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ABSTRACT

Firms invest in scientific research to increase their chances of landing lucrative procurement contracts with the U.S. government. This is an important, but understudied channel through which the government encourages corporate research, particularly when other market mechanisms are insufficient. Using data on $2.3 trillion in contracts matched to 4,323 publicly traded manufacturing firms from 1980 through 2015, we estimate the effect of procurement contracts on upstream (scientific publications) and downstream (patents) corporate R&D. We document a positive effect of contracts on publications, and show that the effect is stronger when market incentives are weak. Procurement contracts encourage publications that: (i) are not used in the firm's internal inventions, (ii) spill over to rivals' inventions, and (iii) are not protected by patents. However, the effect has weakened over time, because the U.S. government has emphasized reduced cost and increased efficiency and transparency in contract awards. Following such policy reforms as the Federal Acquisition Streamlining Act of 1994, the share of R&D contracts in all contracts declined from a high of 25 percent in 1998 to 7 percent in 2015, while the share of commercial contracts grew from 6 percent to 14 percent over the same period. Our results imply that the reorientation of government procurement toward commercially proven technologies has contributed to the withdrawal of corporations from participating in scientific research.

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1 Introduction

Between 1980 and 2015, American businesses funded \$1.7 trillion in basic and applied research, which accounted for 45 percent of all research performed in the United States.[1] By lowering the cost of research and increasing its private value, the U.S. government plays an important role in encouraging corporations to participate in research. The government affects cost directly using subsidies and grants (Bloom, Griffith and Van Reenen, 2002; Fleming et al., 2019; Wallsten, 2000), and indirectly via spillovers from government funded research in national laboratories and universities (Adams, Chiang and Jensen, 2003; Cohen, Nelson and Walsh, 2002; Goolsbee, 1998; Jaffe and Lerner, 2001; National Academies of Sciences, Engineering, and Medicine, 2021). At the same time, government procurement contracts can increase the private value of upstream research through guaranteed downstream markets.[2] This channel is particularly effective at driving corporate research when private markets are insufficient. Weak market incentives arise when commercial applications for novel technologies lie in the future (Weiss, 2014), knowledge spills over to rivals (Arora, Belenzon and Sheer, 2021; Bloom, Schankerman and Van Reenen, 2013), and incomplete contracts and asymmetric information make markets for technology inefficient (Arrow, 1962; Edler and Georghiou, 2007; Kremer, Levin and Snyder, 2020). In this paper, we document the government's role in de-risking upstream corporate research by guaranteeing downstream markets, and explore how this role has changed over time.

The development of the laser exemplifies how procurement contracts can drive corporate research by filling voids in commercial demand.[3] The U.S. Air Force Office of Scientific Research, Advanced Research Projects Agency, and the U.S. Army Signal Corps all funded competing research teams in the R&D race to build the first laser. Military contractor Hughes Research Laboratories demonstrated the Ruby laser on May 16, 1960. Yet, it took many years for commercial laser markets to develop. Throughout the 1960s, it was government support for measurement and optical communication lasers that enabled corporate research laboratories to scale and improve the technology. By 1969, the Department of Defense's share as a laser customer was 63.4 percent (Bromberg, 1991). In the early 1970s, growth in military laser procurement slowed, universities curtailed their laser purchases, and companies redirected their R&D toward civilian applications that held promise for short-term payoffs. The large potential gains from

[1] Data are from Tables 2, 3, and 4 of the National Patterns of R&D Resources series published by the National Center for Science and Engineering Statistics (National Science Foundation, 2019).

[2] The government also affects the value of corporate R&D by designing patent policies, enforcing antitrust laws, and setting regulations (see Aschhoff and Sofka, 2009; Bloom, Van Reenen and Williams, 2019; Cunningham, Ederer and Ma, 2021; Jaffe, Newell and Stavins, 2003). These indirect mechanisms are outside the scope of the present paper.

[3] Appendix A summarizes the steps in a typical government procurement process.

supplanting existing telephone networks motivated corporate investment in heterojunction semiconductor lasers. The first fiber optics communications were demonstrated at Bell Labs in 1976. By the 1980s, lasers had become prominent in the consumer economy as supermarket scanners and optical discs (Hecht, 2010). There is little doubt that the development of the commercial laser industry was enabled by government demand in the technology's early years.[4]

In 2015, the U.S. government awarded businesses $440 billion in procurement contracts.[5] Of those procurement dollars, $39 billion were for R&D services, compared to just $4 billion in grants to businesses.[6] That year, the government's total support for R&D performed in all government, university, business, and nonprofit laboratories was $120 billion.[7] Despite their large size, we know relatively little about the effect of procurement contracts on corporate R&D, and how the effect operates. Most prior studies examine the public funding mechanism by focusing on grants from the Small Business Innovation Research program and the National Institutes of Health (e.g., Audretsch, Link and Scott, 2002; Azoulay et al., 2019; Howell, 2017; Lerner, 1999; Wallsten, 2000). Several studies investigate spillovers from national laboratories (e.g., Adams, Chiang and Jensen, 2003; Jaffe and Lerner, 2001; Link, Siegel and Van Fleet, 2011; Link and Scott, 2020; Mowery and Ziedonis, 2001) or universities (e.g., Cohen, Nelson and Walsh, 2002; Tartari and Stern, 2021). Procurement contracts are the focus of only a handful of studies (e.g., Barder, Kremer and Levine, 2005; Howell et al., 2021; Lichtenberg, 1988; Moretti, Steinwender and Van Reenen, 2019; Slavtchev and Wiederhold, 2016). Yet, none distinguish between upstream and downstream R&D. This distinction is important because weak private market incentives should be especially relevant for upstream research. Guaranteed demand should be more consequential for technologies that cannot be easily commercialized via private markets, either because they do not have clear commercial applications, or because competition makes it harder for the original inventors to appropriate sufficient private returns (for example, due to

[4] Mowery (1998) makes a similar case for commercial aerospace, semiconductors, computers, and software.

[5] Data extracted using the Advanced Search tool from the USAspending.gov website. The following filters were used: (i) time period = fiscal year 2015; (ii) award type = grants vs. contracts and contract IDVs; (iii) recipient type = businesses; and (iv) product or service code = research and development (USAspending.gov, 2021*b*). Not all procurement contracts are reported publicly either because the work is classified or sensitive, or because the amount is below the reporting threshold, which ranges between $2,000 and $25,000 during our sample years.

[6] It is important to distinguish between R&D contracts and grants (David, Hall and Toole, 2000). Under a contract, the contractor provides research services to the government for a fee. Under a grant—a form of financial assistance—the government transfers something of value (either money or in kind) to the grantee so the grantee can carry out activities to benefit the public (Datalab, 2020). The economic mechanisms behind the effects are also different. While grants are typically used to lower the cost of R&D, which is mostly relevant for small firms, R&D contracts are used as a "ticket" by large firms to gain access to lucrative downstream production contracts.

[7] Data are from Table 2 of the National Patterns of R&D Resources series published by the National Center for Science and Engineering Statistics (National Science Foundation, 2019). The $120 billion figure included $53 billion for government entities, $34 billion for universities, $27 billion for corporations, and $6 billion for other nonprofits. The $27 billion in grants and contracts to firms from National Science Foundation (2019) survey data and the $39 billion in contracts to firms from USAspending.gov (2021*b*) administrative data are not consistent for reasons outlined by Pece (2016).

knowledge spillovers and weak patent protection).

An important contribution of this paper is distinguishing between scientific research ("R") and downstream development ("D") in corporate R&D. Yet, a clear distinction may be difficult to draw, both conceptually and empirically. Science can be defined as a systematic enterprise directed toward a better understanding of the universe, while technology is concerned with the application of knowledge for practical purposes.[8] The main difference between scientific and technical knowledge is that the former is concerned with general or universal laws, while the latter explains how and why specific artifacts work. Because both advance understanding, this distinction is more a matter of degree than a stark dichotomy. Empirically, using publications to measure scientific research and patents to measure technology presents challenges as well.[9] Clearly, advances in technology can find their way into publications, and scientific knowledge sometimes can be patented (Murray and Stern, 2007). Yet, our premise is that research output should appear in the scientific literature disproportionately more than technology development does.[10]

With these caveats in mind, we begin by estimating the effect of government procurement contracts on R&D expenditures, publications, and patents. We extend the panel of 4,323 firms and 58,245 firm-year observations from Arora, Belenzon and Sheer (2021) by adding data on $2.3 trillion in contracts awarded by the Department of Defense (DoD), Department of Energy (DoE), Health and Human Services (HHS), and Veterans Affairs (VA). We measure firms' contracting activities using the value of contracts awarded, upstream research using publications authored by corporate scientists, and downstream development using patents.

We then study how the composition of government procurement contracts has changed over time. Sweeping policy changes in the 1980s and 1990s shifted the composition of contracts away from mission-focused technologies that met unique government specifications (which accounted for the majority of procurement dollars in the 1960s and 1970s) toward commercial items and dual use technologies (Weiss, 2014).[11] Arguably, this reorientation toward technologies with proven commercial markets reduced the government's role in de-risking upstream research.

We present two sets of findings. The first documents an effect of contracts on corporate publications,

[8]Technology consists of "both a set of specific designs and practices, and a body of generic knowledge that surrounds these and provides understanding of how things work, key variables effecting performance, the nature of currently binding constraints, and promising approaches to pushing these back" (Nelson, 1996, p. 350).

[9]Publications are peer-reviewed journal articles and conference proceedings.

[10]Arora, Belenzon and Sheer (2021) validate this premise using the Carnegie Mellon Survey of R&D-performing firms.

[11]Dual use technologies can be used both in military and other strategic uses (e.g., nuclear) and in commercial applications (Code of Federal Regulations, 2000). For example, in 1995, 25 percent of Department of Defense's $8.4 billion science and technology budget was allocated to dual use technologies focused on information technology, advanced materials, advanced manufacturing, and advanced simulation and modelling (Mowery, 1998; U.S. Department of Defense, 1995).

but not on patents. There are three potential explanations for why we do not find an effect for patents: (i) guaranteed demand may reduce the need to exclude rivals through patents; (ii) the government may restrict patenting due to disclosure concerns; and (iii) market incentives are likely to be stronger for downstream development, rendering guaranteed markets less effective. We explore the mechanism behind the effect of contracts on publications. Guaranteed demand should affect corporate research when capturing private returns in private markets is difficult. Consistent with this argument, we find a larger effect of contracts on publications that are: (i) not cited by the firm's own patents (missing downstream applications); (ii) cited by rival firms' patents (indicating a strong market stealing effect due to spillovers to close product-market competitors); and (iii) not protected by the firm's own patents. In addition, we find a stronger effect for larger firms, which is consistent with manufacturing capabilities and complementary assets being necessary to execute complex downstream government contracts.[12]

A major empirical challenge is how to deal with the endogeneity of procurement contracts (David, Hall and Toole, 2000). Common shocks can affect both corporate R&D and the allocation of government contracts. If the government targets fields that experience positive technology or demand shocks, our OLS estimates would be upward-biased. If, on the other hand, contracts target fields that experience negative shocks, our OLS estimates would be downward-biased. We take two approaches to mitigate this concern. Following existing literature, the first uses aggregate industry variation in government procurement as an instrument for contracts awarded to a focal firm. The identifying assumption is that aggregate changes in contracts at the industry level are unrelated to the firm's idiosyncratic shock in the innovation equation, and that firm exposure to these changes is pre-determined. The second approach exploits a quasi-natural experiment surrounding the end of the Cold War, which triggered substantial reallocation in government contracts due to changes in national priorities. For example, information technology and healthcare industries benefited from increased contract funding, while defense industries saw their funding drop significantly. Arguably, these changes arose from new geopolitical conditions, rather than from technology or demand shocks.[13] Our causal estimates point to a positive effect of contracts on corporate publications, but not on patents. We estimate that a $5 million increase in R&D contracts leads to one additional publication.[14] The causal estimates are larger than OLS, suggesting that contracts

[12] Appendix Figure A1 illustrates an intricate process used to procure technology-intensive defense products.

[13] A concern is that the Cold War ended *because* of American technological superiority. This argument may be plausible in the case of defense technologies, but not energy or health technologies. Our results are robust to excluding Department of Defense contracts from our analyses. Also, our analysis is conducted at the firm level, which further mitigates the identification concern, because it is unlikely that any single firm was responsible for the end of the Cold War.

[14] Gross and Sampat (2020) trace the origins of R&D contracts to the Office of Scientific Research and Development during World War II. They note that contracting for R&D services allowed the government to balance flexibility, the

target fields that experience negative technology or demand shocks.[15]

Second, we show that the effect on publications was stronger before the mid-1990s, when policy reforms changed the composition of procurement contracts. By dollar value, the share of R&D contracts in all contracts fell from a high of 25 percent in 1998 to 7 percent in 2015 (see the solid line in Figure 1). Within-firm estimates indicate that R&D contracts decreased by almost 22 percent per decade. We interpret this decline as pointing to a reduced importance of R&D races for downstream procurement. At the same time, the share of commercial contract dollars in all contracts increased from 6 percent in 1998 to 14 percent in 2015 (see the dashed line in Figure 1).[16] If the same policy had been in place during the 1960s and 1970s, it would have been unlikely that the government would have been able to replace the missing market demand for the laser technology previously discussed. Such policy would have severely damaged the private returns to innovation in the research intensive early years of the laser industry. The decline in the importance of R&D contracts relative to commercial contracts occurred across a wide range of industries (see Appendix Figure F2). For example, Electronics saw its share of R&D contracts drop from 17 percent in 1998 to just 3 percent in 2015. Conversely, Drugs had the largest increase in the share of commercial contracts, from 14 percent in 1998 to 77 percent in 2015.[17]

The importance of firm scientific capabilities for contract value has fallen as well. Figure 2 shows that the average contract value per $1 million in firm sales has remained relatively stable for firms that perform scientific research (solid line), but has increased sharply for firms that never publish scientific articles, from $2,000 in 1980 to $28,000 in 2015 (dashed line). Concurrently, the number of corporate publications per $1 million in research contracts has declined from 14 in 1985 to 5 in 2015 (shaded area). Arora, Belenzon and Patacconi (2018) document a decline in the stock market value and the mergers and acquisitions value of scientific capabilities. We contribute to those results by showing that corporate science has fallen out of favor not only with investors and managers, but also with the U.S. government.

Our final examination focuses on temporal changes in the relationship between winning R&D races and guaranteed downstream demand. The government has historically awarded a majority of procurement contracts noncompetitively, providing guaranteed demand for firms that were able to demonstrate strong

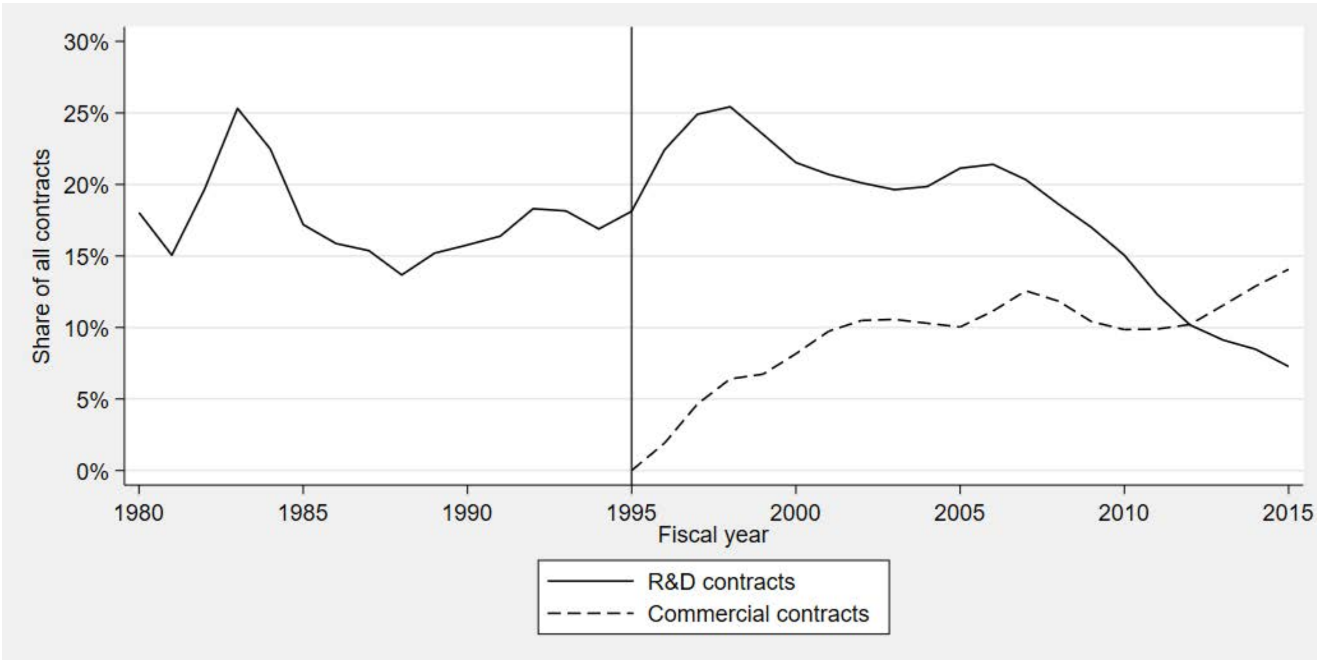
intrinsic uncertainty of research, and coordination and information sharing across efforts when speed was of the essence.

[15]This finding is consistent with government procurement aiming to maintain the existing military-industrial base (Congressional Research Service, 2021*a*). For example, the U.S. Congress appropriated $2.5 billion in 1994 for the Defense Reinvestment and Conversion Initiative, a transition assistance program helping industries affected by post-Cold War reductions in defense spending (U.S. Government Accountability Office, 1997).

[16]Commercial contracts are awarded using streamlined acquisition procedures that are designed to resemble transactions in commercial markets.

[17]Transportation had the smallest increase in the share of commercial contracts. This is not surprising given that the government is the sole buyer of military aircraft and guided missiles, two of the largest industries included in this group.

Figure 1: Share of R&D Contracts in All Contracts Over Time



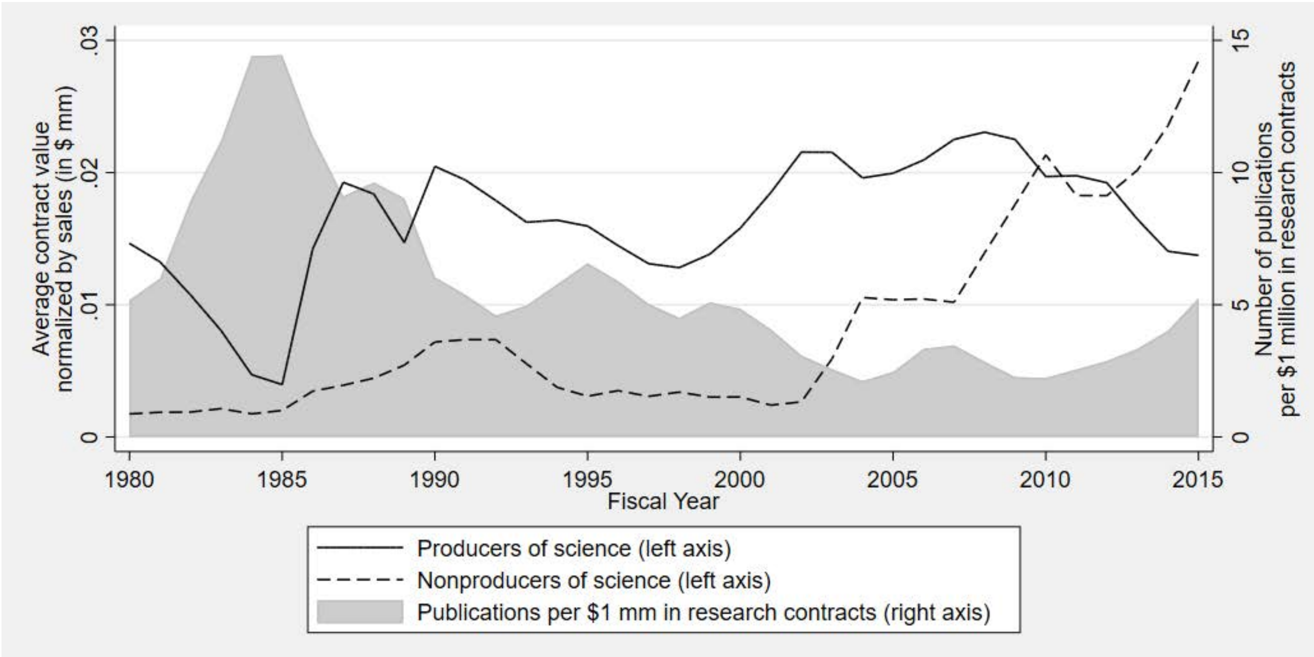
Notes: This figure plots the share of R&D contract dollars in all contracts awarded by DoD, DoE, HHS, and VA for our sample firms over time (solid line). The share of commercial contract dollars in all contracts is presented from 1995 (the first year when the classification is available) through 2015 (dashed line). Commercial contracts use special (usually simplified) requirements that are designed to resemble transactions in the commercial market.

technical capabilities. In noncompetitive procurement, the government either selects the company to buy from or restricts the bidding process to certain suppliers. Over time, pressures to reduce cost and increase efficiency and transparency led to legislative mandates to use competition whenever practicable (Congressional Research Service, 2011). Figure 3 shows that the share of competitive contracts in all contracts (by dollar value) increased from 31 percent in 1980 to 64 percent in 2015. Competition increased even more among service contracts, whether for R&D or non-R&D services. At the same time, the share of noncompetitive product contracts dropped from 74 percent in 1980 to 54 percent in 2015. This change should hamper corporate research if firms participate in upstream research to win competitive R&D races as a pathway to subsequent noncompetitive production contracts.

In summary, these trends underscore three key forces that jointly shape how government procurement contracts drive corporate research: (i) diluted importance of R&D races in securing downstream guaranteed demand; (ii) a rise in the prevalence of commercial contracts, which limits the government's ability to replace missing private demand; and (iii) a larger allocation of contracts to firms that do not participate in scientific research.

The rest of the paper proceeds as follows. Section 2 positions our study in the literature. Section 3

Figure 2: Average Contract Value Over Time



Notes: This figure plots the average contract value awarded to producers and nonproducers of science over time (left axis), and the number of corporate publications per $1 million in research contracts (right axis). We classify a firm as a *producer of science* if its annual number of publications over annual sales is above industry median value. Other firms are classified as *nonproducers of science*. *Average contract value normalized by sales* is the ratio of total contract value and total sales. *Number of publications per $1 million in research contracts* is the ratio of total number of publications to total value of research contracts. Dollar values are adjusted using the GDP Implicit Price Deflator to reflect 2012 dollars (U.S. Bureau of Economic Analysis, 2020).

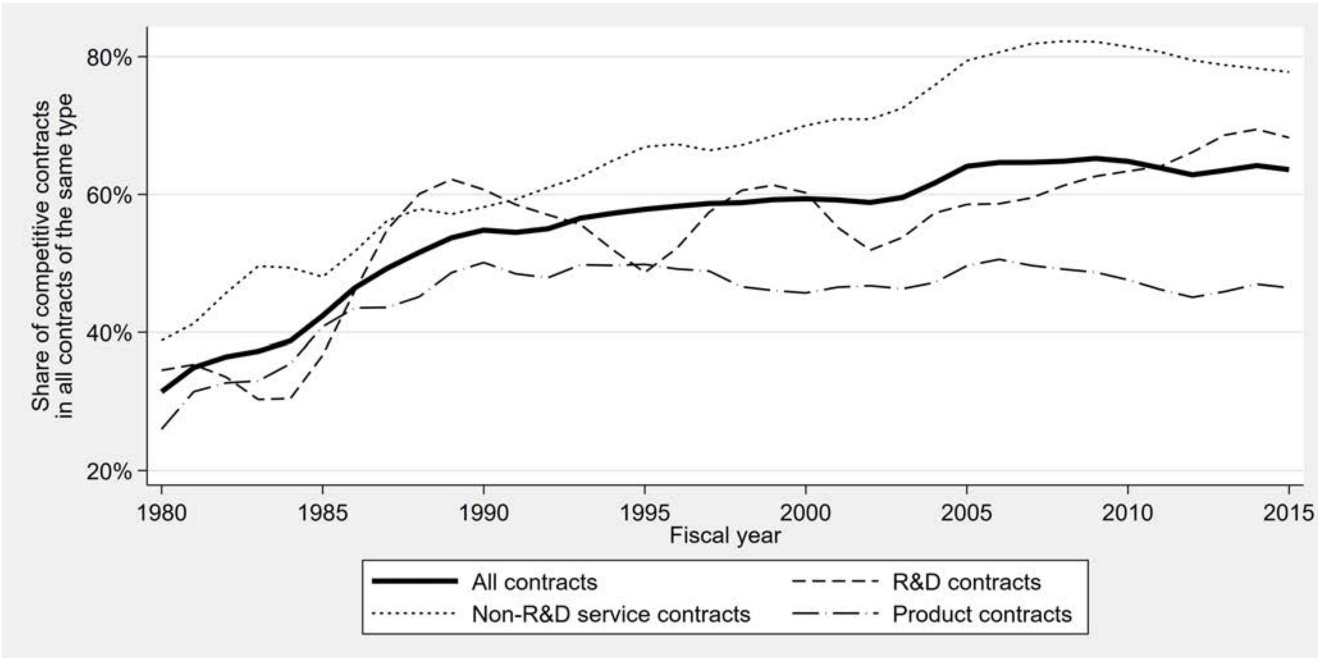
presents the data, Section 4 outlines the econometric specifications, and Section 5 presents the results. Section 6 concludes and suggests directions for future work.

2 Related Literature

A voluminous literature examines the government's effect on corporate R&D through subsidies, public funding, and spillovers from national laboratories and universities (see David, Hall and Toole, 2000). Only a handful of studies examine procurement contracts, and, to the best of our knowledge, none focus on corporate participation in scientific research or test systematically the guaranteed demand mechanism.

Most existing studies focus on lowering the cost of R&D through subsidies (e.g., Bloom, Griffith and Van Reenen, 2002) and public funding. For example, small-firm research shows that Small Business Innovation Research (SBIR) grants crowd out firm-financed R&D expenditures (Wallsten, 2000). Yet, early-stage SBIR awards also increase forward citation-weighted patents, especially for financially constrained firms (Howell, 2017) and the likelihood of raising venture capital (Lerner, 1999). In a recent

Figure 3: Share of Competitive Contracts in All Contracts Over Time



Notes: This figure presents the trend in the share of competitive contract dollars in all contracts of the same type obligated by the DoD, DoE, HHS, and VA to all recipients (not limited to our sample firms). Competitive contracts are awarded using full and open competition.

paper, Howell et al. (2021) evaluate policy reforms aimed at changing how the U.S. Air Force SBIR program procures innovative technologies from small businesses. They compare the conventional approach to R&D contracting, where firms respond to solicitations for specific research topics, with an open approach that allows firms to submit proposals on any topic. Using data on 7,229 proposals submitted during 2017-2019 by 3,170 firms and a regression discontinuity design, they find that winning an open topic R&D competition increases the likelihood of raising venture capital funding and improves the chances of winning a subsequent non-SBIR contract from the Department of Defense. This finding supports the premise of the present paper, with its focus on large firms, that winning R&D races is a pathway to subsequent government contracts.

Large-firm research shows that National Institutes of Health (NIH) grants have a positive effect on corporate R&D (Azoulay et al., 2019). An additional $10 million in NIH grant funding for a research area generates 2.3 additional biopharmaceutical firm patents in that area, or roughly one patent for every 2-3 NIH grants. This result underscores that patents are effective tools for appropriating returns from corporate R&D in the biopharmaceutical industry. Yet, the NIH's tendency to fund new ideas has declined over time (Packalen and Bhattacharya, 2020). Between the 1990s and the 2000s, grant support shifted away from "edge science" and toward more traditional science. This coincides with the shift in procurement contracts away from cutting-edge, mission-focused technologies and toward commercial items. It suggests that the government's withdrawal from funding risky, explorative science that lays the foundation for later breakthroughs occurred not only in contracts, but also in grants.

Many studies focus on spillovers from government-funded research in national laboratories and universities to corporate R&D (e.g., Cohen, Nelson and Walsh, 2002; Fleming et al., 2019; Jaffe, Fogarty and Banks, 1998; Link, Siegel and Van Fleet, 2011; Link and Scott, 2020). For example, Mowery and Ziedonis (2001) document the relatively limited role of spinoffs in commercializing laboratory-owned technologies. Jaffe and Lerner (2001) show an increase in patenting of federally owned technologies after 1986, with no overall decrease in citation intensity, which they attribute to laboratories reorienting their research toward areas with greater commercial applicability. They also find that laboratories performing a greater share of basic science have fewer patents and cooperative research and development agreements (CRADAs). These patterns complement the trend in commercial contracts from Figure 1. Adams, Chiang and Jensen (2003) find that corporate laboratories that have CRADAs patent more and invest more in R&D expenditures. They also document that CRADAs dominate other channels of technology transfer from federal laboratories to firms. These patterns point to the importance of formal agreements between firms and government entities.

Only a handful of studies examine procurement contracts and are closely related to the present paper. Lichtenberg (1988) investigates the effect of Department of Defense contracts on private R&D expenditures using a panel of 169 U.S. contractors between 1979 and 1984.[18] He distinguishes between competitive procurement (contracts awarded using full and open competition) and noncompetitive procurement (contracts exempted from full and open competition; the list of exceptions is included in Appendix B). He uses aggregate product level contracts to instrument for the contracts awarded to a focal firm.[19] Lichtenberg estimates that a $1 increase in competitive procurement (including both R&D and non-R&D contracts) increases R&D expenditures by $0.54. In addition, a $1 increase in noncompetitive R&D contracts reduces R&D expenditures by more than $2, while noncompetitive non-R&D contracts have no effect on firm R&D investment. He argues that competitive procurement spurs firm-financed R&D because winning contrac-

[18] In contrast, our panel includes more than ten times as many contractors and covers a period six times longer.

[19] The instrument for competitive contracts is constructed as the aggregate annual value of competitive contracts for all the two-digit product or service codes that the focal firm ever sold to the government during 1979-1985. A similar procedure is used for noncompetitive contracts. Moreover, non-government sales are instrumented using the aggregate annual value of sales for all firms in the Compustat 1987 Annual Industrial File with the same industrial classification as the focal firm. Our first instrument follows the same logic. Yet, because aggregate funding may be related to unobserved technological opportunity that also affects corporate R&D, we improve identification by using a second instrument that exploits an exogenous cause for funding redeployment, the end of the Cold War.

tors are almost guaranteed to receive much larger follow-on noncompetitive contracts. This is a key point that we underscore as well. Conversely, noncompetitive R&D contracts reduce R&D expenditures for both winners (who let the government sponsor the cost of R&D) and losers (who reduce expenditures because the follow-on contracts are no longer at stake). These findings are consistent with the view that R&D contracts drive corporate science because they represent a "ticket to play" in the lucrative downstream government market.

Recently, Moretti, Steinwender and Van Reenen (2019) study the impact of government-funded R&D on corporate R&D investment and productivity growth using industry-country data from OECD countries and firm data from France (i.e., a panel of 12,539 French firms between 1980 and 2015). They document a "crowding in" effect, whereby increases in government-funded R&D for an industry or firm drive private R&D in that industry or firm. In the firm-level analysis, they use industry-level defense R&D subsidies to instrument for the public R&D funding received by a focal firm. At the mean values of public and private R&D in France, they estimate that a €1 increase in government-funded R&D generates €0.85 of additional corporate R&D. Moreover, they estimate that the induced increases in corporate R&D result in significant productivity gains. These results are consistent with the argument that government-funded R&D, and especially defense-related R&D, are important policy tools for driving corporate R&D investment.

Our work is different from previous studies on procurement contracts in several important ways. First, our paper is the first to examine the effect of procurement contracts separately on corporate research ("R") and development ("D"). The distinction between "R" and "D" is critical, in our view, because the economic mechanism behind the effect—guaranteed demand—should be more relevant for upstream rather downstream R&D. In fact, consistent with the guaranteed demand mechanism, our results show an effect of contracts only for upstream research (publications), especially when private markets are insufficient. Second, in terms of identification, both Lichtenberg (1988) and Moretti, Steinwender and Van Reenen (2019) aggregate funding to predict contracts for a focal firm. We do the same with our first instrument. But we also present causal evidence using the end of the Cold War as a quasi-natural experiment that exploits changes in aggregate funding driven by geopolitical forces, not firm-specific shocks. Third, we extend the work by Lichtenberg (1988) by dynamically matching contracts from multiple agencies to a large number of firms and their subsidiaries, which is essential for creating a long panel that is representative of publicly traded U.S. manufacturing firms. Forth, similar to Lichtenberg (1988), we distinguish between R&D and non-R&D contracts. But we also distinguish between commercial and noncommercial contracts. As a result, we are able to systematically investigate an important, but understudied, channel through which the U.S. government affects corporate investment in upstream research: guaranteeing downstream demand through procurement contracts.

3 Data

We combine data from two primary sources: (i) corporate R&D data, including matched patents from PATSTAT and academic publications from Web of Science, obtained from Arora, Belenzon and Sheer (2021); and (ii) government procurement contracts data obtained from the Federal Procurement Data System (FPDS).[20] Our data construction work is detailed in Appendix B.

3.1 Corporate Publications and Patents

We extend the panel from Arora, Belenzon and Sheer (2021) by matching firms to government procurement contracts awarded from 1980 through 2015. We focus on "prime" contracts awarded to firms that work directly with the government, manage any subcontractors, and are responsible for ensuring contract completion. We account for changes in company names and ownership structures over time (e.g., due to mergers, acquisitions, or spinoffs), which is essential for constructing accurate contract flows in a long panel.

Our sample includes 4,323 publicly-traded manufacturing firms headquartered in the U.S. that had at least one year of positive R&D expenditures and at least one granted patent during 1980-2015. We use data on firm accounting measures (e.g., sales and R&D expenditures sourced from Standard & Poor's Compustat North America), publications (sourced from Clarivate Analytics' Web of Science), and patenting (sourced from the European Patent Office's PATSTAT database). Similar to Arora, Belenzon and Patacconi (2018) and Arora, Belenzon and Sheer (2021), we measure firms' upstream research using publications authored by their corporate scientists, and downstream development using granted patents. In addition, we measure contracting by the flow of contracts awarded to the firms. Appendix Table C1 presents definitions and sources for the variables used in our econometric analyses.

3.2 Government Procurement Contracts

We collect all the prime procurement contracts awarded by the Department of Defense (DoD), Department of Energy (DoE), Health and Human Services (HHS), and Veterans Affairs (VA).[21] The USAspending.gov

[20] Data were downloaded from the federal government's USAspending.gov and beta.SAM.gov websites.

[21] These four agencies awarded more procurement contract dollars during 2008-2015 than any other federal agency.

archives only go back to fiscal year 2001. To match our full sample period, we also collect historical data on all prime procurement contracts awarded by the aforementioned agencies during fiscal years 1980-2000 from beta.SAM.gov.[22]

We match the names of contract recipients with the names of ultimate owners and their subsidiaries from our panel of manufacturing firms (see Appendix B for details). We identify 2,247 U.S.-headquartered manufacturing firms that receive a total of $2.3 trillion in procurement contracts during the sample period.[23] Contractors typically receive multiple government contracts per year.[24] We calculate the total value of contracts at the firm-year level by aggregating all the contracts and modifications awarded to a focal firm and its subsidiaries each fiscal year.

To describe the products and services purchased in each contract, agencies use four-digit codes maintained by the U.S. General Services Administration. Appendix Tables F13 and F14 present the 24 letter codes used to classify services, and the 78 two-digit numerical codes used to classify products. These codes are relatively stable over time, so they can be used for our long panel. Using the *Product or Service Code* field, we separate contracts into R&D contracts (that involve R&D services) vs. non-R&D contracts, as detailed in Appendix B. We further divide non-R&D contracts into non-R&D service contracts vs. product contracts. In addition, we use crosswalks between product or service codes, North American Industry Classification System (NAICS) codes, and Standard Industrial Classification (SIC) codes to identify the correct four-digit industry (SIC4) for each procurement contract. This allows us to calculate the value of procurement contracts for each industry-year, which is essential for constructing our instrumental variables.

Using the *Commercial Items Acquisition Procedures* field, we break down non-R&D contracts into commercial contracts vs. noncommercial contracts.[25] Commercial contracts are awarded using special (usually simplified) requirements intended to resemble more closely those customarily used in the commercial market. Acquisition procedures for commercial items incorporate more streamlined purchasing

[22]The government reports *obligations* for procurement contracts, not actual *outlays*. An obligation is the government's promise to spend funds (immediately or later) as a result of entering into a contract, so long as the agreed-to actions take place. An outlay takes place when those funds are actually paid out to the contractor (Datalab, 2020).

[23]This represents 32 percent of the $7.1 trillion in procurement contracts awarded by the four agencies during 1980-2015 to all for-profit recipients (including privately held firms, foreign firms, and those not engaged in manufacturing or R&D). For comparison, in 2015 U.S. government agencies awarded 4 percent of all procurement dollars to firms located outside the U.S. (U.S. Government Accountability Office, 2019).

[24]We match 2.5 million different contract IDs to sample firms and their subsidiaries. Because multi-year contracts are not unusual, the average contract value is $958 million (and the median is $15 million), which is much larger than the average *annual* contract value for our sample firms.

[25]The R&D service contracts coded as having used acquisition procedures for commercial items represent less than 0.7 percent of the value of all R&D contracts awarded to our sample firms. Therefore, we do not break down contracts for R&D services into commercial vs. noncommercial.

practices and free market principles while exempting contractors from the requirement to submit certified cost or pricing data.[26] These procedures were introduced at scale with the passage of the Federal Acquisition Streamlining Act of 1994, which established a statutory preference for procuring commercial items (Barry, 1995). This breakdown into commercial vs. noncommercial contracts allows us to test the theory that government contracts affect corporate R&D by guaranteeing demand, especially when market mechanisms are insufficient (e.g., for technologies that may not have existing commercial applications). If, over time, procurement contracts shifted toward funding technologies that already have viable market applications, then the government's role in driving corporate research would have eroded.

3.3 Descriptive Statistics

Table 1 presents descriptive statistics over the sample period of 1980-2015 for the main variables used in the econometric analyses. Approximately 68 percent of firms perform scientific research (i.e., have at least one publication during the sample period). These firms publish an average of 18 scholarly publications per year (and a median of 1). By construction, all firms have at least one patent during the sample period. Firms produce an average of 23 patents per year (and a median of 1). Approximately 52 percent of firms receive at least one contract during the sample period (we refer to these firms as contractors).

Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
					Distribution	
	Obs.	Mean	Std. dev.	10th	50th	90th
R&D expenditures ($ mm)	52,122	114.8	568.1	0.6	10.6	156.0
Publications	43,989	17.9	98.4	0.0	1.0	21.5
Patents	58,245	22.9	134.3	0.0	1.0	33.0
All contracts ($ mm)	37,101	61.7	814.2	0.0	0.0	11.8
R&D contracts ($ mm)	37,101	10.4	183.5	0.0	0.0	0.2
Non-R&D contracts ($ mm)	37,101	51.4	656.4	0.0	0.0	10.0
R contracts ($ mm)	37,101	1.6	30.6	0.0	0.0	0.0
D contracts ($ mm)	37,101	8.7	158.5	0.0	0.0	0.0
Commercial contracts ($ mm)	24,002	7.1	78.4	0.0	0.0	1.7
Noncommercial contracts ($ mm)	24,002	52.4	749.4	0.0	0.0	3.8
Sales ($ mm)	57,957	2,702.0	13,019.5	3.5	156.7	4,555.5
R&D stock ($ mm)	58,245	446.5	2,550.0	0.7	28.0	516.8

Notes: This table displays descriptive statistics for the main variables used in the econometric analyses. The unit of analysis is a firm-year. Publication and contract statistics are only provided for firms that perform scientific research and contractors, respectively. Commercial and noncommercial contracts are only summarized for fiscal years 1995-2015.

The distribution of contracts is highly skewed. Contractors receive an average of $62 million in

[26] Examples of commercial items include transportation equipment, computers, medicine, and fuel that have been sold or leased to the general public. In general, the government asks acquisition professionals to use their best judgement to determine (and document) whether a product or service is a commercial item.

procurement contracts per year (with a median of much less than $1 million). Our sample is drawn from a wide distribution of industries, as indicated in Appendix Table F12. The two-digit industries (SIC2) most represented are Chemicals and drugs (757 firms), Electronic equipment (650 firms), and Instruments (645 firms). Appendix Table F15 presents the classification of industries into several main groups. The largest average annual contracts are in Transportation ($760 million), while the smallest are in Drugs ($7 million), as can be seen in Appendix Table F16. Among contractors, the number of publications per $1 million in contracts ranges from a low of 0.03 in Transportation to a high of 11.64 in Drugs.[27] Industries with the lowest and highest numbers of patents per $1 million in contracts are Transportation and Chemicals, respectively.[28] Among R&D contractors, the average number of publications per $1 million in R&D contracts ranges from a low of 0.17 in Transportation to a high of 109.14 in Drugs. Meanwhile, the average number of patents per $1 million in R&D contracts ranges from a low of 0.36 in Transportation to a high of 53.71 in Chemicals.

The composition of government contracts varies by main industry and over time, as shown in Appendix Figure F2. In 1994, just before the passage of the Federal Acquisition Streamlining Act, the industries with the highest share of R&D contracts in all contracts were Chemicals (29 percent) and Business services (14 percent). In 2015, the industries with the highest share of commercial contracts in all contracts were Drugs (77 percent) and Electronics (54 percent).

Table 2 presents mean comparison tests between 802 R&D contractors and the other 3,531 firms in our sample. On average, R&D contractors are much larger ($6 billion vs. $1.5 billion in annual sales), invest more in R&D ($300 million vs. $42 million per year), but have lower R&D intensity ($1.5 million vs. $5.5 million in R&D expenditures per $1 million in sales) compared to other firms. In addition, R&D contractors perform more upstream research (0.5 vs. 0.3 annual publications per $1 million in R&D expenditures), and about half as much downstream development (0.6 vs. 1.2 patents per $1 million in R&D expenditures) as other firms.[29] These descriptive statistics suggest that publishing firms are more likely to win R&D contracts.

[27] Between 1980 and 2015, contractors in Drugs published a total of 248,116 publications and received $21,308 million in contracts. Therefore, the number of publications per $1 million in contracts was $248,116/21,308 = 11.64$.

[28] Transportation has an average of 0.07 patents per $1 million of contracts, while Chemicals has an average of 5.20.

[29] A comparison between R&D contractors and other firms in the same industry is included in Appendix Table F17.

Table 2: R&D Contractors vs. Other Firms

	(1) Difference in means	(2)	(3) R&D contractors	(4)	(5) Other firms	(6)
	R&D contractors - Other firms	t	Mean	Std. dev.	Mean	Std. dev.
Sales ($ mm)	4,594.75	38.26	6,048.9	18,324.7	1,454.2	10,088.8
R&D expenditures ($ mm)	258.48	47.76	300.4	1,011.3	41.9	170.0
R&D intensity	-4.02	-2.82	1.5	31.7	5.5	171.0
Publications per $1 mm in R&D expenditures	0.23	5.15	0.5	5.8	0.3	3.9
Patents per $1 mm in R&D expenditures	-0.55	-1.26	0.6	4.2	1.2	52.6

Notes: This table displays mean comparison tests between R&D contractors and other firms. *R&D intensity* is calculated as R&D expenditures divided by sales. The two-sample t-tests use unequal variances.

4 Econometric Specifications

Our econometric analysis proceeds in three steps. First, we estimate the relationship of contracts with R&D expenditures, publications, and patents. We distinguish R&D contracts from non-R&D contracts because winning a competitive R&D contract is typically how firms access guaranteed demand (i.e., noncompetitive product contracts) for technology-intensive products.[30]

Second, we explore the potential mechanism behind the effect—guaranteed demand—and the conditions when the effect is stronger. We expect guaranteed demand to drive upstream corporate science when market incentives to conduct risky research are weak. We test three such conditions, when the research is (i) not used in the internal inventions of the firm, (ii) used by close product-market competitors, and (iii) not protected by patents. In addition, we examine whether the effect is stronger for larger firms, which would be consistent with manufacturing capabilities and complementary assets being required to handle complex downstream government contracts.

Third, we explore temporal changes in the composition of procurement contracts within our sample, in support of the patterns shown in Figure 1, and in the relationship between procurement contracts and firm scientific capabilities.

[30]In our sample, 60.5 percent of firms that receive an R&D contract subsequently win at least one non-R&D contract. Among R&D contractors, the average annual non-R&D contract value is $117 million, almost five times larger than the average annual R&D contract value. The competition for the Joint Light Tactical Vehicle illustrates the relationship between R&D contracts and subsequent product contracts. AM General, Lockheed Martin, and Oshkosh each won R&D contracts in 2012 for the engineering and manufacturing development phase of this competition—totaling approximately $185 million. This positioned Oshkosh to win a $6.7 billion contract in 2015 for low rate initial production of 16,901 vehicles. Full-rate production for an additional 54,600 vehicles is expected to continue through 2042 (Congressional Research Service, 2020).

4.1 The Relationship of Upstream and Downstream Corporate R&D with Procurement Contracts

We estimate the following specification for the relationship of R&D expenditures, publications and patents (denoted by $y_{i,t}$) with procurement contracts:

$$\ln(y_{i,t}) = \alpha_0 + \alpha_1 \ln(Contracts_{i,t-1}) + \boldsymbol{Z}'_{i,t-1}\boldsymbol{\omega} + \boldsymbol{\eta}_i + \boldsymbol{\tau}_t + \epsilon_{i,t} \tag{1}$$

$Contracts_{i,t-1}$ are lagged contract awards to focal firm i at year $t-1$ (in Section 5.4 we show that our results are not sensitive to specific lag structures). In our main specifications we focus on R&D contracts. In the robustness section we show that our results hold for using total contracts and noncompetitive contracts. The vector $\boldsymbol{Z}$ includes time-varying controls, such as the natural logarithms of sales and R&D stock. The vectors $\boldsymbol{\eta}$ and $\boldsymbol{\tau}$ are firm and year fixed effects, respectively, and ϵ is an *iid* error term. Standard errors are clustered at the firm level. Dollar values are adjusted using the GDP Implicit Price Deflator to reflect constant 2012 dollars (U.S. Bureau of Economic Analysis, 2020). One dollar is added to contracts, sales, and R&D stock values, and one unit is added to publications and patents, before calculating natural logarithms.

We expect $\hat{\alpha_1} > 0$ in the publication equation. When technologies are novel and unproven, guaranteed demand can fill in for missing private demand. In this case, the government can act as an early or lead user that bears the cost of learning and refining novel products. When technologies have immediate applications, markets may still fail to reward corporate investment in research under weak appropriability conditions (e.g., when the science spills over to rivals). In that case, guaranteed demand is a non-market mechanism to reward corporate R&D. Excluding competition via noncompetitive procurement contracts may be more beneficial to firms when patent protection is weak, as is likely the case with upstream scientific research.

Conversely, there are several reasons why we expect no or little effect of procurement contracts on patents. First, guaranteed demand may reduce the need to exclude rivals via costly patenting. Second, some government contracts may prohibit patenting altogether (e.g., those for sensitive defense technologies). Third, market incentives may already be stronger for downstream R&D, rendering guaranteed demand less effective in driving corporate development.

4.2 Instrumental Variable Strategy

A major econometric challenge is dealing with the endogeneity of contracts. Common shocks can affect both corporate R&D and contract funding. If the government targets firms that experience positive technological or demand shocks, $\hat{\alpha_1}$ will be upward-biased. However, if contracts target firms that experience negative shocks, $\hat{\alpha_1}$ will be downward-biased.

We take two approaches to mitigate this concern. The first is to construct an instrument that exploits variation in aggregate industry R&D contracts to predict R&D contracts awarded to a focal firm, building on Moretti, Steinwender and Van Reenen (2019). The advantage of this instrument is that it allows us to predict R&D contracts over time for sample firms and estimate the effect of R&D contracts controlling for time-invariant firm heterogeneity. The limitation of this approach is that changes in aggregate industry R&D funding may still be related to unobserved or miss-measured temporal shocks that directly affect the focal firm's publications and patents. That is, changes in contracts across industries over time might be related to technology or demand shocks that affect firm R&D decisions. Therefore, we develop a second instrument that exploits variation in aggregate contracts unrelated to such shocks.

Our second instrument exploits a quasi-natural experiment around the collapse of the former Soviet Union. The end of the Cold War triggered massive reallocation in government contracts. Changes in government funding in that period were driven by geopolitical forces arguably unrelated to technological shocks. The limitation of this instrument is that it does not vary within firms. There is only one change per firm (pre- and post- the end of the Cold War), which means that our causal estimates cannot use the traditional firm fixed-effects methodology. To control for firm time-invariant unobserved heterogeneity, we follow Blundell, Griffith and Van Reenen (1999) and include the pre-sample mean of the dependent variable as a separate control. We describe the two identification strategies in detail below.

4.2.1 Instrumenting for R&D Contracts Using Industry R&D Funding

A simple identification strategy might be to instrument for a focal firm's R&D contracts using R&D contracts awarded to its four-digit industry (SIC4) that year. However, this instrument may still be endogenous (e.g., when a firm dominates its SIC4 industry, it is possible that industry R&D contracts respond to the same technological shocks as firm R&D). Hence, we take advantage of changes in R&D funding at a higher level of aggregation, the three-digit industry (SIC3). We "distribute" these changes across SIC4 industries according to time-invariant industry shares. Doing so lowers the power of our instrument in the first stage, but increases its validity.

We follow Moretti, Steinwender and Van Reenen (2019) and build our instrument as $Industry\ R\&D\ funding_{i,t} = (Industry\ R\&D\ contracts_t - Firm\ R\&D\ contracts_{i,t}) \times Industry\ share$. $Industry\ R\&D\ contracts_t$ is the total value of R&D contracts awarded to the firm's SIC3 industry in year t, net of the firm's own R&D contracts. *Industry share* is calculated by dividing the total value of R&D contracts awarded to the SIC4 industry during 1980-2015 by the total value of R&D contracts awarded to the higher-level SIC3 industry during 1980-2015. Appendix D provides further details on this instrument, including an example.

4.2.2 Quasi-natural Experiment: Contract Reallocation Due to the End of the Cold War

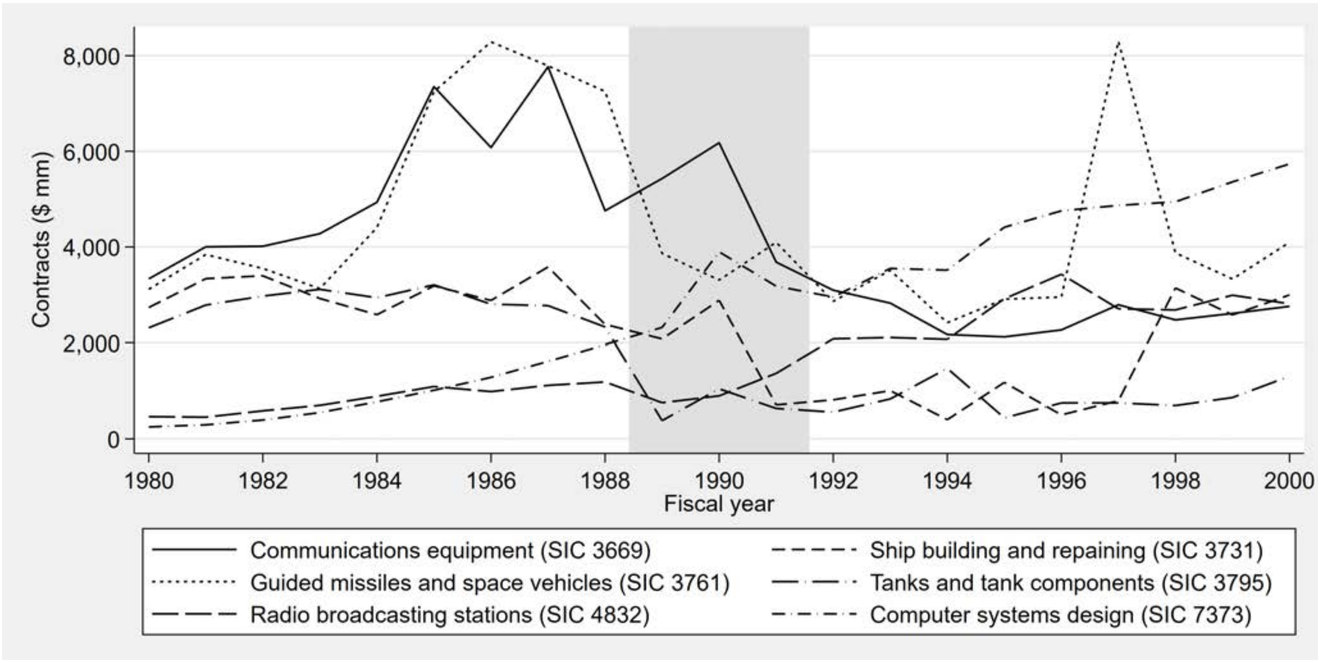
During the Cold War (1948-1989), government procurement focused on achieving and sustaining technological superiority for the purpose of national security (Weiss, 2014). The large scale (especially in nuclear programs) and long duration of Cold War threats led to procurement budgets that were dominated by the Department of Defense and exceeded previous peacetime expenditures (Mowery, 2012). The end of the Cold War removed the perception of an existential threat to the United States, and resulted in a significant reallocation of procurement priorities. Between 1988 and 1992, Department of Defense procurement obligations dropped 36 percent, while Department of Health and Human Services obligations more than tripled (from a much smaller baseline).[31]

Government demand in the form of procurement contracts increased in some industries and decreased in others (see Figure 4). Appendix Table F18 shows annual procurement contracts awarded by the Departments of Defense, Energy, Health and Human Services, and Veterans Affairs to various SIC4 industries in 1988 and 1992. The average change was a $91 million reduction in federal contract funding to an industry, which is nine times larger than the average R&D contract value awarded in a year to contractors in our sample.[32] However, the overall reduction in government procurement did not affect all industries to the same extent. Among the "winners" receiving increased funding after the end of the Cold War were IT industries (e.g., Computer integrated systems design, Information retrieval services) and health industries (e.g., Medicinal chemicals and botanical products, Health and allied services). Among the "losers" were defense industries (e.g., Tanks and tank components, Guided missiles and space vehicles). Because the reallocation between industries was caused by geopolitical circumstances unrelated to technological shocks,

[31] The Department of Defense awarded $226.7 billion in contracts in 1988 and $145.3 billion in 1992 (using constant 2012 dollars). Meanwhile, the Department of Health and Human Services awarded $1.1 billion in contracts in 1988 and $3.4 billion in 1992.

[32] The four agencies collectively awarded $261.5 billion in procurement contracts in 1988 and $185.4 billion in 1992 (using constant 2012 dollars).

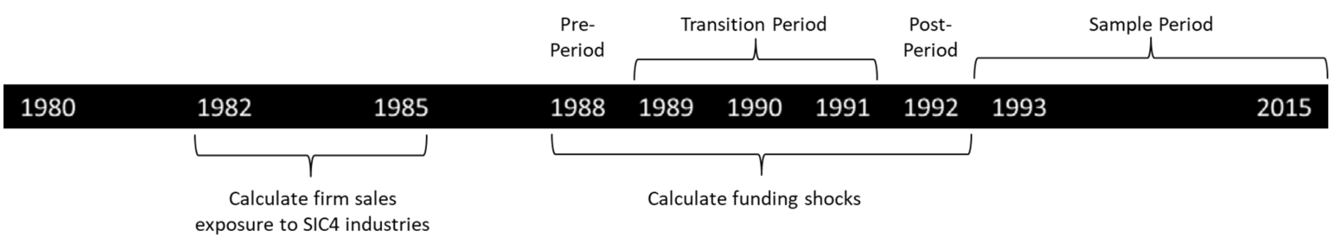
Figure 4: Government Procurement Contracts During and After the Cold War



Notes: This figure plots the aggregate value of procurement contracts awarded by DoD, DoE, HHS, and VA to various industries. Dollar values are adjusted using the GDP Implicit Price Deflator to reflect constant 2012 dollars (U.S. Bureau of Economic Analysis, 2020).

we exploit the end of the Cold War as a quasi-natural experiment. Figure 5 shows the timeline used to calculate our second instrumental variable.

Figure 5: The Cold War Identification Strategy Timeline



Specifically, we take advantage of variation in the value of all contracts awarded to various industries to instrument for R&D contracts awarded to firms during 1993-2015. Many of our sample firms operate in multiple business segments. As a result, they were affected by changes in procurement contracts across multiple industries. To estimate the "average" shock experienced by each firm, we use the shares of firm sales in each industry as weights. We calculate this second instrumental variable as $Cold\ War\ shock_i = \sum_j \Delta Contracts_j \times Share\ of\ sales_{i,j}$. Here, $Cold\ War\ shock_i$ is the instrument for firm i, and it does not vary over time. The subscript j indexes SIC4 industries. We calculate $\Delta Contracts_j$ as the difference between pre (1988) and post (1992) periods in federal procurement contracts awarded to industry j. $Share\ of\ sales_{i,j}$ is the share of firm i's sales during 1982-1985 that came from industry j, calculated using the Compustat Segments dataset (Standard & Poor's, 2018).[33] We use a multi-year lag in calculating the share of sales to alleviate concerns that firms might have anticipated the end of the Cold War and its differential impacts on various industries. Under that scenario, firms might have entered industries where they anticipated growing procurement funding, and exited industries where they anticipated shrinking procurement funding.

4.3 The Changing Nature of Procurement Contracts

We estimate the following specification for trends in the value of government procurement contracts:

$$\ln(Contract\ flow_{i,t}) = \beta_0 + \beta_1 Time\ trend_t + \boldsymbol{Z}'_{i,t-1}\boldsymbol{\omega} + \boldsymbol{\eta}_i + \epsilon_{i,t} \tag{2}$$

We present specifications where we use the different types of procurement contracts described in Section 3, including R&D contracts and commercial contracts, as the dependent variable. We also report results where the dependent variable is the share of R&D or commercial contracts in all contracts. The indices i and t denote firms and years, respectively. $Time\ trend_t$ is the focal year t minus 1980, presented in decennial units. The other elements of the specification are the same as described in section 4.1.

We are interested in the estimate of β_1. Consistent with the trends in Figure 1, we expect $\hat{\beta}_1 < 0$ for the share of R&D contracts regression, and $\hat{\beta}_1 > 0$ for the share of commercial contracts regression.

4.4 The Relationship between Contracts and Firm Scientific Capabilities Over Time

We estimate the following specification for changes in the relationship between contract value and firm scientific capabilities over time:

$$\begin{aligned} \ln(Contracts_{i,t}) &= \gamma_0 + \gamma_1 Time\ trend_t + \gamma_2 \ln(Publications_{i,t-1}) \\ &+ \gamma_3 Time\ trend \times \ln(Publications_{i,t-1}) + \boldsymbol{Z}'_{i,t-1}\boldsymbol{\omega} + \boldsymbol{\eta}_i + \epsilon_{i,t} \end{aligned} \tag{3}$$

[33] For example, Komatsu Ltd. operated only in industry 3531 Construction machinery and equipment during 1982-1985, generating 100 percent of its sales from that industry. As a result, the firm's *Cold War shock* came entirely from reallocations in contracts awarded to industry 3531. In contrast, Caterpillar Inc. generated 76 percent of its sales during 1982-1985 from industry 3531 Construction machinery and equipment, and 24 percent from industry 3519 Internal combustion engines, not elsewhere classified. As a result, 76 percent of this firm's *Cold War shock* came from reallocations in contracts awarded to industry 3531, and 24 percent from reallocations to industry 2519.

where $Contracts_{i,t}$ is the flow of procurement contracts awarded to firm i in year t. $Time\ trend_t$ is the focal year t minus 1980, presented in decennial units. Once again, the other elements of the specification are described in Section 4.1.

We are interested in the estimate of γ_3, and expect $\hat{\gamma_3} < 0$. This prediction is consistent with the view that the importance of scientific capabilities for getting government contracts has decreased over time (as contracts have increasingly been awarded for commercial items and dual-use technologies).

5 Estimation Results

5.1 R&D Equation

We begin by examining the relationship between procurement contracts and R&D expenditures. Table 3 presents the within-firm estimation results. The general pattern points to a positive relationship between contracts and R&D expenditures, consistent with prior studies (e.g., Lichtenberg, 1988; Moretti, Steinwender and Van Reenen, 2019). Columns 1-2 present OLS estimates, which indicate positive associations across contract types.[34]

Columns 3 and 4 present causal estimates using two-stage-least-squares (2SLS). In the first stage, we predict R&D contracts awarded to a focal firm using the *Industry R&D funding* instrument (see Column 1 in Appendix Table D2). The first stage results confirm that firm-level R&D contracts are a function of industry-level R&D funding. In the second stage, we estimate R&D expenditures as a function of the predicted R&D contracts (see Column 3 in Table 3). As expected, $\hat{\alpha_1} > 0$. The IV estimate is larger than OLS, suggesting that contracts might target fields affected by negative technological shocks. Evaluated at the sample means, the IV estimate indicates that a \$1 million increase in R&D contracts leads to a \$1.7 million increase in R&D expenditures.[35]

Our second identification strategy exploits the *Cold War shock* as a quasi-natural experiment for exogenous changes in government funding across industries. In the first stage, we predict the R&D contracts awarded to a focal firm using our instrument (see Column 2 in Appendix Table D2) and find that firm-level R&D contracts are a function of changes in industry funding triggered by the end of the Cold War. In the second stage, we once again estimate R&D expenditures as a function of the predicted R&D

[34] In unreported specifications, we also split R&D contracts into "R" vs. "D" contracts. The coefficient estimates are positive, statistically different from zero, and close in size.

[35] Average values for R&D expenditures and R&D contracts are \$107 million and \$6 million, respectively. The marginal effect of an additional \$1 million in R&D contracts is $0.098(107 + 0.000001)/(6 + 0.000001) = 1.748$ million in R&D expenditures.

contracts (see Column 4 in Table 3). Because the instrument does not vary over time, we report pooled estimates and rely on pre-sample information regarding R&D expenditures to replace the unobservable firm fixed effect (similar to Blundell, Griffith and Van Reenen, 1999). The coefficient estimate once again indicates a positive effect of contracts on R&D expenditures.[36]

Table 3: Estimation Results for the R&D Equation

	(1)	(2)	(3)	(4)
	ln(R&D expenditures)			
	All contracts	R&D contracts	2nd stage IV, Ind. R&D funding	2nd stage IV, Cold War shock
ln(All contracts)$_{t-1}$	0.006			
	(0.001)			
ln(R&D contracts)$_{t-1}$		0.006	0.098	0.134
		(0.001)	(0.029)	(0.047)
ln(Non-R&D contracts)$_{t-1}$		0.005		
		(0.001)		
ln(R&D stock)$_{t-1}$	0.539	0.536	0.516	0.967
	(0.013)	(0.013)	(0.014)	(0.017)
Pre-sample mean R&D expenditures				-0.125
				(0.014)
Sample years	1980-2015	1980-2015	1980-2015	1993-2015
Firm fixed effects	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
Weak identification (Kleibergen-Paap)			52.65	15.72
Firms	4,145	4,145	4,127	
Observations	47,753	47,580	46,354	4,610
Adjusted R-squared	0.938	0.938	0.175	0.880

Notes: This table presents the estimation results for the relationship between contracts and R&D expenditures. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

5.2 Publication Equation

Table 4 presents the estimation results for publications, our measure of upstream corporate R&D. Columns 1-2 present OLS results for the relationship between different contract types and publications. Column 1 shows that publications are positively associated with *All contracts*. Unlike the R&D equation results, the coefficient estimate on *R&D contracts* is much larger than on *Non-R&D contracts*. This finding is consistent with the view that R&D races drive upstream research, and motivates our focus on *R&D contracts* in the instrumental variable equations. Because the government buys all types of products and

[36]One caveat is that the R&D expenditures reported by contractors are not all firm-financed, as the government reimburses *Independent R&D* costs as indirect expenditures on government contracts. We do not observe the reimbursement amounts.

services, including some that don't have clear technological links (such as office supplies, clothing, and food services), using *All contracts* likely introduces noise in our estimates. Using *R&D contracts* allows us to mitigate that noise.

Columns 3 and 4 present the IV results. Column 3 shows results from the second stage of 2SLS regressions using *Industry R&D funding* as the instrumental variable. Evaluated at the sample means, $5 million in additional R&D contracts lead to one additional publication.[37] The IV estimate is larger than OLS, suggesting that government contracts target fields where corporations face negative technology or demand shocks.

Column 4 presents the estimation results based on the *Cold War shock* instrumental variable approach. Evaluated at the sample means, the estimate indicates that to obtain one additional publication, R&D contracts need to increase by $0.06 million.[38] This estimate is substantially larger than the estimate from Column 3 for two potential reasons. Our first instrument may not fully resolve the downward bias in estimate because aggregate industry variation in funding can still be correlated with firm-specific, time invariant unobserved heterogeneity. Or, the Cold War instrument does not fully remove firm time-invariant heterogeneity using the pre-sample mean, making it sensitive to temporal reallocation of contracts away from innovating firms (as shown in Figure 2 and Section 5.8).[39]

5.3 Patent Equation

Table 5 presents the within-firm estimation results for patents, our measure of downstream corporate R&D. Columns 1-2 present our OLS results. Similar to the publication estimates, we find a positive relationship between *All contracts* and patents. Column 2 shows that this relationship is mostly driven by *R&D contracts*.[40]

Estimation results using *Industry R&D funding* and *Cold War shock* as instrumental variables are included in Columns 3 and 4, respectively. The coefficient estimates on R&D contracts are no longer statistically different from zero (Column 3) or negative (Column 4). Interpreted together, these results cast doubt on the existence of a causal relationship between R&D contracts and patents.

[37] Average values for publications and R&D contracts are 13 and $5 million, respectively. The marginal effect of an additional $1 million in R&D contracts is $0.069(13+1)/(5+0.000001) = 0.193$ publications.

[38] Average values for publications and R&D contracts are 44 and $0.64 million, respectively. The marginal effect of an additional $1 million in R&D contracts is $0.229(44+1)/(0.64+0.000001) = 16.102$.

[39] In unreported specifications, we split the sample into two sub-periods using 1998 as the cutoff year. We find that the effect of R&D contracts on corporate publications is positive and significant during 1980-1997, but not during 1998-2015. Section 5.7 examines how the effect of contracts on publications has changed over time.

[40] In unreported specifications, we once again split R&D contracts into "R" vs. "D" contracts. The coefficient estimates are positive, statistically different from zero, and close in size, which indicates that the relationships of patents with research contracts and development contracts, respectively, are equally strong.

Table 4: ESTIMATION RESULTS FOR THE PUBLICATION EQUATION

	(1)	(2)	(3)	(4)
			ln(Publications)	
	All contracts	R&D contracts	2nd stage IV, Ind. R&D funding	2nd stage IV, Cold War shock
ln(All contracts)$_{t-1}$	0.006			
	(0.001)			
ln(R&D contracts)$_{t-1}$		0.011	0.069	0.229
		(0.002)	(0.031)	(0.065)
ln(Non-R&D contracts)$_{t-1}$		0.004		
		(0.001)		
ln(R&D stock)$_{t-1}$	0.197	0.194	0.178	0.164
	(0.014)	(0.013)	(0.014)	(0.015)
Pre-sample mean publications				0.641
				(0.031)
Sample years	1980-2015	1980-2015	1980-2015	1993-2015
Industry fixed effects	No	No	No	No
Firm fixed effects	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)			60.68	23.47
Firms	4,318	4,318	4,302	
Observations	53,554	53,373	52,076	5,779
Adjusted R-squared	0.863	0.862	0.003	0.534

Notes: This table presents the estimation results for the relationship between contracts and publications. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

Our key finding—that R&D contracts affect publications—is consistent with firms investing in upstream research to increase their chances of winning R&D races as a pathway to guaranteed demand. If contracts drove corporate R&D simply by lowering costs (i.e., the public funding mechanism), we would expect to find an effect on patents as well. Conversely, the effect of guaranteed demand should be stronger when market incentives are weak, which is more likely to occur in the case of upstream research than downstream development (due to fewer immediate market applications, higher spillovers to rivals, and weaker patent protection).

5.4 Robustness Checks

We present several robustness checks for the effect of R&D contracts.[41]

[41] In unreported specifications, we find that our results in Tables 3, 4, and 5 are robust to using different firm sub-samples. For example, when using only publishing firms, the 2SLS coefficient estimates on *R&D contracts* in the publication equation are 0.059 (using the *Industry R&D funding* instrument) and 0.213 (using the *Cold War shock* instrument). When using only

Table 5: ESTIMATION RESULTS FOR THE PATENT EQUATION

	(1)	(2)	(3)	(4)
			ln(Patents)	
	All contracts	R&D contracts	2nd stage IV, Ind. R&D funding	2nd stage IV, Cold War shock
ln(All contracts)$_{t-1}$	0.009			
	(0.002)			
ln(R&D contracts)$_{t-1}$		0.012	-0.037	-0.252
		(0.002)	(0.042)	(0.080)
ln(Non-R&D contracts)$_{t-1}$		0.007		
		(0.002)		
ln(R&D stock)$_{t-1}$	0.344	0.341	0.349	0.408
	(0.019)	(0.019)	(0.020)	(0.016)
Pre-sample mean patents				0.650
				(0.055)
Sample years	1980-2015	1980-2015	1980-2015	1993-2015
Industry fixed effects	No	No	No	No
Firm fixed effects	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)			60.68	23.65
Firms	4,318	4,318	4,302	
Observations	53,554	53,373	52,076	5,779
Adjusted R-squared	0.825	0.824	0.083	0.333

Notes: This table presents the estimation results for the relationship between contracts and patents. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

First, we explore whether our results are robust to using *All contracts* and *Noncommercial contracts* instead of *R&D contracts*. Appendix Table E3 presents the second stage estimation results for the effect of total contracts on R&D expenditures, publications, and patents.[42] *All contracts* have a positive effect on R&D expenditures and publications, but no effect on patents. Consistent with our theoretical predictions, we obtain similar results when using *Noncommercial contracts* as the predictor variable, as reported in Appendix Table E4.

Second, a concern is that our results are driven by Department of Defense contracts, which may have specific secrecy requirements that can affect patenting behavior, as well as undermine our identification strategy that treats the end of the Cold War as an exogenous shock on our sample firms. As shown in Appendix Table E5, our results are not driven solely by Department of Defense R&D contracts. The

contractors, they are 0.084 and 0.273, respectively.

[42]In Columns 1, 3, and 5, the instrument is *Industry funding*, a modified version of our first instrument, where we use the value of all contracts to calculate the industry-level exogenous variable. In Columns 2, 4, and 6, the instrument is the familiar *Cold War shock*.

coefficient estimates on *Non-defense R&D contracts* are significantly larger in both the R&D expenditures equation and the publication equation.[43] In unreported specifications, we also find that our results are robust to dropping firms operating primarily in the Transportation industry, which are the main recipients of Department of Defense contract dollars.

Third, because *Publications* and *Patents* are over-dispersed count variables, Columns 1 and 4 in Appendix Table E6 present estimations using Poisson pseudo-maximum likelihood regressions. Consistent with our OLS results, we find that *R&D contracts* are positively related to both publications and patents. To check whether our preferred data transformation (i.e., taking the natural logarithm of publications or patents plus one) impacts our analyses, we also present OLS and 2SLS estimations where we use an inverse hyperbolic sine transformation.[44] Consistent with previous results, Columns 3 and 6 in Appendix Table E6 show that R&D contracts have a positive effect on publications, but not on patents. The coefficient estimate on *R&D contracts* for the publication equation is very close in size with our main specification in Table 4.

Forth, our results are not sensitive to the specific lag structure assumed in our main specifications. Checking the sensitivity of our of results to lag structure is important because we do not observe the actual annual spending associated with contract awards. To construct our panel, we aggregate contract *obligations*, not actual *outlays*, at the firm-year level. Since multi-year contracts are common, the outlays may occur one, two, or more years after the original obligation date. Moreover, there is typically a lag between the year when the R&D activity is conducted and the publication year or patent grant year. Therefore, the specific lag structure between receiving an award and publishing a scholarly paper or receiving a patent is unclear. However, our results are robust to using two, three, four, and five year lags in the publication and patent equations. Appendix Table E7 indicates that R&D contracts have a positive effect on publications regardless of the specific lag structure used. The coefficient estimates increase slightly compared to our main specification in Table 4. In unreported specifications, we still find no effect of R&D contracts on patents despite using two, three, four, or five year lags.

Our analysis thus far has focused on the number of publications and patents, rather than on their quality. Our final robustness check examines the sensitivity of our results to controlling for quality using citations. Appendix Table E8 presents estimation results using quality-adjusted publication and patent flows.[45] As before, *All contracts* and *R&D contracts* drive firms to increase high-quality publications, but

[43]Evaluated at the sample means, the coefficient estimate in Column 3 of Appendix Table E5 indicates that a $1 million increase in *Non-defense R&D contracts* leads to 49 additional publications.

[44]The inverse hyperbolic sine is calculated as $asinh(x) = ln(x + \sqrt{x^2 + 1})$.

[45]For the quality-adjusted publication flow, we weight each publication by its normalized citations, calculated as (Forward

not high-quality patents.

5.5 Industry Variation

Table 6 shows how the effect of R&D contracts on publications and patents varies by main industry. Column 1 presents OLS results using *Publications* as the dependent variable. The coefficient estimates indicate that the relationship between contracts and publications is positive across all industries. Column 2 presents estimates from the second stage of 2SLS regressions using *Industry R&D funding* and its interactions with industry indicator variables as instrumental variables. The coefficient estimates suggest that the effect of contracts on publications is robust across a majority of industries. However, the Kleibergen-Paap rk Wald F statistic is just 0.51, indicating that the excluded instruments are only weakly correlated with the endogenous regressors.

Column 3 presents OLS results using *Patents* as the dependent variable. The coefficient estimates show that the correlation between contracts and patents is positive for all industries. However, we do not find evidence of a causal effect of R&d contracts on patents across a variety of industries in Column 4.

5.6 Exploring the Guaranteed Demand Mechanism

We examine how the effect of R&D contracts on publications varies with characteristics of science. Based on the argument that procurement contracts drive corporate research when market incentives are weak, we anticipate a larger effect on publications that are: (i) not cited by the firm's own patents (missing downstream applications); (ii) cited by rival firms' patents (the science spills over to close product-market competitors); and (iii) not protected by the firm's own patents (hence, the science is harder to appropriate).

Table 7 presents the within-firm estimation results from the second stage of 2SLS regressions using *Industry R&D funding* as an instrument for *R&D contracts*. The construction of the own use, spillovers, and scope of patent protection measures is detailed in Appendix B.

Columns 1 and 2 compare the effect on publications with and without downstream applications inside the inventing firm. Consistent with our prediction, the coefficient estimate is positive and statistically significant when the science does not have internal use (Column 2).[46] Evaluated at the sample means, \$4.6 million in additional R&D contracts lead to one additional publication.[47] Columns 3 and 4 compare

citations it received from other publications up to the year 2016) / (Average forward citations received by all publications published in the same journal-year). For the quality-adjusted patent flow, we weight each patent by its normalized citations, calculated as (Forward citations it received from other patents up to the year 2016) / (Average forward citations received by all granted patents in the same 4-digit International Patent Classification (IPC)-year).

[46] We obtain qualitatively similar results when using the *Cold War shock* as an instrument for *R&D contracts*.

[47] Average values for publications used internally and R&D contracts are 13 and \$5 million, respectively.

Table 6: Variation by Main Industry

	(1)	(2)	(3)	(4)
	ln(Publications)		ln(Patents)	
	OLS	2nd Stage IV, Ind. R&D funding	OLS	2nd Stage IV, Ind. R&D funding
ln(R&D contracts)$_{t-1}$	0.016	0.133	0.018	0.016
	(0.004)	(0.036)	(0.004)	(0.059)
ln(R&D contracts)$_{t-1}\times$ [Transp. = 1]	-0.009	-0.167	0.003	-0.151
	(0.008)	(0.051)	(0.009)	(0.110)
ln(R&D contracts)$_{t-1}\times$ [Chemicals = 1]	-0.001	-0.374	-0.013	-0.289
	(0.007)	(0.181)	(0.011)	(0.170)
ln(R&D contracts)$_{t-1}\times$ [Drugs = 1]	-0.009	-0.032	-0.011	-0.417
	(0.006)	(0.063)	(0.006)	(0.118)
ln(R&D contracts)$_{t-1}\times$ [Electronics = 1]	-0.005	-0.112	-0.010	0.251
	(0.005)	(0.063)	(0.006)	(0.110)
ln(R&D contracts)$_{t-1}\times$ [Buss. services = 1]	-0.010	-0.076	0.003	0.072
	(0.008)	(0.069)	(0.012)	(0.169)
ln(R&D stock)$_{t-1}$	0.196	0.182	0.344	0.359
	(0.013)	(0.015)	(0.019)	(0.023)
Sample years	1980-2015	1980-2015	1980-2015	1980-2015
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Weak identification (Kleibergen-Paap)		0.51		0.51
Observations	53,693	52,076	53,693	52,076
Adjusted R-squared	0.862	-0.143	0.824	-0.408

Notes: This table presents the estimation results for the relationship of contracts with publications and patents by main industry. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

the effect of R&D contracts on publications when the science has low vs. high spillover to product-market rivals. Consistent with our prediction, the coefficient estimates indicate that the effect is strong when rival patents cite the firm's publications. The last two columns compare the effect on publications with low vs. high protection from the firm's own patents. In line with our expectations, the coefficient estimates indicate that the effect is strong when publications are unlikely to be protected by a patent.

In summary, the results presented in this table indicate that the effect of R&D contracts on corporate science is larger when firms have lower ability to appropriate returns from participating in upstream research.

Table 8 further shows that the effect of contracts on publications increases in firm size, underscoring the importance of complementary assets and scale for meeting the complex requirements of downstream procurement contracts. Consistent with the premise that R&D contracts are the "ticket to play" in the government market, we show in Appendix Table E10 that receiving R&D contracts has a positive effect

Table 7: Guaranteed Demand Mechanism

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Publications)		ln(Rival citations)		ln(Publications)	
	Internal use	No internal use	Low rival use	High rival use	Low protection	High protection
$\ln(\text{R\&D contracts})_{t-1}$	-0.037	0.077	-0.001	0.304	0.069	0.019
	(0.014)	(0.031)	(0.001)	(0.109)	(0.031)	(0.017)
$\ln(\text{R\&D stock})_{t-1}$	0.020	0.179	0.000	0.142	0.177	0.022
	(0.005)	(0.014)	(0.000)	(0.063)	(0.014)	(0.005)
Sample years	1980-2015	1980-2015	1980-2015	1980-2015	1980-2015	1980-2015
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)	60.63	60.63	45.44	9.52	60.63	60.63
Firms	4,302	4,302	4,231	732	4,302	4,302
Observations	52,074	52,074	45,664	6,184	52,074	52,074
Adjusted R-squared	-0.112	-0.014	-0.027	-2.748	0.003	-0.018

Notes: This table presents second stage results from estimating how the effect of R&D contracts on publications varies by characteristics of the science. *Industry R&D funding* is used as an instrument for *R&D contracts*. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

on the value of subsequent procurement contracts.

5.7 Changes Over Time

Table 9 presents how the value and composition of procurement contracts have changed over time. Column 1 shows that total contract size increased by 26 percent per decade, or effectively doubled over the complete sample period.[48]

Columns 2 and 3 show that the increase in total contract value was driven by non-R&D contracts, and by a rise in commercial contracts (awarded using special requirements designed to more closely resemble the commercial market, as detailed in Appendix B). The estimates imply that the annual value of R&D contracts decreased by almost 22 percent per decade, while the annual rival of commercial contracts almost doubled per decade.[49] Evaluated at the sample mean of $4.6 million in annual commercial contracts, the estimate in Column 3 indicates an increase of about one $0.4 million per year.[50]

Consistent with Figure 1, Column 4 shows that the share of R&D contracts in all contracts decreased by 0.083 over the sample period, while Column 6 shows that the share of commercial contracts increased

[48]When dropping the controls for R&D stock, the coefficient estimate on *Time trend* increases to 0.864, indicating that a substantial part of the increase in contract value is explained by sample firms getting bigger over time.

[49]The specifications in Columns 3, 6, and 7 use data from fiscal years 1995-2015 because the data element that allows us to identify commercial contracts was only introduced following the Federal Acquisition Streamlining Act of 1994.

[50]Average values for commercial contracts and time trend are $4.6 million and 2.44, respectively. The increase in average contract value per decade was calculated as $2.002(\$4.6 + 0.000001)/2.44 = 3.774$.

Table 8: Variation by Firm Size

	(1)	(2)	(3)
		ln(Publications)	
	OLS	2nd stage IV, Ind. R&D funding	2nd stage IV, Cold War shock
ln(R&D contracts)$_{t-1}$	0.005	-0.103	-0.180
	(0.002)	(0.071)	(0.196)
ln(R&D contracts)$_{t-1}\times$ [Large = 1]	0.010	0.260	0.335
	(0.003)	(0.082)	(0.193)
[Large = 1]	0.188	3.489	4.483
	(0.046)	(1.072)	(2.518)
ln(R&D stock)$_{t-1}$	0.192	0.164	0.165
	(0.014)	(0.014)	(0.013)
Pre-sample mean publications			0.692
			(0.024)
Sample years	1980-2015	1980-2015	1993-2015
Firm fixed effects	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes
Weak identification (Kleibergen-Paap)		8.59	0.93
Observations	53,416	51,803	5,755
Adjusted R-squared	0.863	-0.385	0.641

Notes: This table presents results from estimating how the relationship between R&D contracts and publications varies by firm size. *Large* is an indicator variable equal to one when a firm's annual sales are above the median for its industry, where the median is calculated over the sample period of 1980-2015. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

by 0.626 between 1995 and 2015. Both trends make it less likely for contracts to drive upstream corporate research in recent years. A smaller share of contract R&D suggests that there may be fewer technology races leading to lucrative downstream guaranteed markets. A higher share of commercial contracts indicates that the effectiveness of procurement contracts in replacing weak market incentives should have fallen as well.

Columns 5 and 7 present variation by main industries. Column 5 shows a decline in the share of R&D contracts in all contracts across industries, with the exception of Drugs, where the share of R&D contracts has increased slightly over time. This pattern is consistent with the reallocation of government research funds (including both grants and contracts) away from chemistry and electrical engineering and toward life sciences fields. For example, between 1980 and 2015, the share of federal research funds obligated to life sciences increased from 36 percent to 49 percent (Merrill, 2018).

Column 7 documents a rise in the share of commercial contracts in all industries. Transportation experienced the smallest increase. A potential explanation for this pattern is that, for national security reasons, some industries included in this group simply do not have a commercial market. For example, the government is the only buyer of guided missiles and fighter aircraft. As a result, the sweeping policy changes of the 1980s and 1990s have had a more limited impact in shifting Transportation contracts toward commercial items.

In summary, the evidence presented in this table is consistent with the patterns presented in Figure 1. Over time, the composition of government contracts has shifted away from technology races and toward buying products and services that already have proven commercial markets. These changes are evident across most industries, with the possible exception of life sciences. Appendix Table E9 shows that the documented changes are robust to considering non-linear time effects.

Table 9: Procurement Contracts Over Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Contract value			Contract composition			
	ln(All contracts)	ln(R&D contracts)	ln(Comm. contracts)	Share R&D/ All contracts	Share R&D/ All contracts	Share comm./ All contracts	Share comm./ All contracts
Time trend	0.380	-0.169	2.002	-0.023	-0.030	0.281	0.296
	(0.101)	(0.071)	(0.111)	(0.008)	(0.008)	(0.038)	(0.029)
Time trend x [Transp. = 1]					0.016		-0.159
					(0.025)		(0.050)
Time trend x [Chemicals = 1]					0.013		-0.004
					(0.034)		(0.064)
Time trend x [Drugs = 1]					0.044		0.033
					(0.016)		(0.047)
Time trend x [Electronics = 1]					0.010		-0.066
					(0.015)		(0.032)
Time trend x [Buss. services = 1]					0.007		0.186
					(0.019)		(0.232)
ln(R&D stock)$_{t-1}$	0.493	0.200	0.319	0.003	0.002	-0.016	-0.020
	(0.074)	(0.042)	(0.071)	(0.004)	(0.004)	(0.016)	(0.018)
Sample years	1980-2015	1980-2015	1995-2015	1980-2015	1980-2015	1995-2015	1995-2015
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms	4,322	4,323	3,620	1,838	1,838	1,461	1,461
Observations	53,534	53,678	37,011	17,927	17,927	12,198	12,198
Adjusted R-squared	0.659	0.589	0.635	0.299	0.299	0.078	0.079

Notes: This table presents OLS estimates for changes in procurement contract value and composition over time. *Time trend* is divided by 10. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

5.8 The Changing Relationship Between Contracts and Firm Scientific Capabilities

Table 10 examines the relationship between *All contracts* and scientific capabilities measured by the stock of corporate publications. Column 1 shows that scientific capabilities are positively related to the size of procurement contracts. Yet, this relationship is weakening over time, as shown in Column 2. Columns 3-5 indicate that this pattern is robust for different firm sub-samples and additional controls.

The evidence presented in this table is consistent with Figure 2, indicating that the importance of scientific capabilities for contract value has fallen over time. This result complements Arora, Belenzon and Patacconi (2018), who document a decline in the stock market value and mergers and acquisitions value of scientific capabilities. Taken together, the evidence suggests that corporate science has fallen out of favor not only with investors and managers, but also with the U.S. government.

Table 10: Contracts and Scientific Capabilities Over Time

	(1)	(2)	(3) ln(All contracts)	(4)	(5)
	All firms	All firms	Publishing firms	Contractor firms	All firms
ln(Publications stock)$_{t-1}$	0.310	0.328	0.320	0.478	0.251
	(0.043)	(0.061)	(0.062)	(0.074)	(0.076)
Time trend × ln(Publications stock)$_{t-1}$		-0.028	-0.048	-0.083	-0.055
		(0.016)	(0.017)	(0.018)	(0.025)
ln(Patents stock)$_{t-1}$					0.335
					(0.074)
Time trend × ln(Patents stock)$_{t-1}$					0.013
					(0.026)
Time trend		0.402	0.474	0.602	0.394
		(0.048)	(0.062)	(0.070)	(0.060)
ln(R&D stock)$_{t-1}$	0.377	0.395	0.433	0.515	0.261
	(0.036)	(0.036)	(0.042)	(0.050)	(0.040)
Sample years	1980-2015	1980-2015	1980-2015	1980-2015	1980-2015
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	No	No	No
Observations	53,534	53,534	41,741	34,484	53,534
Adjusted R-squared	0.676	0.659	0.655	0.551	0.660

Notes: This table presents OLS estimates for changes in the relationship between total contracts and scientific capabilities over time. *Time trend* is divided by 10. One is added to logged variables. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity.

6 Discussion and Conclusion

Corporate participation in scientific research can help firms gain access to guaranteed downstream markets. We provide the first systematic evidence in support of the government's role in de-risking upstream research via the guaranteed demand mechanism. We present two sets of results. First, we document a positive effect of government contracts on publications ("R"), and show that the effect is stronger when market incentives are relatively weak. This finding supports the view that firms invest in upstream research to increase their chances of winning R&D races as a pathway to downstream guaranteed demand. The hope for market exclusivity (in the form of noncompetitive product contracts) induces corporate investments in upstream research, which is harder to protect with patents. Second, we show that the effect was stronger before the mid-1990s, when policy reforms such as the Federal Acquisition Streamlining Act of 1994 changed the composition of procurement contracts. The government's new emphasis on reducing cost and increasing efficiency and transparency in procurement is evidenced by a falling share of R&D contracts and rising shares of commercial and competitive contracts.

With the above findings, we make two main contributions. First, we help explain why corporations are withdrawing from scientific research (e.g., Arora, Belenzon and Patacconi, 2018; Arora, Belenzon and Sheer, 2021; Mowery, 1998, 2009). Our results show that firms invest in research to win contracts, yet research has become less important for government demand. Recent studies show that the composition of corporate R&D has shifted away from research and toward development. Specifically, the share of research in business R&D has dropped from a high of 31 percent in 1986 to just 20 percent in 2015.[51] Moreover, the annual number of corporate publications has steadily declined since the mid-1990s (Arora, Belenzon and Sheer, 2021). In addition, the market value attributed to firm scientific research capabilities (i.e., the "shadow price" of scientific publications) has also fallen over time (Arora, Belenzon and Patacconi, 2018). This means that investors value corporate research less today than in the past. The same pattern holds for managers, who are willing to pay less today for the scientific capabilities of their acquisition targets than in years prior. The present paper reinforces these trends by showing that scientific research has fallen out of favor with the U.S. government as well. Once the government began competing with the commercial market, corporations had fewer incentives to perform risky upstream scientific research, and more incentives to invest in downstream development of commercially viable products and services. By emphasizing commercially proven technologies and de-emphasizing leading-edge, mission-driven technologies, the government has potentially amplified the corporate withdrawal from science.

Second, we add to the literature on the effect of government policy on innovation (e.g., Bloom, Van Reenen and Williams, 2019; Edler and Georghiou, 2007; Mowery, 2010; Mowery, Nelson and Martin, 2010; Rogerson, 1989; Slavtchev and Wiederhold, 2016). Our results show that procurement policy—an area that has not received as much scholarly attention as the public funding and tax policies—should also be considered a national innovation policy. Legislative and executive actions, such as the Buy American Act of 1933, have long used procurement contracts to boost domestic economic activity and support targeted geographies or industries. President Biden's Executive Order on Ensuring the Future Is Made in All of America by All of America's Workers, signed January 25, 2021, is just a recent example. Yet, to

[51] Data are from Tables 2, 3, and 4 of the National Patterns of R&D Resources series published by the National Center for Science and Engineering Statistics (National Science Foundation, 2019).

the best of our knowledge, the present paper is the first to estimate the effect of procurement contracts separately on upstream research and downstream development, and to investigate the guaranteed demand mechanism. By providing evidence that R&D contracts have a positive effect on upstream corporate research, we advance the understanding of how, and under what conditions, government contracts affect the U.S. innovation ecosystem.

While we document that, on average, publicly-traded firms perform more upstream research when they receive procurement contracts, this effect may mask substantial heterogeneity. The R&D race leading up to the production of stealth aircraft exemplifies it (Westwick, 2019). In the 1970s, Northrop Corporation and Lockheed Corporation competed to design and build the first operational stealth aircraft. The main technical challenge was to minimize the diffraction of radar waves after they hit the aircraft's surface. Northrop CEO Tom Jones once remarked: "We knew that it was the laws of physics that caused radar to be invented in the first place" (Grant, 2013, p. 5). Understanding those laws eventually led to defeating radar tracking.

In the late 1950s, Soviet physicist Pyotr Ufimtsev had worked on the problem of diffraction, how water, sound, or light waves interact with the edges of an object. Ufimtsev discovered "fringe currents," nonuniform components that helped account for how diffraction happens around corners. This discovery became the basis for stealth aircraft development, but not in the Soviet Union. While the Soviet Defense Ministry showed no interest in Ufimtsev's findings, the U.S. Department of Defense did. During the Cold War, the agency funded the translation of Russian scientific journals to see what they could gleam and apply to military programs. Ufimtsev's 1962 book, "Method of Edge Waves in the Physical Theory of Diffraction," was published in English in 1971.

Both Northrop and Lockheed understood the basic science of radar waves, but not fringe currents. Once they were able to access Ufimtsev's findings, and the mathematical theory and equations that anchored them, firms could begin to design aircraft with minimal radar footprints. Northrop invested heavily in the science behind the Physical Theory of Diffraction, while Lockheed relied on numerical simulations. Northrop radar expert John Cashen remarked: "I could see the waves [...] We didn't need a computer program to tell us what the [radar cross section] could be. That was the difference between Northrop and Lockheed" (Grant, 2013, p. 8). Interestingly, Lockheed won the first contract to produce the F-117 stealth fighter, but Northrop won the bigger contract to produce the B-2 stealth bomber because they were able to build planes with curvatures or "big bellies." Northrop was able to predict how waves would behave when they hit curved surfaces due to their deep understanding of diffraction around corners.

To what extent this example is representative of firms' strategic choices in response to R&D races, and the implications of different R&D choices for winning a single or subsequent innovation contests, remains an empirical question and a potentially fruitful avenue for future research.

Another promising direction for future research would examine the effect of government procurement on small firms by studying the vertical coordination between "prime" contractors and subcontractors in the federal supply chain. The Federal Acquisition Regulation specifies that the government-wide target for small businesses is at least 23 percent of the total value of all prime contracts awarded each year. Studying the implications of such policy would deepen substantially our understanding of the effect of public demand on the American innovation ecosystem as a whole.

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A Federal Procurement Background

Procuring goods and services for the U.S. government through an advertised, competitive process goes back as far as the Revolutionary War (Wittie, 2003).[52] In modern times, the Armed Services Procurement Act of 1947 and the Federal Property and Administrative Services Act of 1949 provided comprehensive legislative frameworks for defense and civilian procurement, respectively. Also noteworthy was the Competition in Contracting Act of 1984 that established "full and open competition" as the standard for federal procurement contracts.

A.1 Procurement Process

The U.S. government's procurement process typically begins with federal acquisition professionals determining an agency's requirements for goods and services, and the most appropriate method for purchasing them (Congressional Research Service, 2021*b*). In general, solicitations for contracts above $25,000 are posted on the System for Award Management website, beta.SAM.gov.[53] In response, interested firms prepare and submit offers.[54] Agency personnel then evaluate the offers using the source selection method and criteria described in the solicitation, in accordance with Federal Acquisition Regulation.[55] The agency awards a contract to a firm only after determining that the company is responsible, meaning it has adequate resources to perform the contract (financial, organizational, technical skill, production facilities, etc.) as well as a satisfactory record of performance, integrity, and business ethics. The next steps include contract performance and administration (e.g., invoice processing and payments, performance monitoring, and contract modifications), followed by contract closeout.

A.2 Policy Changes

During the Cold War (1948-1989), government procurement focused on achieving and sustaining technological superiority for the purpose of national defense (Weiss, 2014). Federal agencies acquired products and services that met government requirements and specifications, and were often unproven in commercial markets (Howell et al., 2021). In the case of defense R&D, which represented the majority of R&D contracts, the Department of Defense was often the sole customer (Mowery, 2012). As shown in Figure A1, the government's acquisition procedures could be very complex. R&D races were often used to develop new products at the technological leading-edge. Winners were rewarded with noncompetitive production contracts. This incentivized firms to perform upstream science and enabled contractors to mitigate the market risk of performing scientific research that didn't yet have commercial applications.

The composition of procurement contracts began shifting toward dual use technologies and commercial items in the 1980s, and accelerated in the 1990s. Numerous policy changes were made in response to the end of the Cold War, increased global trade, constrained defense budgets, and the need to attract nontraditional, innovative suppliers from the much larger commercial markets, especially those in the growing IT sector (Mowery, 1998; Weiss, 2014). Specifically, the U.S. government implemented sweeping patent and intellectual property reforms, acquisition reforms, and organizational reforms. For example, the Bayh-Dole Act of 1980 and its extensions allowed contractors to retain ownership of inventions made with federal funding. The Stevenson-Wydler Technology Innovation Act of 1980 and its extensions gave businesses access to technologies developed in federal laboratories. The Competition in Contracting Act

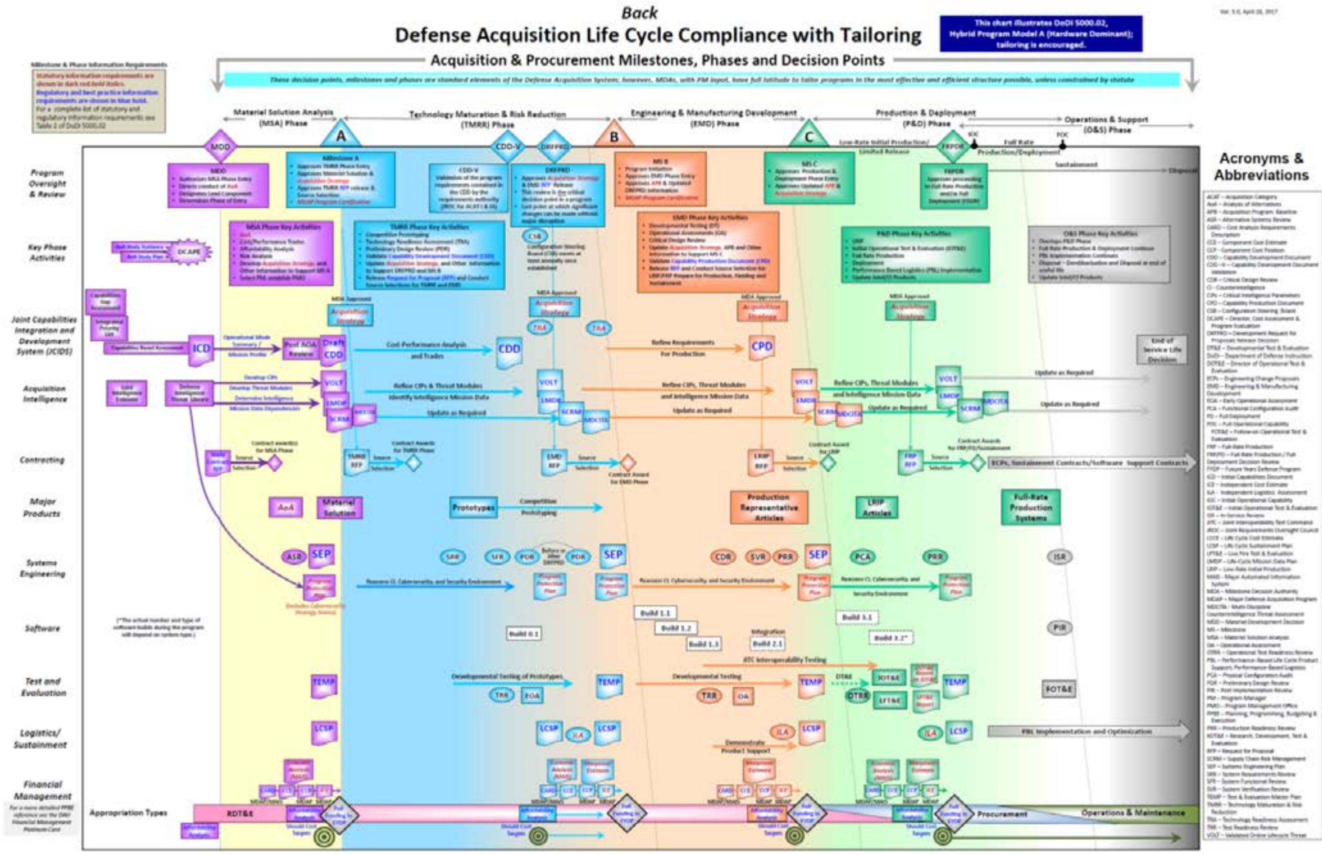
[52]For example, the Continental Congress passed a resolution on November 20, 1775 to appoint a committee responsible for advertising, receiving proposals, and contracting rations for two new military battalions.

[53]Other procurement methods include using a government purchase card (i.e., a credit card), placing a task or delivery order against an existing contract, or ordering from a General Services Administration schedule. For R&D contracting, firms can also submit unsolicited proposals or compete in government-sponsored challenges and prize competitions.

[54]Firms can also participate in government procurement by serving as subcontractors to "prime" government contractors.

[55]The two primary methods of source selection are sealed bidding and negotiated contracting. The latter is typically used for R&D contracts.

Figure A1: Defense Acquisition Life Cycle



Notes: This figure shows a process map of the milestones, phases, and decision points typically included in the defense acquisition life cycle for hardware-dominant programs (Defense Acquisition University, 2020).

of 1984 mandated that all procurement contracts be awarded based on full and open competition unless regulatory or statutory exclusions applied. The Goldwater-Nichols Department of Defense Reorganization Act of 1986 reworked the military command structure and implemented shared procurement across the military branches. The Defense Acquisition Workforce Improvement Act of 1990 established education and training standards for government acquisition professionals. The organizational reforms included the creation of new "hybrid" forms of public-private partnering (Weiss, 2014). One example is the SEMATECH industrial consortium, which was formed in 1987 with funding from the Defense Advanced Research Projects Agency and the involvement of 14 American semiconductor manufacturers.

These policy changes culminated in the Federal Acquisition Streamlining Act of 1994, which enabled simplified acquisition procedures and established a statutory preference for government procurement of commercial items (Barry, 1995). Procurement dollars were reallocated *away from* mission-focused technologies that met government specifications and *toward* dual use technologies that had both government and commercial potential. Driven by pressures to reduce cost and increase efficiency and transparency, the government began competing with the commercial market for technologies that already had low(er) commercial risk. As a result, corporations had fewer incentives to perform upstream scientific research, and more incentives to invest in downstream development of commercially viable products and services.

B Data Construction

B.1 Collecting Procurement Contracts

The U.S. General Services Administration manages the Federal Procurement Data System (FPDS), the central repository of information on U.S. government procurement contracts. FPDS contains detailed information on all contract transactions above the micro-purchase threshold, which generally ranges from $2,000 to $25,000, depending on the fiscal year, type of award recipient, and place of performance.[56]

The Federal Funding Accountability and Transparency Act of 2006 (FFATA) required that federal contract, grant, loan, and other financial assistance awards of more than $25,000 be displayed on a publicly accessible website.[57] In response, the U.S. Department of the Treasury developed USAspending.gov as the official public source of federal government contract data (pulled from FPDS) and grant, loan, and other financial assistance data (reported to the Data Act Broker managed by the U.S. Department of the Treasury). The "Custom Award Data" section of the USAspending.gov website allows the public to view and download award transactions for fiscal years starting in 2001.[58] We used it to download .csv files containing transactions for all prime procurement contracts, awarded by all federal agencies and sub-agencies, for all locations, during fiscal years 2001-2020.[59]

We supplemented these data with historical contract transactions from beta.SAM.gov, a website managed by the U.S. General Services Administration. The website allows the public to download FPDS award transactions after creating user accounts. We used it to download .csv files containing prime award transactions for procurement contracts awarded by the Departments of Defense, Energy, Health and Human Services, and Veterans Affairs for all locations during fiscal years 1980-2000.

The federal government reports *obligations* for procurement contracts, not actual *outlays*. An obligation is the government's promise to spend funds (immediately or later) as a result of entering into a contract, so long as the agreed-to actions take place. An outlay takes place when those funds are actually paid out to the contractor (Datalab, 2020). If the entire amount initially obligated is not used, the last modification will display a negative dollar amount. For example, if an initial contract award was for $100,000 and an agency only used $90,000 of that initial obligation, the last transaction associated with award the would display an amount of -$10,000 (Datalab, 2020).

B.2 Matching Contracts to Firms

We merged the contract data with the panel of U.S.-headquartered publicly traded firms from Arora, Belenzon and Sheer (2021). We string-matched more than 800,000 contractor names against almost 60,000 firm names (including ultimate owners and their subsidiaries).[60] Specifically, we used *matchit*, a Stata tool that can join observations from two datasets based on string variables that are not exactly the same (Raffo, 2020), to perform vectoral decomposition of firm names using five-character grams. Then, we applied Jaccard similarity scoring. For each contractor, we retained the five best potential matches (in decreasing order of similarity score, as long as the score was above 0.5). Next, we completed a four-step process to clean the potential matches.

[56] Other exceptions to the reporting rule include classified contracts, as well as contracts that contain sensitive information about recipients, locations, and operations. For obvious reasons, we cannot estimate the precise value of these unreported contracts.

[57] FFATA was amended by the Government Funding Transparency Act of 2008, which required prime contractors to report details on their first-tier subcontractors, and expanded with the Digital Accountability and Transparency Act of 2014, which established government-wide financial data standards (USAspending.gov, 2021*a*).

[58] An award usually is made up of a series of transactions, which include the initial award and any subsequent modifications, such as additions or continuations of funding and changes to the scope of work (USAspending.gov, 2020).

[59] Award types include prime awards for contracts, contract indefinite delivery vehicles (IDV), grants, direct payments, loans, insurance, and other financial assistance (USAspending.gov, 2021*c*).

[60] We standardized recipient names using the same code as used by Arora, Belenzon and Sheer (2021) to identify the best possible matches to the panel of firms.

Step 1. We removed unicode and special characters, as well as legal suffixes (e.g., inc, corp, ltd) and conjunctions (e.g., and, on, at) from names, generating "core" versions of contractor and firm names. We reapplied the *matchit* tool to evaluate the quality of the match between these "core" names. This time, we used bigrams in the vectoral decomposition, and dropped potential "core" matches that had a Jaccard similarity score below 0.65.

Step 2. We removed generic words from firm names (e.g., terms describing an industry or activity), generating "nongeneric" versions of contractor and firm names. We reapplied the *matchit* tool to evaluate the quality of the match between these "nongeneric" names. Once again, we used bigrams in the vectoral decomposition, and dropped potential "nongeneric" matches that had a Jaccard similarity score below 0.65.

Step 3. We calculated the Levenshtein distance between "nongeneric" names, and dropped potential matches with an edit distance greater than 15. For each contractor, we retained only the best potential match (in decreasing order of "core" and "nongeneric" similarity scores).

Step 4. We manually cleaned potential matches that had similarity scores below 0.9, discarding any obvious mis-matches.

We obtained a dataset of 27,434 contractors matched to 10,814 ultimate owner and subsidiary names. We aggregated contracts by firm-year, then allocated contracts matched to subsidiaries to the appropriate ultimate owners using the dynamic match produced by Arora, Belenzon and Sheer (2021). In summary, we identified 2,247 U.S.-headquartered manufacturing firms (i.e., ultimate owners) that received a total of $2.3 trillion in procurement contract obligations during 1980-2015. Table F12 presents the distribution by two-digit SIC code, while Table F11 displays the largest contractors (by total value of contracts won) in each decade covered by our sample.

C Variable Construction

Table C1 includes definitions and sources for all the variables used in our econometric analyses. The steps used to split procurement contracts into various types (e.g., R&D vs. non-R&D), assign contracts to industries, and create variables for several characteristics of science are detailed below.

C.1 Contract Variables

To describe the products and services acquired in each procurement award, agencies use four-digit Product and Service Codes (PSC) that mirror the Federal Supply Classification (FSC) codes.[61] Currently, the PSC/FSC classification consists of 24 service categories (see Table F13) and 78 product groups (see Table F14). The product groups are further subdivided into 645 classes, as defined in the FPDS Product and Service Codes Manual (U.S. General Services Administration, 2021).

We link the PSC/FSC classification to NAICS industries using the crosswalk from the U.S. Defense Logistics Agency (2020), and then link NAICS industries to SIC industries using the crosswalk from the NAICS Association (2020). This allows us to identify the SIC4 industry for 71 percent of procurement contract dollars awarded between 1980 and 2015.

We use the *Product or Service Code* field to split all contracts into R&D contracts (service codes starting with the letter A) vs. non-R&D contracts (service codes starting with letters B through Z and product codes starting with any number).[62] In the procurement contract data, codes for R&D services are composed of two alphabetic and two numeric digits:

- 1st digit: always the letter A to identify R&D services,

[61] The FSC is a government-wide commodity classification system designed for grouping, classifying, and naming all personal property items (U.S. Defense Logistics Agency, 2003).

[62] When a contract action includes more than a single product or service, the awarding agency uses the code corresponding to the predominant product or service.

- 2nd digit: alphabetic A to Z to identify the major category,
- 3rd digit: numeric 1 to 9 to identify a subdivision of the major category, and
- 4th digit: numeric 1 to 7 to identify the appropriate stage of R&D:
    1. Basic research,
    2. Applied research and exploratory development,
    3. Advanced development,
    4. Engineering development,
    5. Operational systems development,
    6. Management and support, and
    7. Commercialization (U.S. General Services Administration, 2021).

We use these patterns to split R&D contracts into research contracts vs. development contracts. Specifically, we code the first two stages of R&D (i.e., Basic research and Applied research and exploratory development) as *R contracts*, and the other five stages as *D Contracts*. We further divide non-R&D contracts into non-R&D service contracts vs. product contracts.

We use the *Commercial Items Acquisition Procedures* field to split non-R&D contracts into commercial contracts vs. noncommercial contracts.[63] Contracts were awarded using commercial item procedures only after the passage of the Federal Acquisition Streamlining Act of 1994. Therefore, our data separating commercial vs. noncommercial contracts only span 1995-2015. While some R&D service contracts were awarded using streamlined commercial item procedures, they represent less than 0.7 percent of the value of all R&D contracts awarded to sample firms. Therefore, we do not break down R&D contracts into commercial vs. noncommercial contracts.

We also use the *Extent Competed* field to distinguish contracts that were awarded competitively from those awarded noncompetitively. In general, federal agencies are required to use full and open competition when awarding procurement contracts (U.S. Government Accountability Office, 2014). Competitive procedures include sealed bids, competitive proposals, or a combination of competitive procedures. However, the Competition in Contracting Act of 1984 authorized noncompetitive contracting under certain conditions.[64] We aggregate competed and total contracts by year and contract type to produce the trend lines in Figure 3.

C.2 Characteristics of Science Variables

We measure several characteristics of corporate science. First, we split the annual publication flow into: (i) publications cited by the firm's own patents; and (ii) publications not cited by the firm's own patents. We use the non-patent literature citations file from Arora, Belenzon and Sheer (2021) to do so. The number of unique publications that receive one or more citations from the firm's own patents is aggregated at the firm-year level into the variable *Internal use publications*. The remaining annual publication flow is captured in the variable *No internal use publications*.

Second, we identify science that spills over to close product-market rivals. We use *Rival citations*, a measure of rivalry-weighted external citations from patents of other panel firms to the focal firm's publications, also sourced from Arora, Belenzon and Sheer (2021). Product-market rivalry is calculated

[63] This field indicates whether the solicitation used the special requirements for the acquisition of commercial items, supplies, or services. Those requirements are intended to more closely resemble the commercial market as defined by Federal Acquisition Regulation Part 12 (FPDS, 2020).

[64] The Federal Acquisition Regulation currently identifies seven exceptions to full and open competition: (i) only one responsible source and no other supplies or services will satisfy agency requirements; (ii) unusual and compelling urgency; (iii) industrial mobilization; engineering, developmental, or research capability; or expert services; (iv) international agreement; (v) authorized or required by statute; (vi) national security; and (vii) public interest (Federal Acquisition Regulation, 2019).

Table C1: Variable Definitions

Variable	Definition	Source
Publications	Sum of scholarly, peer-reviewed publications that have at least one author affiliated with the focal firm and were published in the focal year. Appendix C details how we split this variable into *Internal use* vs. *No internal use* (to capture the focal firm's own use of science) and *High protection publications* vs. *Low protection publications* (to capture the scope of protection offered by the focal firm's own patents).	Clarivate Analytics' Web of Science (Arora, Belenzon and Sheer, 2021)
Publications stock	Calculated using a perpetual inventory method with a 15 percent depreciation rate (Hall et al., 2005), such that the stock in year t is $Publications\ stock_t = Publications_t + (1-\delta) Publications\ stock_{t-1}$, where $\delta = 0.15$.	
Patents	Sum of patents granted by the U.S. Patent and Trademark Office to the focal firm in the focal year.	European Patent Office's PATSTAT database (Arora, Belenzon and Sheer, 2021)
Rival citations	Sum of rivalry-weighted external citations from patents of other panel firms to the focal firm's publications, sourced from Arora, Belenzon and Sheer (2021). The product-market rivalry is calculated as the Mahalanobis similarity of vectors representing the shares of industry segment sales for each pair of firms.	European Patent Office's PATSTAT database, Standard & Poor's Compustat Segments (Arora, Belenzon and Sheer, 2021)
All contracts	Sum of all contract awards associated with a firm-year ($ mm).	USAspending.gov, beta.SAM.gov
R&D contracts	Sum of R&D contract awards associated with a firm-year ($ mm).	
Non-R&D contracts	Sum of non-R&D contract awards associated with a firm-year ($ mm).	
R contracts	Sum of research contract awards associated with a firm-year ($ mm).	
D contracts	Sum of development contract awards associated with a firm-year ($ mm).	
Commercial contracts	Sum of commercial contract awards associated with a firm-year ($ mm).	
Noncommercial contracts	Sum of noncommercial contract awards associated with a firm-year ($ mm).	
Time trend	Focal year minus 1980 (in decennial units).	
Sales	Sales for the focal firm-year ($ mm).	Standard & Poor's Compustat North America (Arora, Belenzon and Sheer, 2021)
R&D stock	Calculated using a perpetual inventory method with a 15 percent depreciation rate, such that the stock in year t is $R\&D\ stock_t = R\&D\ expenditures_t + (1-\delta) R\&D\ stock_{t-1}$, where the focal firm's *R&D expenditures* in year t are based on Compustat data and $\delta = 0.15$. Expressed in $ mm.	Standard & Poor's Compustat North America (Arora, Belenzon and Sheer, 2021)
Industry R&D funding	Calculated by multiplying the level of R&D contracts obligated to the focal firm's SIC3 industry (not including the contracts obligated to the focal firm that year) times the share of R&D contracts obligated to the focal firm's SIC4 industry (averaged over the sample period of 1980-2015). Expressed in $ mm.	USAspending.gov, beta.SAM.gov
Cold War shock	Calculated using the difference in contract values between pre (1988) and post (1992) periods for each SIC4 industry, weighted by the focal firm's sales exposure to different SIC4 industries. Expressed in $ mm. The sales exposure is calculated as the share of the focal firm's sales during 1982-1985 that came from each SIC4 industry.	USAspending.gov, beta.SAM.gov, Standard & Poor's Compustat North America

Notes: This table displays definitions and sources for the variables used in our econometric analyses. Dollar values are deflated using the GDP Implicit Price Deflator to reflect constant 2012 dollars (U.S. Bureau of Economic Analysis, 2020).

as the Mahalanobis similarity of vectors representing the shares of industry segment sales for each pair of firms. In Table 7, firm-years with rival citations above the median (relative to the firm's SIC4 industry) are included in the *High rival use* regression, while the remaining firm-years are included in the *Low rival use* regression.

Third, we split the annual publication flow into: (i) publications that have low patent protection;

and (ii) publications that have high patent protection. We measure the textual proximity of publications (abstract and title) to patents (claims) for all Web of Science publications and USPTO patents for our sample period using a three-step procedure.

Step 1: Bag of words. We extract all words from the claims text of patents, and the titles and abstracts of publications. For each document (patent or publication), we create a vector of all word stems. Each word stem is weighted by the inverse of its frequency in the complete patent corpus. For each word in a patent, we create an inverse frequency index as:

$$I_i = N_i \times (1 - \frac{p_i}{P})$$

where N_i is the number of times the ith word stem appears throughout the claims section of patents, p_i is the number of patent documents that contain the ith word stem, and P is the number of patents issued by the USPTO. Each item in the index represents the weight assigned to extracted word stems according to their specificity across all USPTO patent documents. We follow the same procedure for the title and abstract of publications (we treat a publication record as a patent document).

An important part of the word stemming process is mapping acronyms and technical concepts. For example, the acronym RAM refers to random access memory. Thus, in our textual comparison algorithm, when the sequence of words "random access memory" appears, we collapse it into RAM. Acronyms appear in capital letters on patent documents. We retain all words with at least two capital letters and manually search for their meaning. To mitigate cases where an acronym has multiple meanings, we perform the acronym-meaning match at the four-digit IPC level. (Chemical compounds also appear in capital letters, but we leave them unchanged.)

Step 2: Distance between words. Similar ideas might be described using different text. Thus, a major challenge is how to compute the "technical distance" between two words. To address it, we develop a dictionary that aims to measure the probability that two distinct words refer to the same technical concept. We identify words used in patent documents deemed to be technically similar by patent examiners. Specifically, we extract a random sample of about 150,000 non-final rejection letters from the USPTO's Public PAIR (Patent Application Information Retrieval) system. We include only rejections pertaining to novelty or non-obviousness, as outlined in 35 U.S.C. 102 and 35 U.S.C. 103 of the USPTO's Manuals for Patent Examining Procedure. We extract the text of the original patent application associated with a rejection, as well as the text of the prior-art patents cited as the reason for the rejection. When multiple rejections are associated with the same application, we extract the relevant (modified) application claims for each rejection.

Next, we extract all relevant word stems from the claims section of the focal patent application and corresponding prior-art patents.[65] Then, we calculate the proximity between each pair of word stems based on their co-occurrence. To account for the baseline tendency of two word stems to co-occur across two documents, for each rejected application and rejection prior-art patent pair, we construct a control pair by linking the rejected application with a control patent that was not cited as a reason for the rejection but is in the same 4-digit IPC and has the same application year as the rejection prior-art patent. Proximity between word stems is calculated as the ratio of the number of times the pair appears in the rejected application and rejection prior-art patent to the number of times it appears in the rejected application and the control prior-art patent:

$$Proximity_{w1,w2} = \frac{(A \bigcup R)_{w1,w2}}{(A \bigcup C)_{w1,w2}}$$

$(A \bigcup R)_{w1,w2}$ is the number of times the words $w1$ and $w2$ co-occur within the focal application A and rejection prior-art patent R. $(A \bigcup C)_{w1,w2}$ is the number of times the words $w1$ and $w2$ co-occur in the focal application A and control patent C. Because the same word stem pair, $w1$ and $w2$, can co-occur in

[65]We use original applications rather than final patent documents because claims can change during the patent examination process.

more than one application and rejection prior-art patent pair, we average the proximity scores between $w1$ and $w2$ across all application and rejection prior-art patent pairs, denoted by $\bar{P}_{W1_i,W2_i}$.

Step 3: Textual overlap between documents. We construct a similarity score between a pair of documents (i.e., a publication and a patent) based on the "technical distance" between their words. We create a vector of words for each document with their corresponding weights (i.e., inverse frequency) as described in step 1. Then, we calculate the cosine proximity score between the two word vectors $W1$ and $W2$, each vector consisting of n elements, while taking into account the average word pair proximity $\bar{P}_{W1_i,W2_i}$ calculated in step 2:

$$PS_{W1,W2} = \frac{\sum_{i=1}^{i=n} W1_i \times W2_i \times \bar{P}_{w1_i,w2_i}}{\sqrt{\sum_{i=1}^{i=n} W1_i^2}\sqrt{\sum_{i=1}^{i=n} W2_i^2}}$$

We normalize the proximity score $PS_{W1,W2}$ to be between 0 and 1 by dividing it by $\max(PS_{W1_i,W2_i})$. As a result, 1 indicates the highest possible similarity and 0 indicates the lowest possible similarity between two documents.

For each publication between 1980 and 2015, we retain up to five of the highest proximity scores with granted patents. We identify which of those patents are owned by the publishing firm, and retain the top matching publication-patent pair. Publications with proximity scores above the median (relative to the publication year) are coded as "protected" by a patent, while those with scores below the median and those unmatched to firm patents are coded as "unprotected" by a patent.[66] The number of unique publications that are "protected" by the firm's patents is aggregated at the firm-year level into the variable *High protection publications*. The remaining annual publication flow is captured in the variable *Low protection publications*.

D Instrumental Variable Estimation

D.1 Constructing the Industry R&D Funding Variable

Our first instrument exploits variation in aggregate industry R&D contracts to predict R&D contracts awarded to a focal firm. It is important to recognize that R&D contracts awarded to a firm's SIC4 industry may still be endogenous. To mitigate this concern, we take advantage of changes in R&D funding at a higher level of aggregation, the firm's SIC3 industry. We "distribute" these changes across SIC4 industries according to time-invariant industry shares, closely following Moretti, Steinwender and Van Reenen (2019).

We construct our IV in three stages. First, we identify the SIC4 industry for each procurement contract awarded by the Department of Defense, Department of Energy, Health and Human Services, and Veterans Affairs during 1980-2015. For transactions that do not list the recipient firm's NAICS code, we use the *Product or service code* (PSC) field and the PSC-to-NAICS crosswalk from U.S. Defense Logistics Agency (2020) to identify the NAICS code. Then, we use the NAICS-to-SIC crosswalk available from NAICS Association (2020) to identify the SIC4 code. We aggregate all R&D contracts awarded to all firms (not just our panel firms) at the SIC4-year and SIC3-year levels, respectively.

Second, we calculate the share of R&D contracts awarded to the SIC4 industry relative to the R&D contracts awarded to the SIC3 industry that contains it. Specifically, we divide the total value of R&D contracts awarded to the SIC4 industry during 1980-2015 by the total value of R&D contracts awarded to the higher-level SIC3 industry during 1980-2015.

Third, we calculate the instrument as $Industry\ R\&D\ funding_{i,t} = (Industry\ R\&D\ contracts_t - Firm\ R\&D\ contracts_{i,t}) \times Industry\ share$. *Industry R&D contracts$_t$* is the total value of R&D contracts awarded to the firm's SIC3 industry in year t, from which we subtract the firm's own R&D contracts in year t. The reason for excluding firm R&D contracts from the construction of the IV is to avoid a

[66] Our choice of cutoff—the median publication-patent proximity score for all the publications published by sample firms in a given year—allows us to take into consideration how the proximity between papers and patents changes over time.

mechanical correlation between the endogenous variable we want to instrument and the instrument itself. We use a time-invariant *Industry share* because it allows us to smooth out year-to-year variation in the R&D contracts awarded to the SIC4 industry.

Take Boeing as an example. In 2012, Boeing's SIC3 industry ("372 Aircraft and parts") received \$4.2 billion in R&D contracts, including almost \$1 billion for Boeing. Over the sample period of 1980-2015, Boeing's SIC4 industry ("3721 Aircraft") received 85 percent of the R&D contracts awarded to its SIC3 industry ("372 Aircraft and parts"). The instrument for Boeing in 2012 was calculated as $(4.2-1) \times .85 = 2.7$ (in \$ billions).

Using this industry R&D funding measure (rather than the total value of R&D contracts awarded to the firm's SIC4 industry in year t) strengthens the validity of our instrument because it makes it less likely to be related to the focal firm's idiosyncratic technical opportunities.

D.2 First Stage Results

Table D2 shows the first stage results of the two-stage-least-squares (2SLS) instrumental variable estimations used in this paper.

Table D2: Instrumental Variable Estimation (First Stage)

	(1)	(2)	(3)	(4)
	ln(R&D contracts)$_{t-1}$			
	1st stage IV, Ind. R&D funding	1st stage IV, Cold War shock for R&D Expenditures	1st stage IV, Cold War shock for Publications	1st stage IV, Cold War shock for Patents
ln(Industry R&D funding)$_{t-1}$	0.060			
	(0.008)			
ln(Cold War shock 1988-1992)		0.033	0.030	0.030
		(0.007)	(0.006)	(0.006)
Pre-sample mean R&D expenditures		0.068		
		(0.017)		
Pre-sample mean publications			0.386	
			(0.057)	
Pre-sample mean patents				0.530
				(0.070)
ln(R&D stock)$_{t-1}$	0.137	0.280	0.181	0.150
	(0.035)	(0.030)	(0.027)	(0.027)
Sample years	1980-2015	1993-2015	1993-2015	1993-2015
Firm fixed effects	Yes	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes
Observations	52,076	5,154	5,779	5,779
F statistic	34	62	73	77
Adjusted R-squared	0.575	0.056	0.071	0.077

Notes: This table displays first stage OLS regression results. *Industry R&D funding* is calculated by multiplying the level of R&D contracts obligated to the focal firm's SIC3 industry (not including the contracts obligated to the focal firm that year) times the share of R&D contracts obligated to the focal firm's SIC4 industry (averaged over the sample period of 1980-2015). *Cold War shock* is calculated using the difference in contract values between pre (1988) and post (1992) periods for each SIC4 industry, weighted by the focal firm's sales exposure to different SIC4 industries. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level in Column 1, and are robust to arbitrary heteroskedasticity in Columns 2-4.

E Robustness Checks

E.1 Effect of R&D Contracts

Tables E3 through E9 preset several robustness checks for the effect of R&D contracts.

Table E3: Using All Contracts

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(R&D expenditures)		ln(Publications)		ln(Patents)	
	2nd stage IV, Industry funding	2nd stage IV, Cold War shock	2nd stage IV, Industry funding	2nd stage IV, Cold War shock	2nd stage IV, Industry funding	2nd stage IV, Cold War shock
ln(All contracts)$_{t-1}$	0.053	0.092	0.111	0.168	0.045	-0.156
	(0.039)	(0.032)	(0.039)	(0.051)	(0.046)	(0.056)
ln(R&D stock)$_{t-1}$	0.514	0.885	0.140	0.064	0.327	0.513
	(0.026)	(0.046)	(0.026)	(0.047)	(0.032)	(0.050)
Pre-sample mean R&D expenditures		-0.113				
		(0.017)				
Pre-sample mean publications				0.592		
				(0.044)		
Pre-sample mean patents						0.643
						(0.059)
Sample years	1980-2015	1993-2015	1980-2015	1993-2015	1980-2015	1993-2015
Firm fixed effects	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)	5.54	15.11	11.93	17.79	11.93	18.68
Firms	4,144		4,317		4,317	
Observations	47,406	4,609	53,104	5,775	53,104	5,775
Adjusted R-squared	0.212	0.875	-0.576	0.457	0.070	0.305

Notes: This table presents the estimation results for the relationship of all contracts with R&D expenditures, publications, and patents. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

Table E4: Using Noncommercial Contracts

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(R&D expenditures)		ln(Publications)		ln(Patents)	
	2nd stage IV, Industry funding	2nd stage IV, Cold War shock	2nd stage IV, Industry funding	2nd stage IV, Cold War shock	2nd stage IV, Industry funding	2nd stage IV, Cold War shock
ln(Noncommercial contracts)$_{t-1}$	0.058	0.072	0.132	0.141	0.055	-0.144
	(0.048)	(0.021)	(0.045)	(0.038)	(0.055)	(0.046)
ln(R&D stock)$_{t-1}$	0.515	0.916	0.140	0.105	0.327	0.475
	(0.029)	(0.030)	(0.025)	(0.030)	(0.032)	(0.034)
Pre-sample mean R&D expenditures		-0.110				
		(0.015)				
Pre-sample mean publications				0.620		
				(0.033)		
Pre-sample mean patents						0.649
						(0.053)
Sample years	1980-2015	1993-2015	1980-2015	1993-2015	1980-2015	1993-2015
Firm fixed effects	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)	4.91	29.44	10.20	28.97	10.20	30.08
Firms	4,144		4,317		4,317	
Observations	47,441	4,602	53,149	5,769	53,149	5,769
Adjusted R-squared	0.197	0.909	-0.750	0.585	0.045	0.376

Notes: This table presents the estimation results for the relationship of noncommercial contracts with R&D expenditures, publications, and patents. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

Table E5: Using Non-defense R&D Contracts

	(1) ln(R&D expenditures)	(2)	(3) ln(Publications)	(4)	(5) ln(Patents)	(6)
	2nd stage IV, Industry funding	2nd stage IV, Cold War shock	2nd stage IV, Industry funding	2nd stage IV, Cold War shock	2nd stage IV, Industry funding	2nd stage IV, Cold War shock
ln(Non-defense R&D contracts)$_{t-1}$	0.372	0.357	0.281	0.710	-0.147	-0.668
	(0.146)	(0.123)	(0.133)	(0.220)	(0.172)	(0.238)
ln(R&D stock)$_{t-1}$	0.511	0.949	0.174	0.175	0.353	0.428
	(0.017)	(0.020)	(0.015)	(0.014)	(0.022)	(0.020)
Pre-sample mean R&D expenditures		-0.107				
		(0.012)				
Pre-sample mean publications				0.600		
				(0.041)		
Pre-sample mean patents						0.591
						(0.042)
Sample years	1980-2015	1993-2015	1980-2015	1993-2015	1980-2015	1993-2015
Firm fixed effects	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)	11.41	14.70	13.48	15.76	13.48	16.41
Firms	4,128		4,303		4,303	
Observations	46,478	4,631	52,207	5,801	52,207	5,801
Adjusted R-squared	-0.426	0.852	-0.342	0.303	0.023	0.187

Notes: This table presents the estimation results for the relationship of non-defense R&D contracts with R&D expenditures, publications, and patents. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

Table E6: Alternate Publication and Patent Equations

	(1) Publications	(2) Inv. hyperbolic sine(Publications)	(3)	(4) Patents	(5) Inv. hyperbolic sine(Patents)	(6)
	Poisson	OLS	2nd stage IV, Ind. R&D funding	Poisson	OLS	2nd stage IV, Ind. R&D funding
ln(R&D contracts)$_{t-1}$	0.010	0.012	0.071	0.018	0.013	-0.052
	(0.003)	(0.002)	(0.036)	(0.006)	(0.003)	(0.049)
ln(Non-R&D contracts)$_{t-1}$	-0.004	0.005		0.004	0.008	
	(0.006)	(0.002)		(0.004)	(0.002)	
ln(R&D stock)$_{t-1}$	0.586	0.227	0.211	0.506	0.395	0.406
	(0.049)	(0.016)	(0.016)	(0.063)	(0.021)	(0.023)
Sample years	1980-2015	1980-2015	1980-2015	1980-2015	1980-2015	1980-2015
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)			60.63			60.63
Firms	2,842	4,318	4,302	3,908	4,318	4,302
Observations	39,944	53,372	52,074	50,304	53,372	52,074
Adjusted R-squared		0.852	0.017		0.813	0.069

Notes: This table presents the estimation results for the relationship between R&D contracts and publications and patents. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

Table E7: Publication Equation Using Different Lags

	(1)	(2)	(3)	(4)	(5)
			ln(Publications)		
	Finite distributed lags	Two-year lags 2nd stage IV, Ind. R&D funding	Three-year lags 2nd stage IV, Ind. R&D funding	Four-year lags 2nd stage IV, Ind. R&D funding	Five-year lags 2nd stage IV, Ind. R&D funding
ln(R&D contracts)$_{t-1}$	0.007				
	(0.002)				
ln(R&D contracts)$_{t-2}$	0.005	0.072			
	(0.001)	(0.031)			
ln(R&D contracts)$_{t-3}$	0.004		0.086		
	(0.001)		(0.033)		
ln(R&D contracts)$_{t-4}$	0.003			0.090	
	(0.001)			(0.034)	
ln(R&D contracts)$_{t-5}$	0.004				0.090
	(0.002)				(0.035)
ln(R&D stock)$_{t-1}$	0.205				
	(0.019)				
ln(R&D stock)$_{t-2}$		0.159			
		(0.014)			
ln(R&D stock)$_{t-3}$			0.131		
			(0.015)		
ln(R&D stock)$_{t-4}$				0.113	
				(0.015)	
ln(R&D stock)$_{t-5}$					0.094
					(0.016)
Sample years	1980-2015	1980-2015	1980-2015	1980-2015	1980-2015
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)		57.36	50.87	46.69	42.18
Firms	3,059	3,925	3,595	3,301	3,045
Observations	36,804	47,472	43,287	39,476	36,001
Adjusted R-squared	0.880	-0.012	-0.068	-0.092	-0.107

Notes: This table presents the estimation results for the relationship between R&D contracts and publications using different time lags. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

Table E8: Measures of Publication and Patent Quality

	(1)	(2)	(3)	(4)
	ln(Citation-weighted Publications)		ln(Citation-weighted Patents)	
	2nd stage IV, Industry funding	2nd stage IV, Ind. R&D funding	2nd stage IV, Industry funding	2nd stage IV, Ind. R&D funding
ln(All contracts)$_{t-1}$	0.126		0.056	
	(0.039)		(0.049)	
ln(R&D contracts)$_{t-1}$		0.089		-0.023
		(0.032)		(0.043)
ln(R&D stock)$_{t-1}$	0.120	0.166	0.306	0.333
	(0.026)	(0.014)	(0.034)	(0.020)
Sample years	1980-2015	1980-2015	1980-2015	1980-2015
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Weak identif. (Kleibergen-Paap)	11.93	60.63	11.93	60.63
Firms	4,317	4,302	4,317	4,302
Observations	53,104	52,074	53,104	52,074
Adjusted R-squared	-0.511	-0.032	0.020	0.068

Notes: This table presents the estimation results for the relationship between contracts and measures of publication and patent quality. The publication flow is weighted by citations received from other publications, normalized by the journal-year. The patent flow is weighted by citations received from other patents, normalized by International Patent Classification (IPC) class-year. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

Table E9: Non-linear Time Effects

	(1)	(2)	(3)	(4)	(5)
		Contract value		Contract composition	
	ln(All contracts)	ln(R&D contracts)	ln(Comm. contracts)	Share R&D/ All contracts	Share comm./ All contracts
Indicator for Decade = 1980s	Baseline	Baseline		Baseline	
Indicator for Decade = 1990s	0.838	0.057	Baseline	-0.000	Baseline
	(0.128)	(0.080)		(0.017)	
Indicator for Decade = 2000s	1.113	-0.103	1.968	-0.023	0.257
	(0.183)	(0.122)	(0.108)	(0.022)	(0.022)
Indicator for Decade = 2010s	0.962	-0.336	2.452	-0.042	0.470
	(0.222)	(0.146)	(0.148)	(0.024)	(0.064)
ln(R&D stock)$_{t-1}$	0.522	0.174	0.573	-0.002	-0.005
	(0.067)	(0.036)	(0.067)	(0.004)	(0.015)
Sample years	1980-2015	1980-2015	1995-2015	1980-2015	1995-2015
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Firms	4,322	4,323	3,620	1,838	1,461
Observations	53,534	53,679	37,011	17,936	12,204
Adjusted R-squared	0.660	0.590	0.632	0.298	0.081

Notes: This table presents OLS estimates for changes in procurement contract value and composition over time, accounting for non-linear time effects. One is added to logged variables. Standard errors (in parentheses) are clustered at the firm level.

E.2 "Ticket to Play"

Table E10 presents the relationship of all contracts with R&D contracts, estimated using the 2,247 contractor firms in our sample. 2SLS coefficient estimates show that receiving R&D contracts has a positive effect on the value of subsequent procurement contracts. In Column 3, the estimate implies that a $1 million increase in R&D contracts is associated with a $14 million future increase in all contracts, evaluated at the sample means.[67]

Lichtenberg (1984) argues that "federal contracts do not descend upon firms like manna from heaven" (p. 74), but rather respond to firms' own investments in R&D. Mowery (2012) provides a supporting example from the semiconductor industry. He notes that the prospect of winning a large procurement contract supplying semiconductor components for strategic missile guidance systems was the "prize" that motivated Texas Instruments to develop the integrated circuit. Consistent with those arguments, we find evidence to suggest that R&D contracts drive corporate science because they are the "ticket to play" in the government procurement market.

Table E10: R&D Contracts Are the "Ticket to Play"

	(1)	(2)	(3)
		ln(All contracts)	
	OLS	2nd stage IV, Ind. R&D funding	2nd stage IV, Cold War shock
$\ln(\text{R\&D contracts})_{t-1}$	0.256	0.157	0.946
	(0.009)	(0.093)	(0.370)
$\ln(\text{R\&D stock})_{t-1}$	0.555	0.604	0.550
	(0.042)	(0.050)	(0.086)
Pre-sample mean, all contracts			0.170
			(0.060)
Sample years	1980-2015	1980-2015	1993-2015
Firm fixed effects	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes
Weak identification (Kleibergen-Paap)		340.32	16.01
Observations	34,278	32,740	4,130
Adjusted R-squared	0.593	-0.046	0.218

Notes: This table presents the estimation results for the relationship between R&D contracts and all contracts among contractors. One is added to logged variables. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity.

[67] Average values for *All contracts* and *R&D contracts* are $15 million and $1 million, respectively.

F Additional Figures and Tables

Table F11: Largest Contractors Over Time

Decade	Company	All contracts ($ mm)	R&D contracts ($ mm)	Sales ($ mm)	R&D expenditures ($ mm)	Publications (count)	Patents (count)
1980	GENERAL DYNAMICS	41,741	4,357	143,363	4,496	340	377
1980	MCDONNELL DOUGLAS	34,234	3,638	197,205	7,601	1,062	306
1980	GENERAL ELECTRIC	22,172	3,663	633,418	19,427	6,020	9,112
1980	UNITED TECHNOLOGIES	18,703	1,461	294,253	16,555	1,240	2,600
1980	CBS	17,835	2,596	198,005	4,299	3,246	4,169
1980	ROCKWELL AUTOMATION	16,470	7,117	184,839	5,600	2,794	1,804
1980	RAYTHEON	14,379	1,690	124,707	4,302	514	630
1980	LOCKHEED MARTIN	11,778	1,377	153,254	6,314	2,141	410
1980	LITTON INDUSTRIES	9,009	1,106	89,381	1,931	863	507
1980	MARTIN MARIETTA	8,944	3,893	80,362	2,441	738	131
1990	LOCKHEED MARTIN	67,135	21,572	271,608	10,494	3,984	1,423
1990	MCDONNELL DOUGLAS	48,293	8,295	157,802	4,248	803	276
1990	GENERAL DYNAMICS	41,054	6,930	76,350	1,466	219	217
1990	CBS	32,272	3,060	125,330	1,484	1,078	2,457
1990	BOEING	32,231	5,468	470,980	21,286	1,851	1,779
1990	GENERAL ELECTRIC	30,589	6,470	1,036,285	19,978	4,440	8,798
1990	NORTHROP GRUMMAN	26,393	4,911	98,814	2,298	750	882
1990	UNITED TECHNOLOGIES	23,243	2,733	321,761	16,093	1,091	3,454
1990	RAYTHEON	21,418	5,019	173,796	4,939	1,247	1,138
1990	ROCKWELL AUTOMATION	16,356	3,181	146,157	7,983	1,877	1,706
2000	LOCKHEED MARTIN	254,423	77,477	400,471	11,186	2,871	3,013
2000	BOEING	183,829	36,725	667,733	32,370	2,387	3,832
2000	RAYTHEON	74,966	14,171	230,652	5,769	1,986	1,898
2000	UNITED TECHNOLOGIES	49,878	11,261	463,339	16,029	1,033	3,219
2000	GENERAL DYNAMICS	43,384	8,826	233,535	3,807	567	272
2000	NORTHROP GRUMMAN	35,109	7,304	289,648	5,413	1,373	2,454
2000	HONEYWELL INTERNATIONAL	20,417	881	322,527	12,423	1,685	6,381
2000	GENERAL ELECTRIC	20,312	1,130	1,711,577	29,423	6,322	12,774
2000	OSHKOSH	17,858	1,019	37,816	459	4	110
2000	L3 TECHNOLOGIES	15,018	1,183	96,598	2,784	115	323
2010	LOCKHEED MARTIN	183,614	31,787	274,906	4,088	1,241	2,352
2010	BOEING	113,308	9,719	483,246	20,721	1,167	5,003
2010	RAYTHEON	62,844	9,603	143,825	3,606	1,084	2,203
2010	GENERAL DYNAMICS	47,548	621	189,298	2,656	274	136
2010	UNITED TECHNOLOGIES	40,706	5,484	351,065	13,492	889	4,902
2010	MCKESSON	31,960	0	854,633	2,553	812	154
2010	OSHKOSH	14,773	113	46,093	757	11	107
2010	HONEYWELL INTERNATIONAL	14,251	294	223,770	10,579	872	6,608
2010	GENERAL ELECTRIC	12,644	510	833,862	26,122	5,425	11,476
2010	L3 TECHNOLOGIES	10,685	700	79,029	1,834	93	252

Notes: This table displays the 10 largest contractors (by total value of contracts won) in each decade. Contracts, sales, R&D expenditures, publications, and patents are aggregated at the firm-decade level. The 2010s present aggregate data for just seven years.

Table F12: DISTRIBUTION OF FIRMS BY SIC2 INDUSTRY

SIC2 industry	Number of firms	SIC2 industry	Number of firms	SIC2 industry	Number of firms
28	757	32	29	58	5
36	650	22	26	60	4
38	645	49	24	21	4
73	532	27	23	63	4
35	527	29	22	10	3
37	140	51	20	75	3
34	96	59	14	76	3
30	77	79	12	61	3
87	68	1	12	12	2
20	63	65	11	42	2
48	63	23	10	45	2
33	59	24	9	54	2
99	57	16	7	7	2
39	56	31	7	64	2
26	47	78	7	72	2
67	44	82	6	47	2
13	44	15	6	2	1
25	31	17	6	70	1
50	30	62	5		
80	29	14	5		

Notes: This table displays the distribution of sample firms by two-digit SIC code.

Table F13: 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.

Table F14: 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. Groups 21, 27, 33, 50, 57, 64, 82, 86, 90, 92, 97, and 98 are currently unassigned.

Table F15: Classification into Main Industries

Main industry	Included SIC2/SIC3 codes	Description
Transportation	37, 40, 41, 42, 44, 45, 47 and all subordinate SIC3 codes	Firms manufacturing equipment and furnishing services for transportation of passengers and cargo by land, air, and water. Sample products include motor vehicles, aircraft, guided missiles and space vehicles, ships, and railroad equipment.
Chemicals	28 and all subordinate SIC3 codes except 283	Firms producing basic chemicals (e.g., acids, alkalies, salts, and organic chemicals), chemical products used in manufacturing (e.g., synthetic fibers, plastics materials, dry colors, and pigments), and finished chemical products used for ultimate consumption (e.g., cosmetics, and soaps) or as supplies in other industries (e.g., paints, fertilizers, and explosives).
Drugs	283	Firms producing medicinal chemicals, pharmaceutical preparations, biological products, and diagnostic substances.
Electronics	35, 36 and all subordinate SIC3 codes	Firms manufacturing industrial and commercial machinery, equipment, supplies, and computers (e.g., engines and turbines, office equipment, radio and television equipment, communications equipment, and electronic components and accessories).
Business services	73, 87 and all subordinate SIC3 codes	Firms engaged in rendering services to business establishments on a contract or fee basis, such as computer programming and data processing; engineering, architectural, and surveying services; research, development, and testing services; and management and public relations services.

Notes: This table displays the classification scheme used to group sample firms into several main industries. Industries not specifically listed were classified as "Others".

Table F16: Descriptive Statistics by Main Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Transportation		Chemicals		Drugs		Electronics		Business services		Others	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Publications	25	62	34	104	76	211	9	47	26	183	12	74
Patents	56	150	51	107	26	73	38	155	49	370	23	93
All contracts ($ mm)	760	3,350	10	67	7	69	11	102	12	119	45	417
R&D contracts ($ mm)	148	781	1	8	1	5	2	29	2	19	5	68
Non-R&D contracts ($ mm)	612	2,675	9	62	6	68	9	84	11	104	40	359
R contracts ($ mm)	20	129	0	5	0	2	0	5	1	5	1	14
D contracts ($ mm)	128	676	0	6	0	5	1	25	1	16	4	56
Commercial contracts ($ mm)	23	120	1	6	4	61	1	12	2	30	6	83
Noncommercial contracts ($ mm)	589	2,600	8	62	2	20	8	82	9	86	33	334
Sales ($ mm)	13,013	34,774	5,790	11,488	2,541	7,723	1,954	7,400	2,133	10,612	4,972	19,427
R&D stock ($ mm)	2,300	7,934	818	2,199	1,463	5,142	547	2,305	848	4,186	293	1,216

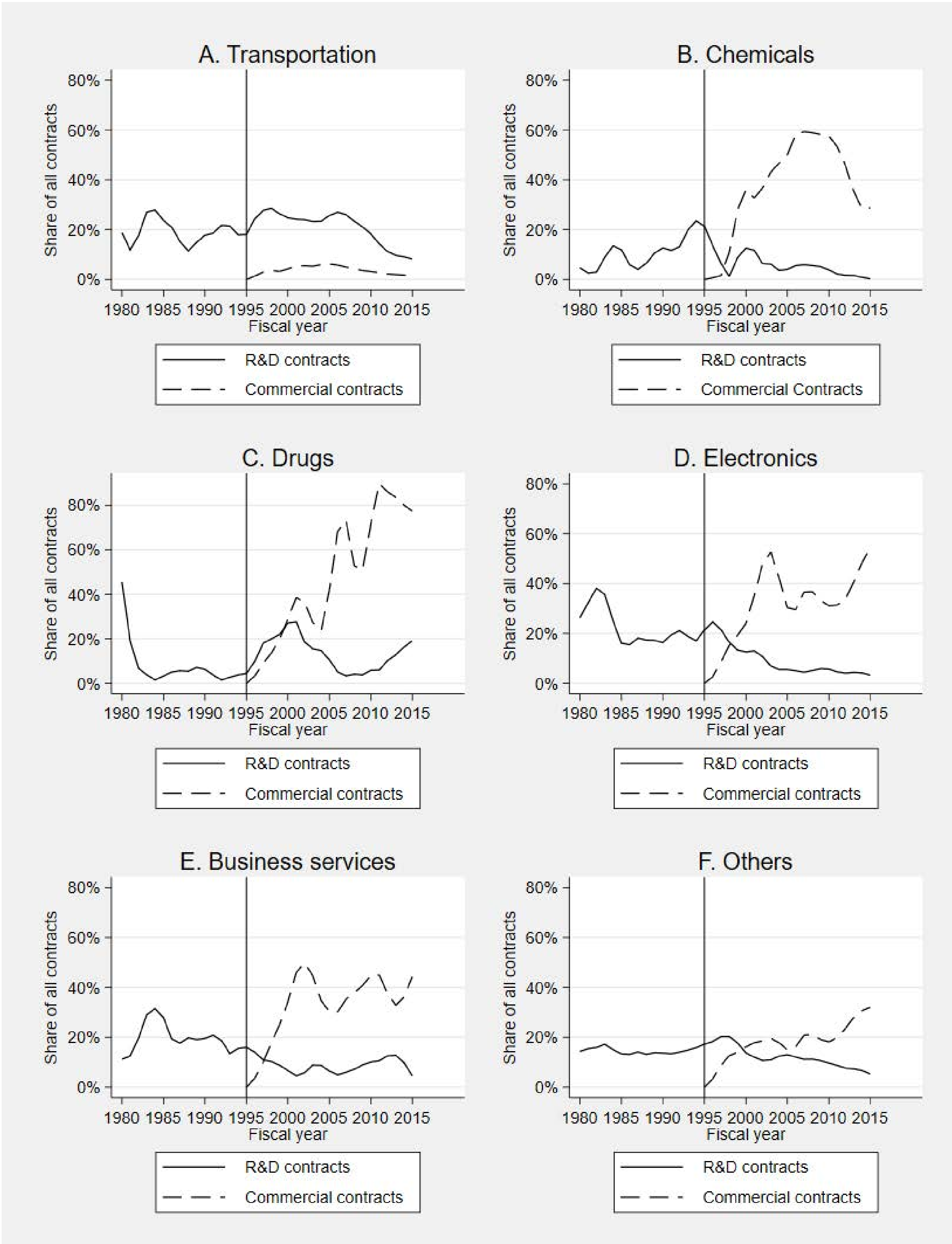
Notes: This table displays descriptive statistics over the sample period of 1980-2015 by main industry. The unit of analysis is a firm-year. Statistics are only provided for contractors.

Table F17: R&D Contractors vs. Other Firms by Main Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Transportation		Chemicals		Drugs		Electronics		Business services		Others	
	Diff.	t	Diff.	t	Diff.	t	Diff.	t	Diff.	t	Diff.	t
R&D expenditures ($ mm)	735.807	12.72	277.671	20.8	438.370	20.5	198.311	25.9	375.524	16.2	116.817	28.9
R&D expenditures normalized by sales (in $ mm)	-0.561	-1.42	-0.225	-2.0	-25.983	-2.3	-0.272	-1.5	-2.948	-1.2	0.082	0.2
Publications per $1 mm in sales	0.046	1.25	0.000	0.0	0.255	1.5	0.439	6.0	0.224	0.9	0.160	3.3
Patents per $1 mm in sales	-0.885	-3.96	0.630	2.1	-0.178	-0.7	-0.982	-0.7	0.099	1.3	-0.685	-3.6

Notes: This table displays mean comparison tests between R&D contractors and other firms within the same main industry. The two-sample t-tests use unequal variances.

Figure F2: Changing Composition of Contracts Over Time by Main Industry



Notes: This figure presents the trend in the share of R&D contracts in all the contracts obligated by the DoD, DoE, HHS, and VA to our sample firms by main industry (solid lines). It also presents the trend in the share of commercial contracts in all contracts (dashed lines). The vertical lines mark the passage of the Federal Acquisition Streamlining Act of 1994.

Table F18: Government Procurement Contracts by SIC4 Industry

Rank	SIC4	1988 Contracts	1992 Contracts	Industry description
1	7373	$1,962	$2,953	Computer integrated systems design
2	4832	$1,189	$2,080	Radio broadcasting stations
3	2411	$3	$843	Logging
4	2833	$1,079	$1,773	Medicinal chemicals and botanical products
5	3446	$758	$1,198	Architectural and ornamental metal work
6	7375	$200	$583	Information retrieval services
7	8099	$109	$418	Health and allied services, not elsewhere classified
8	8742	$122	$401	Management consulting services
9	4581	$2,403	$2,668	Airports, flying fields, and airport terminal services
10	4911	$383	$599	Electric services
...	...	...	...	...
822	3669	$4,757	$3,095	Communications equipment, not elsewhere classified
823	3795	$2,329	$559	Tanks and tank components
824	5171	$6,042	$4,168	Petroleum bulk stations and terminals
825	2394	$3,081	$1,082	Canvas and related products
826	3812	$5,146	$2,209	Search, detection, navigation, guidance, aeronautical, and nautical systems and instruments
827	3281	$4,908	$1,573	Cut stone and stone products
828	3721	$16,211	$12,295	Aircraft
829	3511	$7,347	$3,327	Steam, gas, and hydraulic turbines, and turbine generator set units
830	3769	$7,681	$3,501	Guided missile space vehicle parts and auxiliary equipment, not elsewhere classified
831	3761	$7,253	$2,862	Guided missiles and space vehicles

Notes: This table displays the total procurement contracts (in constant 2012 millions of dollars) awarded by the DoD, DoE, HHS, and VA in 1988 and 1992 to each SIC4 industry. The observations are sorted in descending order of the difference between the pre (1988) and post (1992) period.