(1-p)\beta C$. The probability of at least one successful experiment is $1-(1-P(Yes))^2$.

Recall that $Pr(Yes) = p + (1-p)\beta$ (we are still assuming that $\alpha = 1$), so the probability of at least one successful experiment is $1-(1-p)^2(1-\beta)^2$. Therefore, the expected payoff from two government R&D contracts is $(1-(1-p)^2(1-\beta)^2)\,(p(V-C)-(1-p)\beta C)-2g$. The expected payoff from one government R&D contract is $(p+(1-p)\beta)(p(V-C)-(1-p)\beta C)-g$. Let $X = (1-p)(1-\beta)$. Then, the startup will seek two experiments if:

$$X(1-X)p(V-C) \geq g \tag{7}$$

For this condition to hold, X must be neither too large nor too small. X is small if p is large, and if β is large. Thus, the technology must have an intermediate level of being applicable, and the false positive rate β must also not be too large. Second, the startup should have enough managerial capacity to handle two experiments. Third, the smaller the second potential private market in relation to the first, the lower the benefit from a second experiment.

A.5 Many Government R&D Contracts

The preceding can be generalized. The incremental benefit of the n^{th} R&D contract is $X(1-X)^{n-1}p(V-C)-g$. As n increases, the benefit declines, whereas the cost remains the same. Notice also that the marginal benefit declines very quickly if $1-X$ is small. Recall that $X = \alpha p + (1-\alpha)(1-p) = 1-\alpha-p$ so $1-X = \alpha+p$. This implies that for a given p, $1-X$ increases with α.

More capable startups will run experiments that have greater precision, i.e., a higher α. This implies that the incremental value of the n^{th} R&D contract should be higher. Such startups will also seek more R&D contracts.

A.6 Actual Number of Government R&D Contracts

The discussion thus far has been about the number of experiments (i.e., government R&D contracts) a startup will *seek*. But the award of R&D contracts is competitive. If a startup expects m competitors for each contract, winning a government R&D contract is not guaranteed. Suppose the cost of preparing a bid is d, and the startup wins the bid with probability $\lambda(m)$. If all bidders are the same, $\lambda = \dfrac{1}{m}$. The startup will seek the n^{th} R&D contract if $\lambda(m)\{X(1-X)^{n-1}p(V-C)-g\} \geq d$. If the startup seeks n contracts, it can expect to win $\frac{n}{m}$ of them. Therefore, the startup will seek more R&D contracts to try to win enough of them. However, because it is costly to bid for contracts, the startup will trade off the cost of bidding against the expected benefit of winning an additional R&D contract.

Startups that win more R&D contracts are more likely to find at least one Yes signal and to commercialize the technology in a private market. Therefore, their expected private market revenues will be higher.

More capable startups, with higher α, will seek more R&D contracts and win a greater fraction if their probability of winning is higher than $\frac{1}{m}$. Such startups are more likely to get a Yes signal and have higher private market revenues.

which is

A.7 Testable Predictions

Table A2 summarizes the theoretical predictions regarding the probability that startups receive R&D contracts (Column 2) and the probability that startups receive R&D contracts from two or more distinct contracting offices (Column 3) given different levels of market uncertainty.[34]

Table A2: Testable Predictions

(1)	(2)	(3)
Market uncertainty	Pr(Receive R&D contracts)	Pr(Receive R&D contracts from 2+ offices)
Low (high p)	Low	Low
Medium (medium p)	Medium	High
High (low p)	High	Low

[34]This conceptual framework is still a work in progress.

Appendix B Additional Figures and Tables

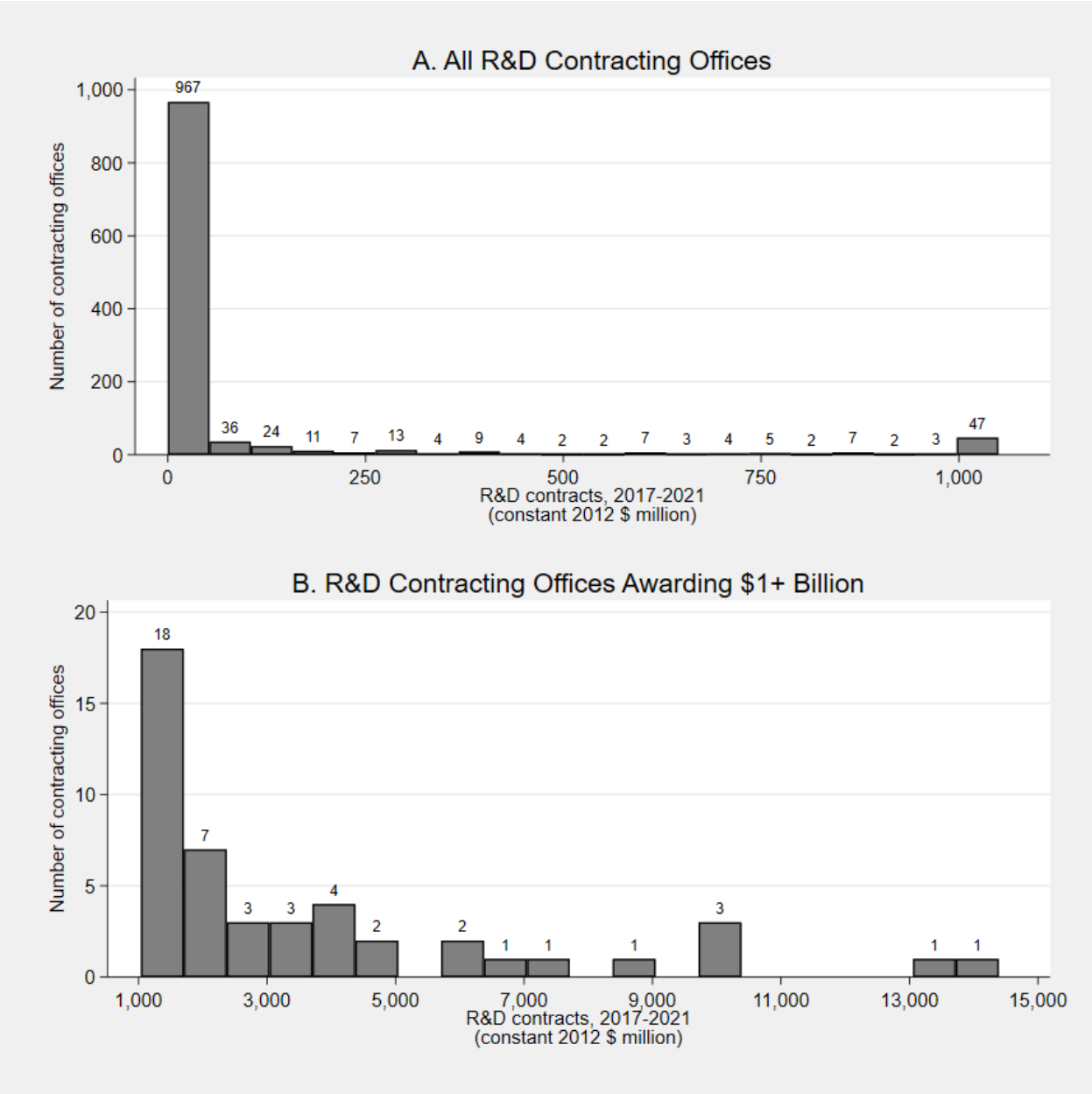


Figure B1: Frequency Distribution of R&D Contract Value Awarded by Each Contracting Office, 2017-2021

Panel A of this figure plots the frequency distribution of the value of R&D contracts (in constant 2012 $ million) awarded by a contracting office during 2017-2021. Panel B restricts attention to R&D contracting offices that awarded more than $1 billion in R&D contracts during 2017-2021.

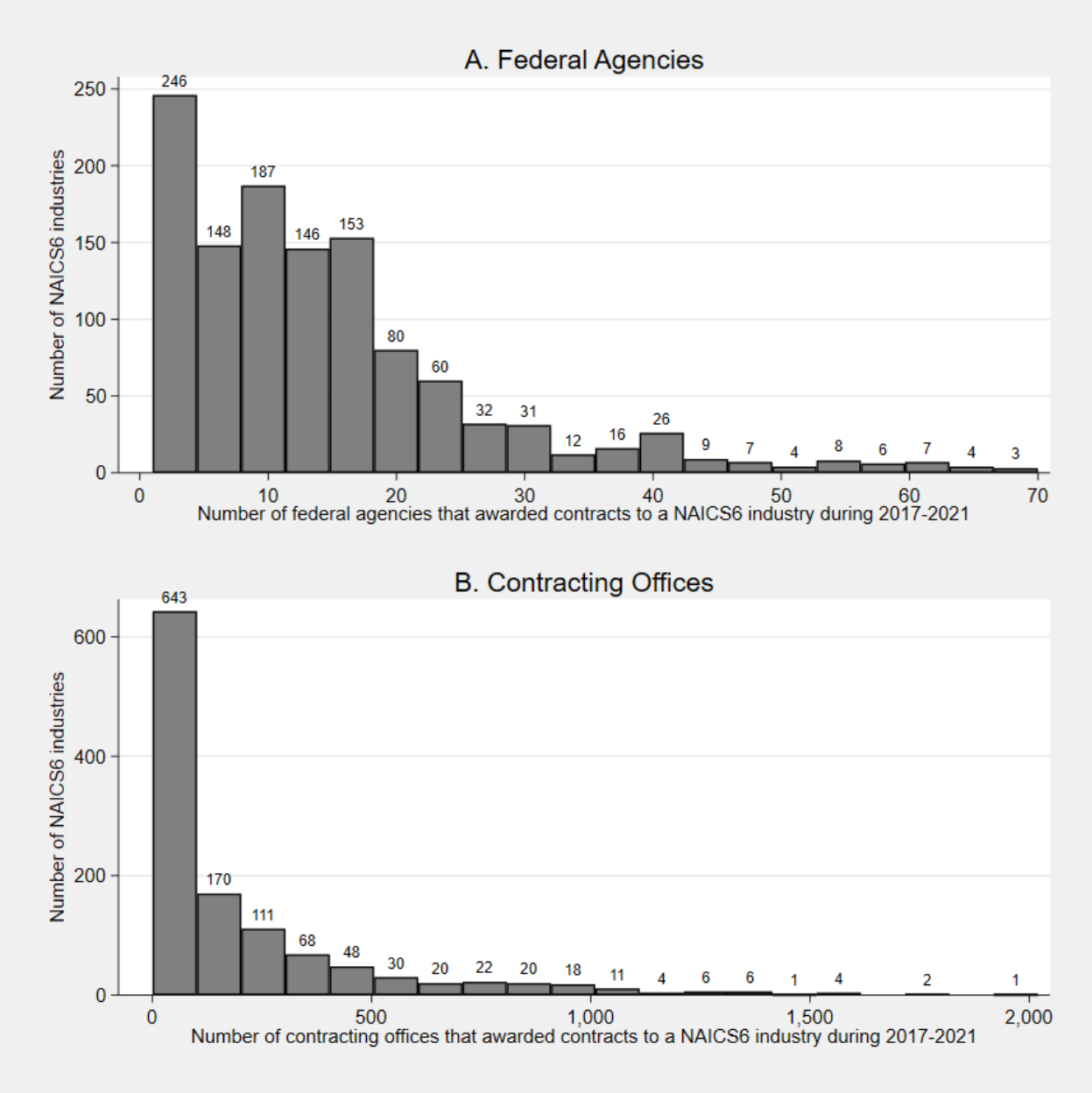


Figure B2: Frequency Distribution of the Number of Federal Agencies and Contracting Offices That Awarded Contracts to a NAICS6 Industry During 2017-2021

This figure plots the frequency distribution of the number of federal agencies (Panel A) and contracting offices (Panel B) that awarded contracts to a NAICS6 industry during 2017-2021.

Table B3: Agency Mission Statements

Federal agency	Mission statement
Defense, Department of	Provide the military forces to deter war and ensure the Nation's security. The Department will continue to provide combat-credible military forces that are capable of defending against aggression that undermines the security of both the United States and its Allies.
National Aeronautics and Space Administration	Explore the unknown in air and space, innovate for the benefit of humanity, and inspire the world through discovery.
Health and Human Services, Department of	Enhance the health and well-being of all Americans, by providing for effective health and human services and by fostering sound, sustained advances in the sciences underlying medicine, public health, and social services.
Energy, Department of	Ensure America's security and prosperity by addressing its energy, environmental, and nuclear challenges through transformative science and technology solutions.
Transportation, Department of	Deliver the world's leading transportation system, serving the American people and economy through the safe, efficient, sustainable, and equitable movement of people and goods.
General Services Administration	Deliver the best customer experience and value in real estate, acquisition, and technology services to the Government and the American people.
Homeland Security, Department of	With honor and integrity, we will safeguard the American people, our Homeland, and our values.
Agency for International Development	On behalf of the American people, promote and demonstrate democratic values abroad, and advance a free, peaceful, and prosperous world.
Interior, Department of the	Protect and manage the Nation's natural resources and cultural heritage; provide scientific and other information about those resources; and honor its trust responsibilities or special commitments to American Indians, Alaska Natives, Native Hawaiians, and affiliated Island Communities.
Education, Department of	Promote student achievement and preparation for global competitiveness by fostering educational excellence and ensuring equal access.

Notes: This table displays the mission statements (current as of July 10, 2024) of the top 10 federal agencies by the value of R&D contracts awarded during calendar years 2017-2021.

Table B4: R&D Contracting by Agency, 2017-2021

Federal agency	Number of R&D contracting offices	R&D contracts (const. 2012 $ mm)
Defense, Department of	442	139,363.86
National Aeronautics and Space Administration	14	46,212.43
Health and Human Services, Department of	36	16,503.95
Energy, Department of	13	10,426.26
Transportation, Department of	25	4,052.31
General Services Administration	31	2,503.48
Homeland Security, Department of	70	1,498.97
Agency for International Development	49	807.44
Interior, Department of the	43	546.06
Education, Department of	7	360.24
Justice, Department of	77	295.01
Commerce, Department of	18	252.78
Veterans Affairs, Department of	45	231.28
Environmental Protection Agency	13	137.44
Treasury, Department of the	6	125.22
Agriculture, Department of	136	119.37
National Science Foundation	1	38.84
Federal Communications Commission	1	37.96
State, Department of	66	30.55
Nuclear Regulatory Commission	1	13.31
Housing and Urban Development, Department of	8	11.33
Smithsonian Institution	19	7.77
Corporation for National and Community Service	1	4.22
Office of Personnel Management	1	4.15
Export-Import Bank of the U.S.	2	3.55
Labor, Department of	6	2.76
Securities and Exchange Commission	1	2.62
National Gallery of Art	1	2.48
Consumer Product Safety Commission	1	2.30
International Boundary and Water Commission:U.S.-Mexico	1	2.30
Federal Mine Safety and Health Review Commission	1	2.13
National Endowment for the Arts	1	1.57
United States Agency for Global Media, BBG	3	1.41
17 other agencies	19	3.26
Total	1,159	223,608.62

Notes: This table displays federal agencies that awarded R&D contracts during calendar years 2017-2021. R&D contracts are deflated using the GDP Implicit Price Deflator to reflect millions of constant 2012 dollars (U.S. Bureau of Economic Analysis, 2021).

Table B5: Department of Energy Contracting Offices, 2017-2021

Contracting office name	Contracting office code	All contracts (const. 2012 $ mm)	R&D contracts (const. 2012 $ mm)	Production contracts (const. 2012 $ mm)
NNSA MO CONTRACTING	892332	65,660.51	9,859.59	55,800.92
SC OAK RIDGE OFFICE	892431	17,932.00	0.00	17,932.00
SC CHICAGO SERVICE CENTER	892430	14,842.93	0.00	14,842.93
SAVANNAH RIVER OPERATIONS OFFICE	893037	10,035.63	177.63	9,858.00
IDAHO OPERATIONS OFFICE	892432	8,213.50	36.61	8,176.88
NNSA NAVAL REACTORS LAB FLD OFFICE	892330	7,354.42	0.00	7,354.42
OFFICE OF RIVER PROTECTION	893040	6,820.30	2.26	6,818.04
RICHLAND OPERATIONS OFFICE	893039	4,393.57	1.36	4,392.21
NNSA NON-MO CNTRCTNG OPS DIV	892331	3,458.21	143.11	3,315.10
HEADQUARTERS PROCUREMENT SERVICES	893030	3,356.03	100.16	3,255.86
EM-PORTSMOUTH/PADUCAH PROJECT OFC	893031	3,290.53	4.48	3,286.05
GOLDEN FIELD OFFICE	892434	2,814.39	0.00	2,814.39
EM-OAK RIDGE	893035	2,596.16	105.57	2,490.59
EM-CARLSBAD	893032	1,579.78	0.62	1,579.16
EM-ENVIRONMENTAL MGMT CON BUS CTR	893033	1,380.45	1.79	1,378.65
NATIONAL ENERGY TECHNOLOGY LAB	892433	1,229.58	7.33	1,222.25
STRATEGIC PETROLEUM RESERVE	892435	1,145.41	0.00	1,145.41
EM-LOS ALAMOS	893034	844.87	0.00	844.87
FEDERAL ENERGY REGULATORY COMM	896030	341.99	2.12	339.87
WESTERN-UPPPER GREAT PLAINS REGION	895034	183.87	0.00	183.87
WESTERN-CORPORATE SERVICES OFFICE	895030	154.51	0.00	154.51
ADVANCED RSRCH PROJ AGENCY ARPA-E	897030	112.89	0.00	112.89
WESTERN-DESERT SOUTHWEST REGION	895031	106.36	0.00	106.36
WESTERN-ROCKY MOUNTAIN REGION	895032	80.91	0.00	80.91
SOUTHWESTERN POWER ADMINISTRATION	895036	68.99	0.00	68.99
WESTERN-SIERRA NEVADA REGION	895033	63.68	0.00	63.68
SOUTHEASTERN POWER ADMINISTRATION	895035	3.90	0.00	3.90

Notes: This table displays the Department of Energy contracting offices that awarded procurement contracts during calendar years 2017-2021. Contracts are deflated using the GDP Implicit Price Deflator to reflect millions of constant 2012 dollars (U.S. Bureau of Economic Analysis, 2021).

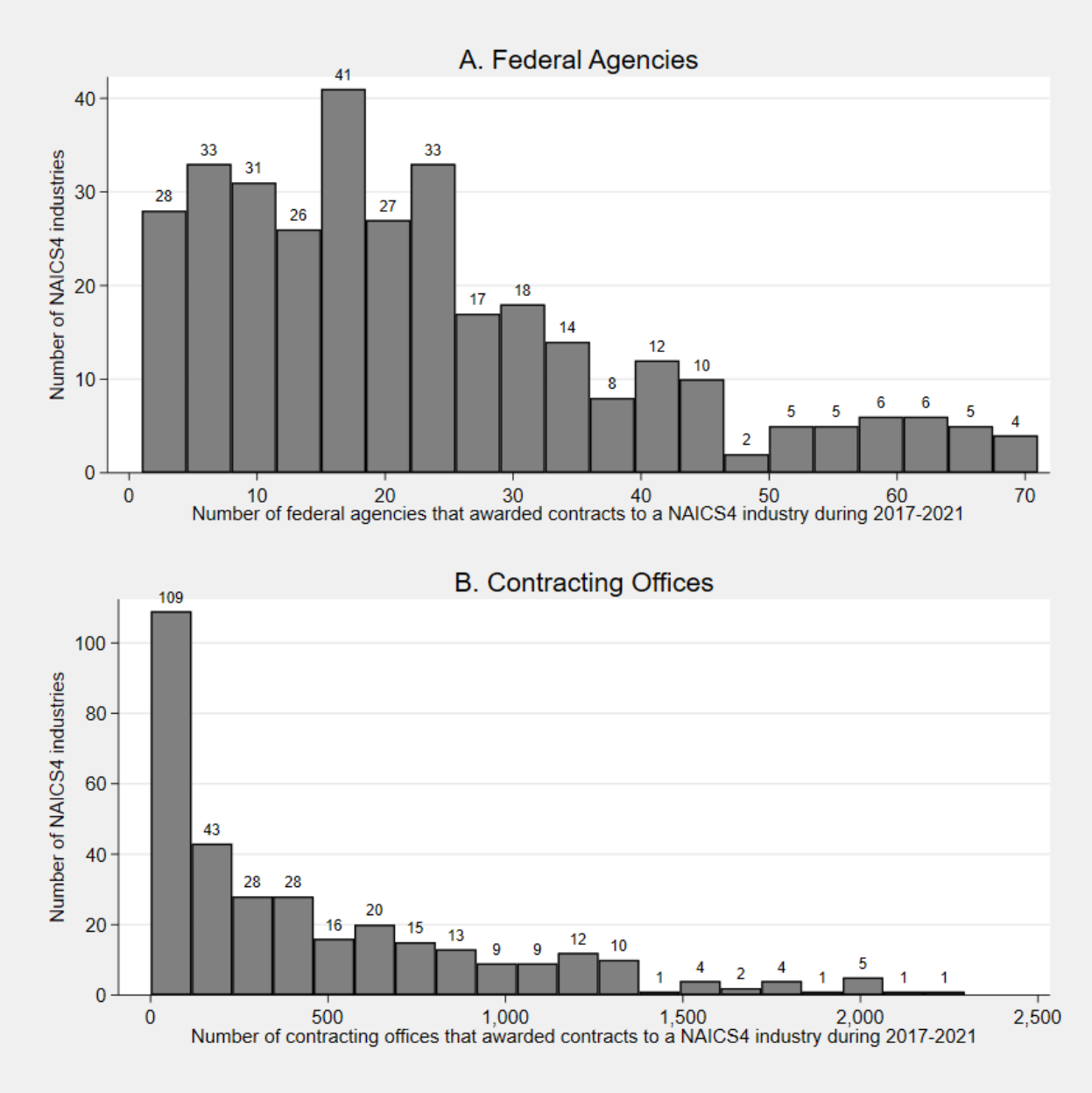


Figure B3: Frequency Distribution of the Number of Federal Agencies and Contracting Offices That Awarded Contracts to a NAICS4 Industry During 2017-2021

This figure plots the frequency distribution of the number of federal agencies (Panel A) and contracting offices (Panel B) that awarded contracts to a NAICS4 industry during 2017-2021.

Table B6: Measures of Experimentation

Paper	Empirical context	Measure	Description	Performance implication
Pisano (1994)	23 pharmaceutical process development projects in 11 firms	*Research %*	Percentage of total project person-hours expended before the first pilot batch of production	Associated with shorter development lead time in chemical projects, but not in biotech projects
Brown and Eisenhardt (1997)	6 business units of publicly traded ICT firms	*Experimental products* (0/1)	Low-cost projects with 5-10 developers; stripped-down products to learn about low-end markets	Units with successful product portfolios probe the future using experimental products
Gruber et al. (2008)	83 VC-backed German high-tech startups	*More than one market opportunity* (0/1)	Indicator equal to 1 if 2+ market opportunities were considered before entry	Positive association with *ln(Sales)*
		ln(Number of alternative market opportunities)	Number of alternative market opportunities considered prior to entry	Positive effect on *ln(Sales)*
Andries et al. (2013)	6 ventures in various industries	*Simultaneous experimentation* (0/1)	Cost-effective portfolio of business model experiments	Lower initial growth, long-term survival
		Focused commitment (0/1)	Persistent focus on one business model	Higher initial growth, short-term survival
Pillai et al. (2020)	Early automobile startups	*Cumulative Model Count*	Cumulative number of unique automobile models released to date by the firm	Positive association with survival length and price advantage
Contigiani and Young-Hyman (2022)	110 ventures in a university competition; 162 MTurk participants	*Experimentation* [0,1]	Combined measure of "quantity" and "quality" of information about experimentation and its timing in the application form and pitch deck (identified using words such as minimum viable product, beta, test, prototype, pilot, etc.)	No association with venture evaluation score, perceived quality, investment decision; negative association of interaction with formal structure with investment likelihood
Koning et al. (2022)	35,262 global high-tech startups	*Using A/B tool* (0/1)	Indicator equal to 1 if the startup used A/B testing technology on its website	Positive effect on *ln(Visits + 1)*
S. Lee and Kim (2023)	38,217 U.S. startups	*A/B testing* (0/1)	Indicator equal to 1 if the startup used A/B testing technology on its website	Moderates the relationship between scaling early and firm failure
Savage and Ziedonis (2024)	621 technology spinoffs from 6 U.S. universities	*Number of SBIR grants*	Number of Phase I SBIR grants awarded to the firm	Founders with heterogeneous knowledge engage in market search at 2-3 times the rate of single-discipline founders.

Notes: This table summarizes the various measures of experimentation used in the empirical literature.

Table B7: Classification Codes for Services

Code	Service category	Code	Service category
A	Research and development	N	Installation of equipment
B	Special studies and analyses – not R&D	P	Salvage services
C	Architect and engineering services – construction	Q	Medical services
D	Automatic data processing and telecommunication services	R	Professional, administrative and management support services
E	Purchase of structures and facilities	S	Utilities and housekeeping services
F	Natural resources and conservation services	T	Photographic, mapping, printing, and publications services
G	Social services	U	Education and training services
H	Quality control, testing, and inspection services	V	Transportation, travel and relocation services
I	Maintenance, repair and rebuilding of equipment	W	Lease or rental of equipment
K	Modification of equipment	X	Lease or rental of facilities
L	Technical representative services	Y	Construction of structures and facilities
M	Operation of government owned facility	Z	Maintenance, repair or alteration of real property

Notes: This table displays the 24 high-level categories used to classify the services purchased by the federal government (as of March 17, 2020).

Table B8: Classification Codes for R&D Services

Code	Stage of R&D	Definition
1	Basic research	Includes all *scientific effort and experimentation* directed toward increasing knowledge and understanding in those fields of the physical, engineering, environmental, social, and life sciences related to long-term national needs. It provides fundamental knowledge ultimately required for the solution of social, economic, political, physical, or military problems. It forms a part of the base for subsequent applied research and exploratory and advanced development in the various disciplines, and new or improved functional capabilities.
2	Applied research and exploratory development	Includes all effort directed toward the solution of specific problems, short of major development projects. This type of effort may vary from fairly fundamental applied research to quite sophisticated breadboard hardware, study, programming, and planning efforts. It would thus include investigations and minor development efforts. The dominant characteristic of this category of effort is that it be pointed toward specific problem areas with a view toward *developing and evaluating the feasibility and practicability of proposed solutions and determining their parameters.*
3	Advanced development	Includes all effort directed toward projects that have moved into, e.g., the development of hardware for testing. The prime result of this type of effort is *proof of design concept and/or prototype.*
4	Engineering development	Includes those projects in full-scale engineering development for government use but which have not yet received approval for production or had production funds included in the budget submission for the current or subsequent fiscal year. Thus, they are characterized by major line item projects.
5	Operational systems development	Includes those projects still in full-scale engineering development but which have received approval for production or production funds have been included in the budget submission for the current or subsequent fiscal year.
6	Management and support	Includes all effort directed toward support installations or operations required for general research and development. Included would be construction of a general nature unrelated to specific programs, maintenance and support of laboratories, operation and maintenance of test ranges, and maintenance of test aircraft, equipment, or ships. Costs of laboratory personnel, either in-house or contractor, would be assigned to appropriate projects or program areas above.
7	Commercialization	Includes all effort directed toward the transition of a product from R&D to commercial sales and usage.

Notes: This table displays the codes corresponding to the seven stages of R&D identified in federal R&D contracts (as of March 17, 2020). The code represents the 4th digit of the product or service code (PSC) used to indicate *what* was bought for each contract action reported in the Federal Procurement Data System (FPDS).

Table B9: Classification Codes for Products

Code	Product group	Code	Product group
10	Weapons	53	Hardware and Abrasives
11	Nuclear Ordinance	54	Prefabricated Structures and Scaffolding
12	Fire Control Equipment	55	Lumber, Millwork, Plywood, and Veneer
13	Ammunition and Explosives	56	Construction and Building Materials
14	Guided Missiles	58	Communications, Detection and Coherent Radiation Equipment
15	Aircraft and Airframe Structural Components	59	Electrical and Electronic Equipment Components
16	Aerospace Craft Components and Accessories	60	Fiber Optics Materials and Components, Assemblies and Accessories
17	Aerospace Craft Launching, Landing, and Ground Handling Equipment	61	Electric Wire, and Power and Distribution Equipment
18	Space Vehicles	62	Lighting Fixtures and Lamps
19	Ships, Small Craft, Pontoons, and Floating Docks	63	Alarm, Signal and Security Detection Systems
20	Ship and Marine Equipment	65	Medical, Dental, and Veterinary Equipment and Supplies
22	Railway Equipment	66	Instruments and Laboratory Equipment
23	Ground Effect Vehicles, Motor Vehicles, Trailers, and Cycles	67	Photographic Equipment
24	Tractors	68	Chemicals and Chemical Products
25	Vehicular Equipment Components	69	Training Aids and Devices
26	Tires and Tubes	70	ADP Equipment Software, Supplies and Support Equipment
28	Engines, Turbines, and Components	71	Furniture
29	Engine Accessories	72	Household and Commercial Furnishings and Appliances
30	Mechanical Power Transmission Equipment	73	Food Preparation and Serving Equipment
31	Bearings	74	Office Machines
32	Woodworking Machinery and Equipment	75	Office Supplies and Devices
34	Metalworking Machinery	76	Books, Maps, and Other Publications
35	Service and Trade Equipment	77	Musical Instruments, Phonographs, and Home Radios
36	Special Industry Machinery	78	Recreational and Athletic Equipment
37	Agricultural Machinery and Equipment	79	Cleaning Equipment and Supplies
38	Construction, Mining, Excavating, and Highway Maintenance Equipment	80	Brushes, Paints, Sealers, and Adhesives
39	Materials Handling Equipment	81	Containers, Packaging, and Packing Supplies
40	Rope, Cable, Chain, and Fittings	83	Textiles, Leather, Furs, Apparel and Shoes, Tents, Flags
41	Refrigeration, Air Conditioning and Air Circulating Equipment	84	Clothing, Individual Equipment, and Insignia
42	Fire Fighting, Rescue, and Safety Equipment	85	Toiletries
43	Pumps and Compressors	87	Agricultural Supplies
44	Furnace, Steam Plant, and Drying Equip, Nuclear Reactors	88	Live Animals
45	Plumbing, Heating and Sanitation Equipment	89	Subsistence (Food)
46	Water Purification and Sewage Treatment Equipment	91	Fuels, Lubricants, Oils, and Waxes
47	Pipe, Tubing, Hose, and Fittings	93	Nonmetallic Fabricated Materials
48	Valves	94	Nonmetallic Crude Materials
49	Maintenance and Repair Shop Equipment	95	Metal Bars, Sheets, and Shapes
51	Hand Tools	96	Ores, Minerals, and Their Primary Products
52	Measuring Tools	99	Miscellaneous

Notes: This table displays the 78 high-level groups used to classify the products purchased by the federal government (as of March 2020). Groups 21, 27, 33, 50, 57, 64, 82, 86, 90, 92, 97, and 98 are unassigned.

Table B10: Main Variables

Variable name	Variable type	Variable description
A. Dependent variables		
Employees	Count	Number of employees employed by the focal firm (and its establishments) in the focal year
Employee growth	Continuous	Percentage change in headcount from the prior year to the focal year
Sales	Continuous	Value (in constant 2012 $ mm) of sales reported by the focal firm (and its establishments) in the focal year
Sales growth	Continuous	Percentage change in sales from the prior year to the focal year
Number of PSC	Count	Number of different product and non-R&D service codes the firm received procurement contracts for in the focal year; R&D service codes are excluded
Successful exit	Indicator	1 if the focal firm went public or was acquired in its first 10 years, 0 otherwise
IPO exit	Indicator	1 if the focal firm went public via IPO or reverse merger in its first 10 years, 0 otherwise
M&A exit	Indicator	1 if the focal firm experienced an acquisition, buyout, or merger of equals in its first 10 years, 0 otherwise
Venture capital raised	Continuous	Value (in constant 2012 $ mm) of venture capital raised by the focal firm (and its establishments) in the focal year
Raised any venture capital	Indicator	1 if the focal firm raised any venture capital in the focal year, 0 otherwise
Value of government sales	Continuous	Value (in constant 2012 $ mm) of all government contracts awarded to the focal firm (and its establishments) in the focal year; sum of R&D contracts and production contracts
Value of private sales	Continuous	Value (in constant 2012 $ mm) of non-government sales to the focal firm (and its establishments) in the focal year; difference between (total) sales and government sales
B. Independent variables		
Number of R&D contracting offices	Count	Number of different contracting offices that awarded R&D contracts to the focal firm (and its establishments) in the focal year
Number of R&D agencies	Count	Number of different agencies that awarded R&D contracts to the focal firm (and its establishments) in the focal year
Received R&D contracts from 2+ offices	Indicator	1 if the focal firm received R&D contracts from two or more contracting offices in the focal year, 0 otherwise
Diversity of contracting offices	Continuous	1 - HHI, where HHI is the Herfindahl-Hirschman index measuring the concentration (across NAICS4 industries) in the procurement portfolios of the contracting offices awarding R&D contracts to the focal firm (and its establishments) in the focal year
Value of R&D contracts	Continuous	Value (in constant 2012 $ mm) of R&D contracts awarded to the focal firm (and its establishments) in the focal year

Notes: This table summarizes the main variables used in the econometric analyses.

Table B10: Main Variables (Cont.)

Variable name	Variable type	Variable description
Value of R&D contracts, first 3 stages	Continuous	Value (in constant 2012 $ mm) of contracts awarded for basic research, applied research, exploratory development, or advanced development to the focal firm (and its establishments) in the focal year
Value of R&D contracts, last 4 stages	Continuous	Value (in constant 2012 $ mm) of contracts awarded for engineering development, operational systems development, management and support, or commercialization to the focal firm (and its establishments) in the focal year
Received an R&D contract	Indicator	1 is the focal firm (and its establishments) received any R&D contracts in the focal year, 0 otherwise
C. Control variables		
Number of R&D contracts	Count	Number of R&D contracts awarded to the focal firm (and its establishments) in the focal year
Number of production contracts	Count	Number of production contracts awarded to the focal firm (and its establishments) in the focal year
Value of production contracts	Continuous	Value (in constant 2012 $ mm) of production contracts awarded to the focal firm (and its establishments) in the focal year
Value of grants	Continuous	Value (in constant 2012 $ mm) of federal grants and other assistance awarded to the focal firm (and its establishments) in the focal year; only available for calendar years 2001-2019
Large	Indicator	1 if the focal firm-year has above-median sales compared to other high-tech startups operating in the same SIC4 industry, 0 otherwise
Age	Count	Focal firm age since its founding (in years)
High growth	Indicator	1 if the focal firm initially registered in Delaware, 0 otherwise
High VC industry	Indicator	1 if the focal firm's industry receives above-median venture capital funding compared to other industries that year, 0 otherwise

Notes: This table summarizes the main variables used in the econometric analyses.

Table B11: Classification of R&D Contracts by Major Area

Code	Description	R&D contracts (const. 2012 $ mm)	Research	Development	Share research in total R&D
AD	Defense Other	14,396.88	7,634.63	6,762.25	53%
AC	Defense Systems	11,807.78	5,062.42	6,745.37	43%
AZ	Other Research and Development	6,062.75	4,399.42	1,663.33	73%
AN	Medical	3,727.20	2,304.69	1,422.51	62%
AJ	General Science/Technology	2,505.15	1,366.81	1,138.34	55%
AR	Space	1,995.90	1,347.83	648.06	68%
AE	Economic Growth	284.11	39.86	244.25	14%
AG	Energy	237.52	174.05	63.47	73%
AH	Environmental Protection	233.22	169.24	63.98	73%
AB	Community Service/Development	223.79	48.57	175.22	22%
AF	Education	199.73	87.50	112.23	44%
AT	Other Transportation	129.70	101.38	28.33	78%
AK	Housing	112.56	0.81	111.75	1%
AS	Modal Transportation	103.96	61.92	42.04	60%
AA	Agriculture	92.82	60.00	32.82	65%
AP	Natural Resource	46.17	40.63	5.53	88%
AM	International Affairs and Cooperation	27.37	22.88	4.49	84%
AL	Income Security	15.51	1.84	13.67	12%
AQ	Social Services	11.40	2.36	9.04	21%
AV	Mining	9.38	5.46	3.92	58%
Total		42,222.90	22,932.30	19,290.60	54%

Notes: This table classifies the R&D contracts awarded to sample startups using the 20 major area R&D codes employed by the U.S. government.

Table B12: Difference in Means Between Sample Firms and Other High-Tech Startups

	(1) Mean for sample	(2) Mean for others	(3) Diff.	(4) t
Employees (#)	13.11	3.60	9.51	390.24
Sales ($ mm)	2.68	0.49	2.19	225.25
Venture capital raised ($ mm)	0.12	0.01	0.11	49.62
Raised any venture capital	0.01	0.00	0.01	203.39
Large	0.56	0.48	0.08	148.76
High growth	0.05	0.01	0.03	251.72
High VC industry	0.87	0.85	0.02	54.65

Notes: This table displays mean comparison tests for the 106,462 startups included in my analysis sample and the 5,839,530 high-tech startups that didn't successfully engage with the government. *Large* identifies firm-years with above-median sales compared to other startups operating in the same SIC4 industry. *High growth* identifies startups that initially registered in Delaware. *High VC industries* identifies firm-years operating in industries with above-median funding relative to other industries in the same year. The two-sample t-tests use unequal variances.

Table B13: Difference in Means at Founding Between Experimenters and Others

	(1) Mean for experimenters	(2) Mean for others	(3) Diff.	(4) t
Employees (#)	8.80	6.15	2.65	8.03
Sales ($ mm)	1.34	1.10	0.24	2.36
Venture capital raised ($ mm)	0.07	0.04	0.03	1.70
Raised any venture capital	0.01	0.01	0.01	4.01
Large	0.64	0.50	0.14	16.66
High growth	0.11	0.05	0.06	15.74
High VC industry	0.94	0.87	0.07	12.74

Notes: This table displays mean comparison tests in the founding year for the 3,623 startups that eventually receive R&D contracts from two or more contracting offices in the same year (suggesting they engage in simultaneous market experimentation) and the other 102,204 sample startups. *Large* identifies firm-years with above-median sales compared to other startups operating in the same SIC4 industry. *High growth* identifies startups that initially registered in Delaware. *High VC industries* identifies firm-years operating in industries with above-median funding relative to other industries in the same year. The two-sample t-tests use unequal variances.

Table B14: Correlations (All Startups)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Employees	1.00								
(2) Sales	0.78***	1.00							
(3) Venture capital raised	0.02***	0.01***	1.00						
(4) Number of R&D contracts	0.07***	0.03***	0.00	1.00					
(5) Number of production contracts	0.07***	0.05***	-0.00	0.06***	1.00				
(6) Number of R&D contracting offices	0.07***	0.03***	0.00***	0.38***	0.05***	1.00			
(7) Value of R&D contracts	0.10***	0.05***	0.00**	0.31***	0.06***	0.33***	1.00		
(8) Value of production contracts	0.11***	0.07***	-0.00	0.07***	0.13***	0.06***	0.09***	1.00	
(9) Value of grants	0.01***	0.01***	0.00**	0.00	-0.00	0.01***	0.01***	0.01***	1.00

Notes: This table displays pairwise Pearson correlations for the main variables included in the empirical analyses. N = 889,805 firm-years (except in row 9, where N = 727,418 firm-years). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table B15: Correlations (Only R&D Contractors)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Employees	1.00								
(2) Sales	0.77***	1.00							
(3) Venture capital raised	0.02***	0.01***	1.00						
(4) Number of R&D contracts	0.12***	0.06***	-0.00	1.00					
(5) Number of production contracts	0.14***	0.10***	-0.00	0.07***	1.00				
(6) Number of R&D contracting offices	0.12***	0.06***	0.00	0.37***	0.05***	1.00			
(7) Value of R&D contracts	0.18***	0.10***	0.00	0.30***	0.07***	0.32***	1.00		
(8) Value of production contracts	0.18***	0.10***	-0.00	0.10***	0.20***	0.08***	0.14***	1.00	
(9) Value of grants	0.02***	0.02***	0.00	0.01*	0.00	0.03***	0.05***	0.00	1.00

Notes: This table displays pairwise Pearson correlations for the main variables included in the empirical analyses for the subsample of R&D contractors. N = 146,227 firm-years (except in row 9, where N = 114,785 firm-years). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table B16: Market Experimentation and (Normalized) Project Failure

	(1) *Low* project failure		(2) *High* project failure		(3) Total	
Received R&D contracts from 2+ offices	Count	%	Count	%	Count	%
Panel A. R&D deobligations normalized by R&D obligations						
No	11,148	83%	2,212	17%	13,360	100%
Yes	2,874	79%	749	21%	3,623	100%
Total	14,022	83%	2,961	17%	16,983	100%
Panel B. R&D deobligations normalized by number of R&D contracts						
No	11,341	85%	2,019	15%	13,360	100%
Yes	2,679	74%	944	26%	3,623	100%
Total	14,020	83%	2,963	17%	16,983	100%

Notes: This table provides a cross-tabulation of market experimentation and project failure for the subsample of 16,983 R&D contractors. Project failure is identified using *normalized* R&D deobligations, calculated as R&D deobligations divided by R&D obligations (Panel A) or the number of R&D contracts (Panel B). Startups were classified as having *High* project failure if their normalized R&D deobligations were in the first decile within their four-digit SIC industry. The remaining startups were classified as having *Low* project failure. The unit of analysis is a firm.

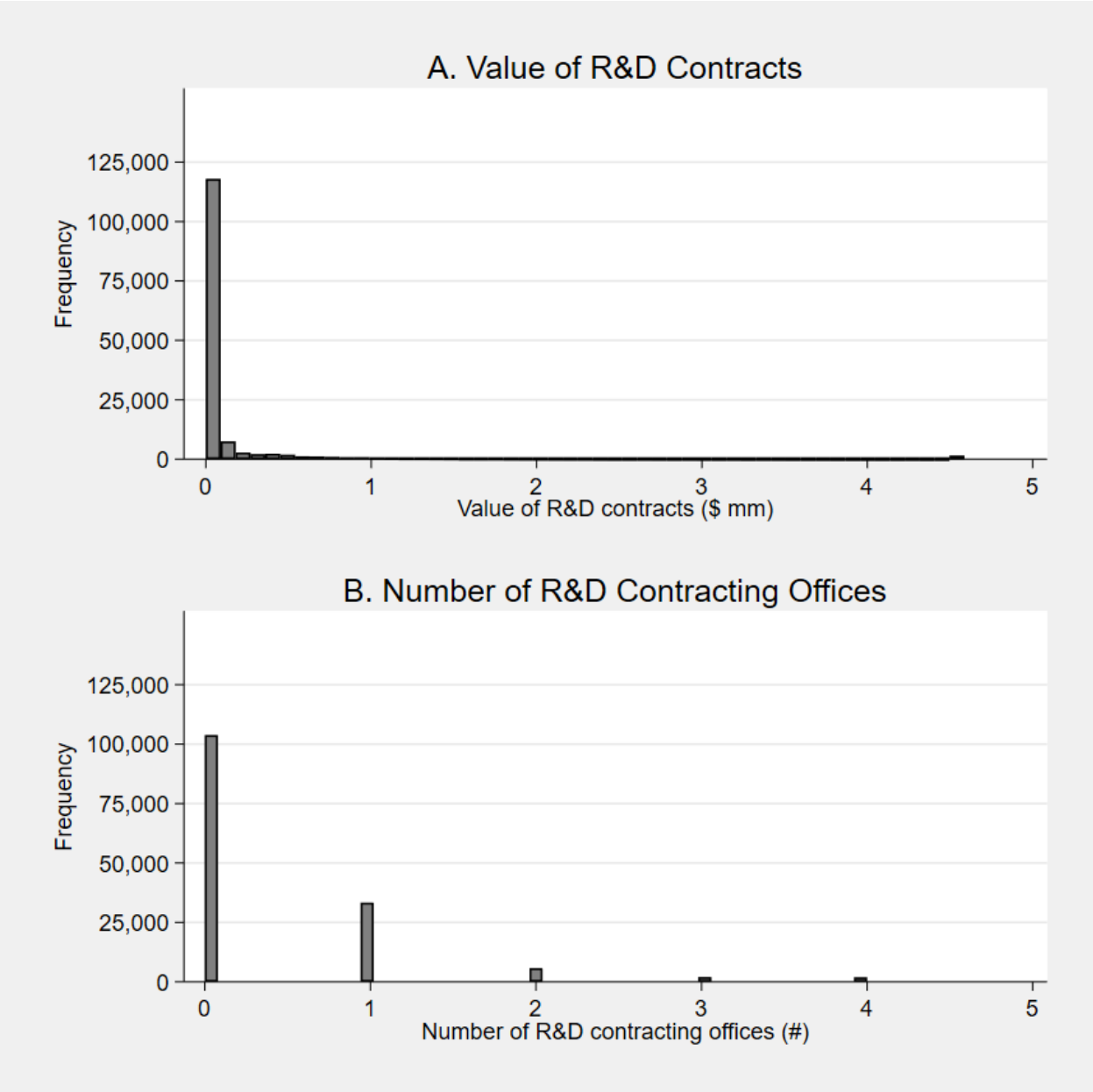


Figure B4: Frequency Distributions (Only R&D Contractors)

This figure plots the frequency distribution of the *Value of R&D contracts* (Panel A) and *Number of R&D Contracting Offices* (Panel B), at the firm-year level, for R&D contractors. These distributions have been winsorized at the 99th percentile for expositional clarity.

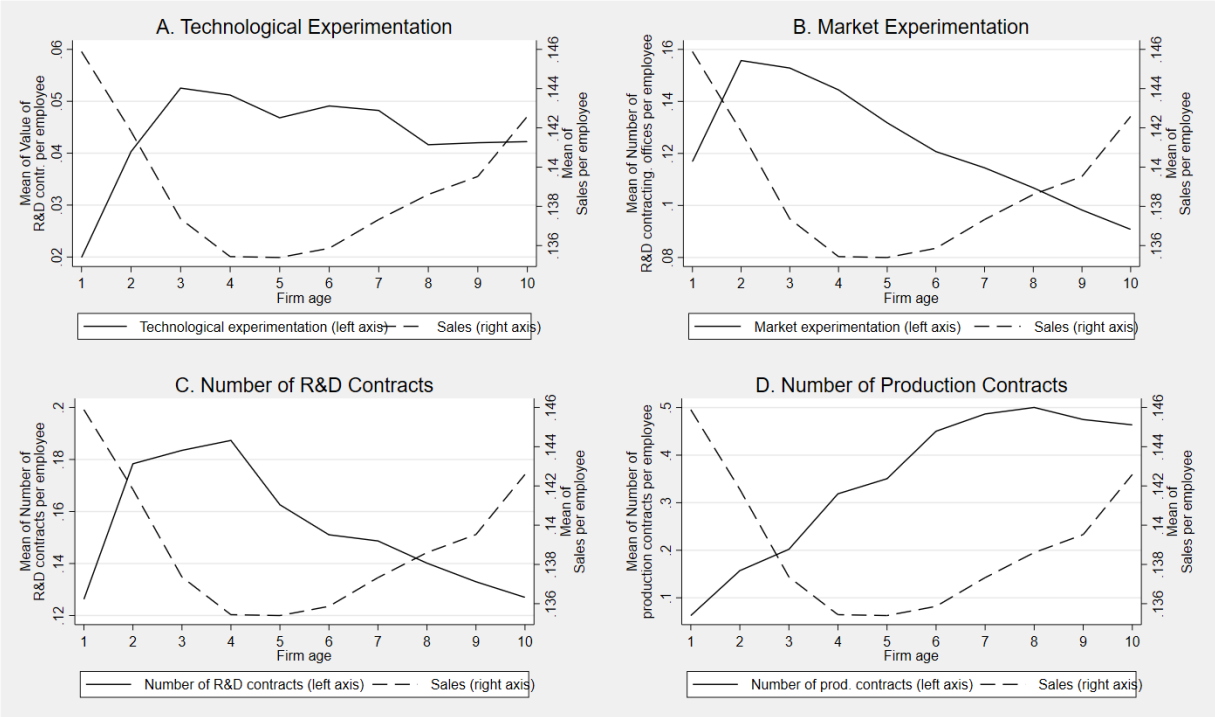


Figure B5: Changes in Experimentation, Contracting, and Sales (Normalized by Headcount) Over Time

This figure plots the changes in experimentation, contracting, and sales as startups age. Conditional on survival, startups grow over time. Therefore, all measures are normalized by headcount. Panel A compares the average Value of R&D contracts to average sales. Panel B compares the average Number of R&D contracting offices to average sales. Panel C compares the average Number of R&D contracts to average sales. Panel D compares the average Number of production contracts to average sales.

Table B17: Robustness of Relationship Between Experimentation and Startup Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Employee growth$_{t+1}$		ln(Employees)$_t$		Employees$_t$		Number of R&D contr. offices$_{t-1}$	Value of R&D contracts$_{t-1}$
	(OLS)	Only R&D contractors (OLS)	Control for age (OLS)	Only R&D contractors (OLS)	Control for age (Poisson)	Only R&D contractors (Poisson)	Narrow window (OLS, first stage)	Narrow window (OLS, first stage)
Number of R&D contr. offices$_{t-1}$	19.835***	14.065*	0.106***	0.093***	0.067***	0.057***		0.334***
	(4.729)	(8.250)	(0.005)	(0.005)	(0.015)	(0.014)		(0.042)
Value of R&D contracts$_{t-1}$	-0.027	-0.789	0.011**	0.009**	-0.009***	-0.008***	0.308***	
	(1.893)	(2.026)	(0.004)	(0.004)	(0.004)	(0.003)	(0.101)	
Value of production contracts$_{t-1}$	0.392	1.622	0.001***	0.001**	0.001**	0.000	0.003***	0.001
	(0.664)	(1.965)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Value of grants$_{t-1}$	-0.329	-13.785*	0.002**	0.013*	0.002	0.007**	0.015	0.001
	(0.285)	(8.115)	(0.001)	(0.008)	(0.001)	(0.003)	(0.013)	(0.002)
ln(Employees)$_t$	-309.380***	-309.138***						
	(26.158)	(76.643)						
Firm age$_t$			-0.036*		0.052***			
			(0.020)		(0.020)			
Treated$_{t-1}$							0.019***	-0.009**
							(0.007)	(0.004)
September$_{t-1}$							1.090***	0.596***
							(0.097)	(0.226)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Industry-year FE	No	No	No	No	No	No	Yes	Yes
Mean DV	25.96	37.13	12.01	18.22	12.01	18.22	0.02	0.01
Firms	86,406	13,469	91,708	14,243	91,708	14,243	6,146	6,146
Observations	533,399	84,340	630,409	99,357	630,409	99,357	31,946	31,946
Adjusted/pseudo R-squared	0.05	0.05	0.89	0.86	0.88	0.90	0.33	0.24

Notes: This table presents additional robustness checks for the relationship between experimentation and startup employment. *Employee growth*$_{t+1}$ is the percentage change in headcount from year t to year $t+1$. In Columns 1, 3, and 5, the analysis sample includes only the years 2001-2019 when grant data are available. In Columns 2, 4, and 6, the analysis samples are further restricted to R&D contractors. In Columns 7 and 8, the analysis sample is restricted to firm-years between 2001 and 2019 with a headcount of up to 100 employees smaller or larger than the applicable employee size standard. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms (Columns 1-6) or industry-years (Columns 7 and 8). * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B18: Robustness of Relationship Between Experimentation and Startup Sales

Dependent variable:	(1) Sales growth$_{t+1}$ (OLS)	(2) Sales growth$_{t+1}$ Only R&D contractors (OLS)	(3) ln(Sales)$_t$ Control for age (OLS)	(4) ln(Sales)$_t$ Only R&D contractors (OLS)	(5) Sales$_t$ Control for age (Poisson)	(6) Sales$_t$ Only R&D contractors (Poisson)
Number of R&D contr. offices$_{t-1}$	99.857**	9.625***	0.120***	0.105***	0.055***	0.058***
	(43.739)	(3.710)	(0.005)	(0.005)	(0.015)	(0.010)
Value of R&D contracts$_{t-1}$	12.411	-2.044	0.014***	0.011***	-0.007*	-0.005*
	(7.782)	(1.744)	(0.005)	(0.004)	(0.004)	(0.003)
Value of production contracts$_{t-1}$	0.720	0.990	0.001*	0.001**	0.001***	0.000*
	(0.889)	(1.444)	(0.001)	(0.001)	(0.000)	(0.000)
Value of grants$_{t-1}$	1.370	-13.998	0.002**	0.013	0.003	0.008***
	(0.996)	(8.660)	(0.001)	(0.009)	(0.004)	(0.002)
ln(Sales)$_t$	-999.471***	-264.425***				
	(370.528)	(22.095)				
Firm age$_t$			-0.048**		0.038	
			(0.023)		(0.030)	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	No	No	No	No	No	No
Mean DV	53.10	39.12	2.34	3.42	2.34	3.42
Firms	85,868	13,420	91,115	14,189	91,117	14,189
Observations	530,317	84,065	626,674	99,023	626,709	99,023
Adjusted/pseudo R-squared	0.24	0.04	0.93	0.90	0.87	0.89

Notes: This table presents additional robustness checks for the relationship between experimentation and startup sales. *Sales growth*$_{t+1}$ is the percentage change in sales from year t to year $t+1$. In Columns 1, 3, and 5, the analysis sample includes only the years 2001-2019 when grant data are available. In Columns 2, 4, and 6, the analysis samples are further restricted to R&D contractors. In Column 7, the analysis sample is restricted to firm-years between 2001 and 2019 with a headcount of up to 100 employees smaller or larger than the applicable employee size standard. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B19: Variation by Industry

Dependent variable:	(1) $\ln(\text{Employees})_t$	(2) Employees_t	(3) $\ln(\text{Sales})_t$	(4) Sales_t
	OLS	Poisson	OLS	Poisson
Number of R&D contr. offices$_{t-1}$	0.115***	0.065***	0.129***	0.079***
	(0.008)	(0.018)	(0.008)	(0.017)
$\times$ *Consumer*	0.011	0.094*	0.022	0.067*
	(0.024)	(0.049)	(0.029)	(0.038)
$\times$ *Manufacturing*	-0.025	-0.138**	-0.028	-0.232***
	(0.026)	(0.057)	(0.027)	(0.050)
$\times$ *HiTech*	-0.014	0.007	-0.015	-0.027
	(0.011)	(0.021)	(0.012)	(0.020)
$\times$ *Health*	-0.028	0.035	-0.043	0.185
	(0.032)	(0.069)	(0.035)	(0.158)
Value of R&D contracts$_{t-1}$	0.011***	-0.010***	0.014***	-0.007**
	(0.004)	(0.003)	(0.005)	(0.003)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001*	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002	0.002**	0.003
	(0.001)	(0.001)	(0.001)	(0.004)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Mean DV	12.00	12.00	2.34	2.34
Firms	91,145	91,145	91,119	91,121
Observations	626,855	626,855	626,696	626,731
Adjusted/pseudo R-squared	0.89	0.88	0.93	0.87

Notes: This table presents the variation in the relationship between market experimentation and startup employment and sales by industry. Industry classification is based on a firm's SIC4 code and the five industry definitions from Fama and French (1993). The excluded industry indicator variable is *Others*. The analysis sample in all columns includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B20: Variation by Awarding Agency (OLS)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Employees)$_t$				ln(Sales)$_t$			
	DoD (OLS)	DoE (OLS)	HHS (OLS)	NASA (OLS)	DoD (OLS)	DoE (OLS)	HHS (OLS)	NASA (OLS)
Number of DoD R&D contr. offices$_{t-1}$	0.100***				0.113***			
	(0.006)				(0.007)			
Number of non-DoD R&D contr. offices$_{t-1}$	0.122***				0.137***			
	(0.008)				(0.009)			
Number of DoE R&D contr. offices$_{t-1}$		0.284***				0.357***		
		(0.077)				(0.077)		
Number of non-DoE R&D contr. offices$_{t-1}$		0.106***				0.119***		
		(0.005)				(0.005)		
Number of HHS R&D contr. offices$_{t-1}$			0.115***				0.129***	
			(0.018)				(0.021)	
Number of non-HHS R&D contr. offices$_{t-1}$			0.106***				0.120***	
			(0.005)				(0.006)	
Number of NASA R&D contr. offices$_{t-1}$				0.074***				0.081***
				(0.014)				(0.016)
Number of non-NASA R&D contr. offices$_{t-1}$				0.109***				0.123***
				(0.005)				(0.006)
Value of R&D contracts$_{t-1}$	0.011***	0.011**	0.011**	0.011**	0.014***	0.014***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001***	0.001***	0.001*	0.001*	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Value of grants$_{t-1}$	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.00	12.00	12.00	12.00	2.34	2.34	2.34	2.34
Firms	91,145	91,145	91,145	91,145	91,119	91,119	91,119	91,119
Observations	626,855	626,855	626,855	626,855	626,696	626,696	626,696	626,696
Adjusted R-squared	0.89	0.89	0.89	0.89	0.93	0.93	0.93	0.93

Notes: This table presents the variation in the relationship between market experimentation and startup employment and sales by awarding agency, estimated using OLS regression. The analysis sample in all columns includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B21: Variation by Awarding Agency (Poisson)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employees$_t$				Sales$_t$			
	DoD (Poisson)	DoE (Poisson)	HHS (Poisson)	NASA (Poisson)	DoD (Poisson)	DoE (Poisson)	HHS (Poisson)	NASA (Poisson)
Number of DoD R&D contr. offices$_{t-1}$	0.054***				0.055***			
	(0.018)				(0.017)			
Number of non-DoD R&D contr. offices$_{t-1}$	0.111***				0.057			
	(0.036)				(0.052)			
Number of DoE R&D contr. offices$_{t-1}$		0.407***				0.574***		
		(0.157)				(0.109)		
Number of non-DoE R&D contr. offices$_{t-1}$		0.067***				0.055***		
		(0.015)				(0.015)		
Number of HHS R&D contr. offices$_{t-1}$			0.201**				0.250***	
			(0.084)				(0.059)	
Number of non-HHS R&D contr. offices$_{t-1}$			0.066***				0.053***	
			(0.015)				(0.015)	
Number of NASA R&D contr. offices$_{t-1}$				0.050				0.012
				(0.054)				(0.073)
Number of non-NASA R&D contr. offices$_{t-1}$				0.068***				0.057***
				(0.015)				(0.015)
Value of R&D contracts$_{t-1}$	-0.009**	-0.009**	-0.009***	-0.009**	-0.007*	-0.007*	-0.007**	-0.007
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Value of production contracts$_{t-1}$	0.001**	0.001**	0.001**	0.001**	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002	0.002	0.001	0.002	0.003	0.003	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.00	12.00	12.00	12.00	2.34	2.34	2.34	2.34
Firms	91,145	91,145	91,145	91,145	91,121	91,121	91,121	91,121
Observations	626,855	626,855	626,855	626,855	626,731	626,731	626,731	626,731
Pseudo R-squared	0.88	0.88	0.88	0.88	0.87	0.87	0.87	0.87

Notes: This table presents the variation in the relationship between market experimentation and startup employment and sales by awarding agency, estimated using Poisson regression. The analysis sample in all columns includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B22: Variation by Contract Characteristics

Dependent variable:	(1) ln(Employees)$_t$	(2)	(3) ln(Sales)$_t$	(4)	(5) Employees$_t$	(6)	(7) Sales$_t$	(8)
	Competitive (OLS)	Set-aside (OLS)	Competitive (OLS)	Set-aside (OLS)	Competitive (Poisson)	Set-aside (Poisson)	Competitive (Poisson)	Set-aside (Poisson)
Number of competitive R&D contr. offices$_{t-1}$	0.100***		0.112***		0.045**		0.025	
	(0.005)		(0.006)		(0.019)		(0.021)	
Number of noncompetitive R&D contr. offices$_{t-1}$	0.140***		0.163***		0.116***		0.120***	
	(0.011)		(0.013)		(0.045)		(0.042)	
Number of set-aside R&D contr. offices$_{t-1}$		0.085***		0.096***		0.049**		0.047**
		(0.007)		(0.007)		(0.020)		(0.019)
Number of not set-aside R&D contr. offices$_{t-1}$		0.128***		0.149***		0.146***		0.148***
		(0.011)		(0.012)		(0.046)		(0.039)
Value of competitive R&D contracts$_{t-1}$	0.010**		0.013***		-0.008**		-0.005	
	(0.004)		(0.005)		(0.003)		(0.004)	
Value of noncompetitive R&D contracts$_{t-1}$	0.010		0.014		0.005		0.016	
	(0.008)		(0.010)		(0.012)		(0.010)	
Value of set-aside R&D contracts$_{t-1}$		0.044***		0.047***		0.009		0.011
		(0.007)		(0.008)		(0.009)		(0.007)
Value of not set-aside R&D contracts$_{t-1}$		0.011***		0.014***		-0.003		-0.002
		(0.003)		(0.004)		(0.003)		(0.003)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001*	0.001*	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002**	0.002**	0.002**	0.002	0.002	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.00	12.00	2.34	2.34	12.00	12.00	2.34	2.34
Firms	91,140	91,140	91,114	91,114	91,140	91,140	91,116	91,116
Observations	626,827	626,827	626,668	626,668	626,827	626,827	626,703	626,703
Adjusted/pseudo R-squared	0.89	0.89	0.93	0.93	0.88	0.88	0.87	0.87

Notes: This table presents the variation in the relationship between market experimentation and startup employment and sales by contract characteristics. Competitive contracts are awarded using full and open competition. Set-aside contracts are reserved for small or disadvantaged businesses. The analysis sample in all columns includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B23: Relationship Between Experimentation and Performance for Pharma vs. ICT Startups

Dependent variable:	(1) ln(Employees)$_t$	(2)	(3) Employees$_t$	(4)	(5) ln(Sales)$_t$	(6)	(7) Sales$_t$	(8)
	Pharma (OLS)	ICT (OLS)	Pharma (Poisson)	ICT (Poisson)	Pharma (OLS)	ICT (OLS)	Pharma (Poisson)	ICT (Poisson)
Number of R&D contr. offices$_{t-1}$	0.045	0.072***	-0.080	0.054**	0.057	0.084***	-0.116	0.053**
	(0.033)	(0.009)	(0.083)	(0.023)	(0.038)	(0.012)	(0.130)	(0.026)
Value of R&D contracts$_{t-1}$	0.009***	0.007	0.007***	0.001	0.010***	0.007	0.006***	0.003
	(0.002)	(0.006)	(0.001)	(0.008)	(0.002)	(0.010)	(0.001)	(0.009)
Value of production contracts$_{t-1}$	0.007**	0.007***	0.004**	0.001	0.008***	0.010***	0.003**	0.003**
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
Value of grants$_{t-1}$	-0.000	0.006**	-0.029	0.010**	-0.004	-0.006	0.005	-0.000
	(0.033)	(0.002)	(0.023)	(0.005)	(0.032)	(0.009)	(0.043)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	15.24	22.80	15.24	22.80	3.22	4.45	3.22	4.45
Firms	1,196	14,741	1,196	14,741	1,196	14,741	1,196	14,741
Observations	7,795	89,510	7,795	89,510	7,795	89,510	7,795	89,510
Adjusted/pseudo R-squared	0.90	0.90	0.88	0.91	0.93	0.92	0.87	0.88

Notes: This table presents the relationship between experimentation and performance for startups in two subsamples. Columns 1, 3, 5, and 7 use startups operating in pharmaceutical product industries, while Columns 2, 4, 6, and 8 use startups operating in communication, computer hardware, computer software, and electronic equipment industries. Industry classification is based on a firm's SIC4 code and the 49 industry definitions from Fama and French (1993). The analysis sample in all columns includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B24: Variation by Industry Munificence

Dependent variable:	(1) $\ln(\text{Employees})_t$	(2) $\ln(\text{Sales})_t$	(3) Employees_t	(4) Sales_t
	(OLS)	(OLS)	(Poisson)	(Poisson)
Number of R&D contr. offices$_{t-1}$	0.099***	0.113***	0.126***	0.108***
	(0.016)	(0.018)	(0.032)	(0.032)
$\times$ *High VC industry*	0.008	0.007	-0.060*	-0.057
	(0.016)	(0.018)	(0.033)	(0.035)
Value of R&D contracts$_{t-1}$	0.011**	0.014***	-0.009**	-0.006
	(0.004)	(0.005)	(0.004)	(0.004)
Value of production contracts$_{t-1}$	0.001***	0.001*	0.001**	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002**	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.004)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Mean DV	12.00	2.34	12.00	2.34
Firms	91,145	91,119	91,145	91,121
Observations	626,855	626,696	626,855	626,731
Adjusted/pseudo R-squared	0.89	0.93	0.88	0.87

Notes: This table presents the variation in the relationship between market experimentation and startup employment and sales by industry munificence. *High VC industry* is an indicator variable equal to 1 if the firm's industry receives above-median venture capital funding compared to other industries that year and 0 otherwise. The analysis sample in all columns includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value $<$ 0.10 ** p-value $<$ 0.05 *** p-value $<$ 0.01

Table B25: Relationship Between Venture Capital Raised and Future Government Contracting

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Value of government sales$_t$		Number of R&D contr. offices$_t$		Value of R&D contracts$_t$	
	(OLS)	(Poisson)	(OLS)	(Poisson)	(OLS)	(Poisson)
Raised any venture capital$_{t-1}$	-0.032*	0.006				
	(0.020)	(0.067)				
Value of venture capital raised$_{t-1}$			-0.000	-0.003	0.000	-0.000
			(0.000)	(0.002)	(0.000)	(0.003)
Number of venture capital deals$_{t-1}$			0.009*	0.066*	0.001	0.009
			(0.005)	(0.038)	(0.009)	(0.081)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.57	0.68	0.07	0.47	0.05	0.34
Firms	102,361	83,621	102,361	15,541	102,361	15,299
Observations	777,039	655,480	777,039	123,347	777,039	121,815
Adjusted/pseudo R-squared	0.65	0.85	0.59	0.30	0.34	0.65

Notes: This table presents the relationship between venture capital raised and future government contracting. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value $<$ 0.10 ** p-value $<$ 0.05 *** p-value $<$ 0.01

Table B26: Relationship Between Experimentation and the Breadth of Products Sold to the Government

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of PSC$_t$						
	Number (OLS)	Value (OLS)	Both (OLS)	Additional controls (OLS)	Additional controls (Poisson)	Narrow window (OLS)	Narrow window (2SLS)
Number of R&D contr. offices$_{t-1}$	0.354***		0.291***	0.306***	0.118***	1.220***	40.040**
	(0.067)		(0.036)	(0.024)	(0.017)	(0.271)	(17.061)
Value of R&D contracts$_{t-1}$		0.108**	0.079*	0.051**	-0.015***	-0.446**	-49.883**
		(0.052)	(0.046)	(0.024)	(0.003)	(0.189)	(23.488)
Value of production contracts$_{t-1}$				0.012***	0.001***	0.413***	0.392***
				(0.005)	(0.000)	(0.056)	(0.093)
Value of grants$_{t-1}$				0.000	0.013***	-0.188	-0.542
				(0.000)	(0.003)	(0.149)	(0.463)
Year FE	Yes	Yes	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	No	No
Industry-year FE	No	No	No	No	No	Yes	Yes
Mean DV	0.61	0.61	0.61	0.67	0.90	1.22	1.22
Firms	102,958	102,958	102,958	91,708	66,786	6,146	6,146
Observations	780,976	780,976	780,976	630,409	471,736	31,946	31,946
Weak identif. (Kleibergen-Paap)							4.01
Adjusted/pseudo R-squared	0.59	0.59	0.59	0.63	0.50	0.17	-3.42

Notes: This table presents the relationship between experimentation and the breadth of products sold to the government. *Number of PSC* is the number of different product and non-R&D service codes the firm received procurement contracts for in the focal year; R&D service codes are excluded. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms (Columns 1-5) or industry-years (Columns 6 and 7). * p-value $<$ 0.10 ** p-value $<$ 0.05 *** p-value $<$ 0.01

Table B27: Alternative Explanation: Learning by Doing

Dependent variable:	(1) $\ln(\text{Employees})_t$	(2) $\ln(\text{Employees})_t$	(3) Employees_t	(4) Employees_t	(5) $\ln(\text{Sales})_t$	(6) $\ln(\text{Sales})_t$	(7) Sales_t	(8) Sales_t
	(OLS)	(OLS)	(Poisson)	(Poisson)	(OLS)	(OLS)	(Poisson)	(Poisson)
Number of R&D contracts won, stock$_{t-1}$	0.009**	0.004*	-0.002*	-0.005***	0.011**	0.005*	-0.001	-0.005***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.004)	(0.003)	(0.001)	(0.002)
Number of R&D contr. offices$_{t-1}$		0.099***		0.075***		0.110***		0.064***
		(0.006)		(0.015)		(0.007)		(0.014)
Value of R&D contracts$_{t-1}$		0.008**		0.001		0.010**		0.003
		(0.004)		(0.002)		(0.005)		(0.002)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001***	0.001***	0.001*	0.001*	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002**	0.002	0.002	0.002**	0.002**	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.01	12.01	12.01	12.01	2.35	2.35	2.35	2.35
Firms	91,708	91,708	91,708	91,708	91,682	91,682	91,684	91,684
Observations	630,409	630,409	630,409	630,409	630,250	630,250	630,285	630,285
Adjusted/pseudo R-squared	0.89	0.89	0.88	0.88	0.93	0.93	0.87	0.87

Notes: This table presents the relationship between learning by doing and startup employment and sales. The analysis sample includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value $<$ 0.10 ** p-value $<$ 0.05 *** p-value $<$ 0.01

Table B28: Robustness to Using Smaller Startups

Dependent variable:	(1) $\ln(\text{Employees})_t$	(2) Employees_t	(3) $\ln(\text{Sales})_t$	(4) Sales_t
	(OLS)	(Poisson)	(OLS)	(Poisson)
Number of R&D contr. offices$_{t-1}$	0.107***	0.072***	0.120***	0.042*
	(0.005)	(0.022)	(0.005)	(0.025)
Value of R&D contracts$_{t-1}$	0.013**	-0.010***	0.015***	-0.005*
	(0.005)	(0.002)	(0.005)	(0.003)
Value of production contracts$_{t-1}$	0.001***	0.000*	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002	0.002**	0.003
	(0.001)	(0.001)	(0.001)	(0.004)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Mean DV	9.33	9.33	1.81	1.81
Firms	89,613	89,613	89,588	89,590
Observations	617,052	617,052	616,896	616,931
Adjusted/pseudo R-squared	0.88	0.84	0.92	0.84

Notes: This table presents the relationship between experimentation and startup employment and sales using smaller startups that had 1-49 employees in their establishment year. The analysis sample includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value $<$ 0.10 ** p-value $<$ 0.05 *** p-value $<$ 0.01

Table B29: Robustness to Using Younger Startups

Dependent variable:	(1) $\ln(\text{Employees})_t$	(2) Employees_t	(3) $\ln(\text{Sales})_t$	(4) Sales_t
	(OLS)	(Poisson)	(OLS)	(Poisson)
Number of R&D contr. offices$_{t-1}$	0.087***	0.036**	0.099***	0.050***
	(0.005)	(0.018)	(0.006)	(0.016)
Value of R&D contracts$_{t-1}$	0.008**	-0.003	0.010**	-0.000
	(0.003)	(0.003)	(0.004)	(0.003)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.000)
Value of grants$_{t-1}$	0.001***	0.001**	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.001)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Mean DV	9.43	9.43	1.74	1.74
Firms	84,832	84,832	84,810	84,813
Observations	436,388	436,388	436,284	436,305
Adjusted/pseudo R-squared	0.90	0.86	0.93	0.84

Notes: This table presents the relationship between experimentation and startup employment and sales using a younger sample of startups tracked for the first seven years of activity (if available). The analysis sample includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B30: Robustness to Using Alternative Measures of Technology Experimentation

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\ln(\text{Employees})_t$			Employees_t			$\ln(\text{Sales})_t$			Sales_t		
	(OLS)	(OLS)	(OLS)	(Poisson)	(Poisson)	(Poisson)	(OLS)	(OLS)	(OLS)	(Poisson)	(Poisson)	(Poisson)
Number of R&D contr. offices$_{t-1}$	0.107***	0.094***	0.109***	0.062***	0.007	0.053***	0.121***	0.111***	0.123***	0.049***	0.009	0.049***
	(0.005)	(0.009)	(0.006)	(0.016)	(0.021)	(0.016)	(0.005)	(0.009)	(0.007)	(0.015)	(0.024)	(0.016)
Value of R&D contracts, first 3 stages$_{t-1}$	0.010***			-0.003			0.011***			0.002		
	(0.004)			(0.003)			(0.004)			(0.002)		
Value of R&D contracts, last 4 stages$_{t-1}$	0.010			-0.012***			0.019			-0.010***		
	(0.012)			(0.002)			(0.015)			(0.002)		
Received an R&D contract$_{t-1}$		0.040***			0.235***			0.038***			0.177***	
		(0.011)			(0.049)			(0.011)			(0.067)	
Number of R&D contracts won$_{t-1}$			0.003			-0.007***			0.005			-0.006***
			(0.003)			(0.002)			(0.004)			(0.002)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**	0.001*	0.001*	0.001*	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002**	0.002**	0.002	0.001	0.002	0.002**	0.002**	0.002**	0.003	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.01	12.01	12.01	12.01	12.01	12.01	2.35	2.35	2.35	2.35	2.35	2.35
Firms	91,708	91,708	91,708	91,708	91,708	91,708	91,682	91,682	91,682	91,684	91,684	91,684
Observations	630,409	630,409	630,409	630,409	630,409	630,409	630,250	630,250	630,250	630,285	630,285	630,285
Adjusted/pseudo R-squared	0.89	0.89	0.89	0.88	0.88	0.88	0.93	0.93	0.93	0.87	0.87	0.87

Notes: This table presents the relationship between experimentation and startup employment and sales using alternative measures of technology experimentation. *Value of R&D contracts, first 3 stages* is the dollar value of contracts awarded for basic research, applied research and exploratory development, or advanced development (see Appendix Table B8 for definitions). *Value of R&D contracts, last 4 stages* is the dollar value of contracts awarded for engineering development, operational systems development, management and support, or commercialization. *Received an R&D contract* is an indicator variable equal to 1 if the startup received any R&D contracts and 0 otherwise. *Number of R&D contracts won* is the count of distinct R&D contracts awarded to the startup. The analysis sample includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B31: Robustness to Using Alternative Measures of Market Experimentation

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ln(Employees)$_t$			Employees$_t$			ln(Sales)$_t$			Sales$_t$		
	(OLS)	(OLS)	(OLS)	(Poisson)	(Poisson)	(Poisson)	(OLS)	(OLS)	(OLS)	(Poisson)	(Poisson)	(Poisson)
Number of R&D agencies$_{t-1}$	0.141***			0.201***			0.157***			0.164***		
	(0.006)			(0.036)			(0.006)			(0.040)		
Received R&D contr. from 2+ offices$_{t-1}$		0.205***			0.237***			0.242***			0.132	
		(0.014)			(0.064)			(0.016)			(0.111)	
Diversity of contr. offices$_{t-1}$			0.189***			0.339***			0.212***			0.240***
			(0.008)			(0.059)			(0.009)			(0.081)
Value of R&D contracts$_{t-1}$	0.016***	0.019***	0.018***	-0.005	-0.002	-0.002	0.020***	0.023***	0.022***	-0.003	-0.000	-0.001
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**	0.001*	0.001*	0.001*	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002**	0.002**	0.002**	0.002	0.002	0.001	0.002**	0.002**	0.002**	0.003	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.00	12.00	12.00	12.00	12.00	12.00	2.34	2.34	2.34	2.34	2.34	2.34
Firms	91,140	91,140	91,140	91,140	91,140	91,140	91,114	91,114	91,114	91,116	91,116	91,116
Observations	626,827	626,827	626,827	626,827	626,827	626,827	626,668	626,668	626,668	626,703	626,703	626,703
Adjusted/pseudo R-squared	0.89	0.89	0.89	0.88	0.88	0.88	0.93	0.93	0.93	0.87	0.87	0.87

Notes: This table presents the relationship between experimentation and startup employment and sales using alternative measures of market experimentation. *Number of R&D agencies* is the number of distinct federal agencies awarding R&D contracts to the startup. *Received R&D contr. from 2+ offices* is an indicator variable equal to 1 if the startup received R&D contracts from 2+ distinct contracting offices and 0 otherwise. *Diversity of contr. offices* is 1 - HHI, where HHI is the Herfindahl-Hirschman index measuring the concentration (across NAICS4 industries) in the procurement portfolios of the contracting offices awarding R&D contracts to the startup. The analysis sample includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01

Table B32: Robustness to Using Longer Time Lags

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\ln(\text{Employees})_t$			Employees_t			$\ln(\text{Sales})_t$			Sales_t		
	Lag = 1 (OLS)	Lag = 2 (OLS)	Lag = 3 (OLS)	Lag = 1 (Poisson)	Lag = 2 (Poisson)	Lag = 3 (Poisson)	Lag = 1 (OLS)	Lag = 2 (OLS)	Lag = 3 (OLS)	Lag = 1 (Poisson)	Lag = 2 (Poisson)	Lag = 3 (Poisson)
Number of R&D contr. offices$_{t-lag}$	0.106***	0.083***	0.060***	0.068***	-0.003	-0.015	0.120***	0.096***	0.073***	0.056***	-0.013	-0.019
	(0.005)	(0.005)	(0.004)	(0.015)	(0.014)	(0.010)	(0.005)	(0.005)	(0.004)	(0.015)	(0.016)	(0.018)
Value of R&D contracts$_{t-lag}$	0.011**	0.010**	0.004	-0.009**	-0.001	-0.000	0.014***	0.012***	0.005	-0.007*	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Value of production contracts$_{t-1}$	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**	0.001*	0.001**	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Value of grants$_{t-1}$	0.002**	0.001**	0.001*	0.002	0.001	0.001	0.002**	0.001**	0.001*	0.003	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	12.00	12.83	13.73	12.00	12.83	13.73	2.34	2.52	2.73	2.34	2.52	2.73
Firms	91,140	88,005	83,693	91,140	88,005	83,693	91,114	87,982	83,670	91,116	87,982	83,672
Observations	626,827	552,527	476,086	626,827	552,527	476,086	626,668	552,390	475,966	626,703	552,412	475,989
Adjusted/pseudo R-squared	0.89	0.91	0.92	0.88	0.89	0.90	0.93	0.94	0.95	0.87	0.87	0.88

Notes: This table presents the relationship between experimentation and startup employment and sales using longer time lags. The analysis sample includes only the years 2001-2019 when grant data are available. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * p-value < 0.10 ** p-value < 0.05 *** p-value < 0.01