Retreating from Science: The Long-Run Effects of the 1970s U.S. Military Disinvestment from University Research*

Daniel P. Gross† Duke University and NBER

Bhaven N. Sampat‡ Johns Hopkins University and NBER

Hansen Zhang§ Duke University

July 2026

Abstract:

Between 1945 and 1970, the U.S. Department of Defense was one of the country's largest funders of university research, and the most important in the physical sciences and engineering. Political pressures subsequently led to this funding declining nearly two-thirds by the mid-1970s and never fully recovering. We show that these cuts were felt across the U.S. research system, with ensuing declines in university scientists, PhD production, and research output. Early career scientists who were DoD-funded in 1970 were more likely than peers to leave universities, with many moving to industry. Though some became more likely to patent, in the aggregate, this appears to have reduced science-linked innovation in related technologies and compressed U.S. leadership in formerly DoD-driven fields. These effects extend to outcomes more closely related to military objectives: fewer PhDs entered the defense industrial base, and an initial increase in science-linked defense patenting in the most exposed technology areas gave way to a long-run decline.

JEL Classification: H56, I23, N42, N72, O31, O32, O33, O38

Keywords: Defense R&D; Military science; University research; Science policy; Mansfield Amendment

*We thank Eli Alster and Andy Howard at OSW CAPE and Mike Lippitz at the Institute for Defense Analyses for helpful conversations and Dror Shvadron for helping construct the PQDT-OpenAlex linkage that allows us to measure PhDs working in the defense industrial base, as well as audiences at Boston University, the 2026 ASSA annual meeting, the CEPR-LSE-Kiel Institute Conference on Defence Economics, and discussant Karthik Sastry for feedback. We also thank Mark McDonough for the policy memo that got this project started, and Jinkang Huo for outstanding research assistance. Duke University's Fuqua School of Business provided financial support. This material is based upon work supported by the National Science Foundation under Grant Nos. 1951470 and 2420824 and the Alfred P. Sloan Foundation under Grant No. G-2023-21064. All errors are our own.

†Duke University Fuqua School of Business, Durham, NC, USA; email: daniel.gross@duke.edu.

‡Johns Hopkins University School of Government and Policy, Washington, DC, USA; email: sampat@jhu.edu.

§Duke University Fuqua School of Business, Durham, NC, USA; email: hansen.zhang@duke.edu.

1 Introduction

Economic growth is widely thought to be a function of accumulated scientific understanding and the capacity to continue producing more of it—the combination of which drives technological advances that increase economic output (Romer 1990). Reflecting the modern importance of science, national innovation systems are often anchored by universities which provide scientific training and produce fundamental breakthroughs (Nelson 1993), contributing not only to productivity-enhancing innovation but also improved health and national security (Bush 1945).

In the United States, most of this activity is publicly funded, reflecting well-known arguments that science and scientific capacity are likely to be undersupplied by private actors (Bush 1945, Nelson 1959, Arrow 1962). For most of the postwar era, public funding for U.S. university research has steadily grown, sometimes explosively, as for biomedical research in the late 1990s (Zerhouni 2006). Sometimes, however, it has shrunk—and occasionally substantially. While a large literature studies how expansions in public research funding have stimulated innovation, less attention has been paid to the impacts of contractions, including the possibility that scientific capacity might be easier to dismantle than build: declines in public investment may alter the size, composition, and impacts of the scientific sector in ways that persist long after research policy stabilizes. Because science and innovation are cumulative and path dependent (Scotchmer 1991), understanding the consequences of large retrenchments may be important to understanding long-run shifts in national innovative capacity and their implications for national economic performance.

In this paper, we study what is perhaps the largest contraction in science funding in U.S. history: the Department of Defense's (DoD) retreat from science in the 1970s. For the first 25 years after World War II, the U.S. military was the world's largest sponsor of university research in the physical sciences and engineering, comparable to the National Institutes of Health's (NIH) scale in the life sciences. The military at this time funded science on the belief that progress in science was essential to maintaining military technological superiority—a view which emerged off the back of the World War II research effort. In the early 1970s, however, the political consensus for military-funded university research collapsed, amid the tensions raised by the Vietnam War. Congress subsequently put significant restrictions on what research the military could fund and reduced its budget. By the mid-1970s, DoD's university research contracts had declined nearly 70% in real dollars from their late 1960s peak, and since then have never fully recovered. Today, DoD is a less prominent patron of U.S. university science than it was during the Cold War.

We probe the effects of this withdrawal on U.S. science and technology using a broad range of data sources, including on DoD research contracts; DoD-funded scientists; university research, scientific employment, and PhD production; individual scientists' employment histories, and measures of national scientific output and technological innovation. Identifying universities, fields, and individuals who were relatively more dependent on DoD research support in 1970, and therefore more exposed to the post-1970 contraction in DoD research funding, we examine post-1970 trajectories in these outcomes in relation to this exposure. Broadly, we find that after 1970, science contracted significantly in the universities and fields DoD was supporting: publications and PhD training declined, and DoD-funded early career scientists became more likely to leave the academy. At the national level, publication output in traditional DoD-supported fields declined relative to other countries, compressing U.S. leadership in global science in these fields. Nationwide science-linked innovation in technology areas most exposed to these cuts declined as well, indicating that the effects of funding cuts extended beyond universities and into downstream sectors.

Underlying this analysis is a new dataset we develop measuring the U.S. postwar university research system, and the military's place in it. Roughly a dozen data sources contribute to our measurement, which we focus around 1960 to 1990. These include contract- and grant-level data for DoD and the National Science Foundation (NSF); university-level financial data; individual-level data on scientists and PhD graduates; and records of publications and patents. Crucially, information from one of these historical datasets—the NSF's National Register of Scientific and Technical Personnel—allows us to identify DoD-funded university scientists in 1970 (on the eve of the military's retreat from science), which provides us a measure of exposure and we can use directly or aggregate. Linking these data sources to common identifiers, we construct several analytical datasets, including university-year, university-field-year, individual-year, country-field-year, and technology-year panels, where we can measure changes in scientific research, technological innovation, and training over time—the three core outputs of the modern research university.

Because military research contracts are issued at the university level (not university-field or investigator level) and realized funding could be endogenous to research potential, we will not use these measures directly. We instead compare universities, departments, individuals, and fields with differential reliance on DoD support prior to the 1970s withdrawal, measured by the DoD-supported share of personnel in 1970—which we show is strongly predictive of universities' actual funding declines. In effect, we evaluate post-1970 changes in the trajectory of units with high versus low pre-1970 military support (for some outcomes, any versus none).

We observe one consistent result across nearly all of our analyses: declining output in the units most exposed to these research funding cuts which persist to at least the end of our sample (1990), and presumably continued after the Cold War ended in 1991 and military research and procurement budgets were reduced even further. Our first set of analyses examines research universities, where we show that university departments with DoD exposure experienced significant reductions in headcount, research output, and PhD production post-1970 relative to unexposed departments at other universities and other departments in the same university.

Our second set of analyses examines individuals. We find that early career university researchers who were DoD-supported in 1970 were more likely than peers to subsequently exit university employment, entering industry at double the average rate. We find attenuated effects for AEC-supported researchers and no such effects for NIH or NSF, and placebo tests on DoD-supported early career researchers a half-decade earlier show no comparable effect—reinforcing that this pattern is likely attributable to the 1970s defense research funding environment specifically. Sectoral reallocation is consistent with contemporary anecdotal accounts, and we speculate that this reallocation may have temporarily augmented some industrial research and innovation outcomes, but at the expense of a weakened scientific base over the longer-term.

Our third set of analyses probes this latter possibility by evaluating national science and technology outcomes. Specifically, we compare the changes in national scientific output (publications) over time across countries and in fields which were more versus less heavily DoD supported prior to 1970, comparing U.S. science to the UK, Germany, and Japan. The evidence suggests foreign catchup after 1970, with no differential pre-trends. When we measure patent classes' exposure to DoD funding cuts based on the rate at which patents in those classes cite science of fields with differential DoD support, we find that science-linked U.S. patenting (patents that cite science and have a U.S. first inventor) declined in more exposed technology areas, relative to others. Taken together, this evidence suggests DoD's withdrawal from science may have materially affected national competitiveness in science and science-linked innovation.

Collectively, these results point to broad impacts of large funding cuts across the scientific enterprise, which in an economic paradigm might be expected to create headwinds for economic progress and growth. But what of their military impacts? In contrast to the traditional economic motivation for innovation studies, the U.S. military's goal for R&D is enhancing military performance—and although national security is one of the original rationales for U.S. science policy (Bush 1945), to our knowledge there is little systematic evidence of how science relates to military outcomes. Though such links are intrinsically difficult to make, due to the large distance between basic research and military technology and strategy, we explore two intermediate links: the number of PhDs entering the defense industrial base, and indicators of science-linked military innovation. We find that the 1970s research funding cuts are associated with large declines in the long-run supply of scientific human capital for defense contractors, and that although science-citing defense sector patenting initially increased in more exposed technology areas as scientists reallocated out of universities and into government or industry, by the 1990s it was no longer keeping pace.

These findings contribute most directly to a small but growing set of economic studies examining the impacts of research funding cuts (e.g., Babina et al. 2023, Tham et al. 2024, Azoulay et al. 2025). Most of this research has studied the effects of localized and/or temporary research funding cuts on investigator-level outcomes, often over short horizons. Less evidence is available on the effects of large, sustained declines in research support on long-term or systemic outcomes, for the simple reason that sharp, distributed changes in the overall scale of science funding are rare, and when they have occurred, have typically arisen from politically-driven structural realignments. Our goal is to study one of the few such episodes since modern U.S. innovation policy emerged after World War II and assess its impact on the overall American techno-scientific enterprise. In this case, the passage of time also enables us to evaluate long-run effects.

This theme places our work naturally into the wider literature studying the effects of innovation policy, much of which emphasizes specifically public investments in science. This literature often relates variation in funding across time, space, or field to outcomes, often using quasi-experimental variation to identify causal effects—such as by comparing just-funded to just-unfunded proposals (e.g., Azoulay et al. 2019, Howell 2017) or exploiting instrumental changes in the scale of support in different subjects (e.g., Myers 2020). As a result, available evidence speaks mainly to the effects of (more commonplace) marginal changes as opposed to (occasional) sweeping disruptions. Where the latter has been studied, it is generally in technology rather than science, and for expansions rather than contractions (Gross and Sampat 2023a, Kantor and Whalley 2025), whose effects may not be symmetric: research capacity may be slow to build, easy to destroy, and hard to recover (Azoulay et al. 2010, Waldinger 2016, Baruffaldi and Gaessler 2026).

Our research is both informed by, and adds to, historical scholarship on twentieth century changes in U.S. R&D policy. Much of this work focuses on policy institutions (e.g., Kevles 1977, Kleinman 1995, Hart 1998) and government-university relations, including vis-à-vis the military (Geiger 1993, Lowen 1997). Universities' place in the postwar military-industrial complex has been a subject of research in science and technology studies (e.g., Leslie 1993), but the nexus of science and national defense has received relatively little empirical attention. This observation in part motivates us to study military research.[1] What the impacts of research on national security are—and even before that, what the relevant endpoints to study are, and how can they be measured—are enormous open questions. Beyond encouraging more work on this problem, we suggest that one path forward in

[1]In this spirit, the paper's focus on defense innovation economics connects it to a wider body of work on defense economics, where scholars have also studied economic incentives in military procurement (Rogerson 1994), learning-by-doing in weapons production (Ilzetzki 2024), and the spillovers of defense R&D (Draca 2013, Gross and Sampat 2023a, 2025b, Gross and Roche 2025, Moretti et al. 2025), among other themes.

our context is to measure the scientific and technical workforce underpinning the defense industrial base—similar to Nice (2025), who specifically emphasizes foreign national STEM advanced degree recipients as an important input to U.S. national security innovation.

Though the scale of the U.S. military's funding for university science in the 1960s was comparable to NIH at the time, the latter is now many multiples of the former. Perhaps as a result, the life sciences have grown far more quickly than the physical sciences and engineering since the 1960s, and are arguably the area in which the U.S. has maintained its largest global edge.[2] A provocative—and to our knowledge, untestable—question is how the trajectory of physical science and innovation might have been different over the past 50 years had DoD stayed in the business of supporting research in its priority fields at a comparable scale to the modern NIH. A second question is whether military research could potentially have such impacts today, in a different (and more mature) scientific and institutional environment. We leave these questions for future work.

We proceed as follows. Section 2 describes the ascendance of the U.S. military as a research funder in and after World War II, its descent after 1970, and the politics of science in this era. Section 3 introduces the data sources we use to document these changes and study their effects. Here we also describe our empirical approach. Section 4 evaluates the effects of the 1970s defense research funding cuts on research universities, including faculty size, trainees, and research output (Section 4.1) and individual scientists' careers (Section 4.2). Section 5 explores the impacts of these cuts on U.S. science and technology broadly. Section 6 discusses the relationship of science to national security and the military returns to research, as well as the challenges of such evaluations. Section 7 concludes by offering potential directions for future research.

2 Historical Background: Defense Research Funding and the U.S. University Research System, 1945-1975

Federal research policy was an invention of the 20th century. Prior to 1940, the U.S. government funded very little research outside of agriculture. World War II, however, motivated a fundamental change in the federal government's relationship to science, as the newly-created Office of Scientific Research and Development (OSRD) partnered with universities and firms in a national effort to develop new weapons, medicines, and other science and technology for war (e.g., Gross and Sampat 2023a,b, 2025b). As the war effort progressed, a consensus emerged that the U.S. government should

[2] As one reflection of the growth of U.S. biomedicine, comparing the 1950-1969 to 2000-2019 periods, the share of U.S. STEM PhD graduates with biological or biomedical science and engineering degrees grew from 26.3% to 33.3%, whereas the share with physics degrees fell from 12.9% to 6.6%. If we include the health sciences in this tally, then health, biological, and biomedical science and engineering have collectively increased from 28.7% to 41.6% of PhD graduates. Calculations based on data from Shvadron et al. (2025a).

continue funding research at universities after it ended, with the view that a productive research enterprise would advance national defense, health, and economic prosperity in peacetime. The implementation of such a policy, however, would inevitably be different than during the war, and the details were contested: whereas Vannevar Bush (architect of the wartime research effort) argued for a singular "National Research Foundation", run by scientists, that would fund undirected basic research by the country's best scientists and best universities, Senator Harley Kilgore (D-WV), a New Deal Democrat concerned about the concentration of power, proposed an agency which would fund basic and applied research focused on problems of public interest, with a broad geographical and institutional distribution of funding and political accountability.

While these alternatives were debated by Congress, OSRD's residual research contracts were transferred to other agencies, setting the stage for a more fragmented institutional arrangement than Bush or Kilgore had advocated. The Office of Naval Research (ONR) took ownership of military science and technology; the Atomic Energy Commission (AEC), nuclear research; and the National Institutes of Health (NIH), biomedical research. Thereafter, these agencies' research budgets began to grow. Congressional appropriations for military research accelerated in the early 1950s as the Cold War began to take root and especially in the late 1950s and early 1960s when the Space Race began. By the mid 1960s, DoD was investing nearly (2025 USD) $80 billion per year in R&D, and the recently-created National Aeronautics and Space Administration (NASA) another $50 billion—together over 4x the rest of the federal government combined.

Much of this funding was for technology development. But mission agencies were also significant sponsors of university research, with DoD the country's largest source of research funding outside of biomedicine. Contemporaries in the mid-1960s recognized that "Congress has been quite liberal in permitting the mission-oriented agencies to support basic research," arguing that the U.S. would not have attained its "reputation for world leadership" in science and technology without it (Brooks 1965, p. 89). As Nelson and Wright (1992, p. 1951) similarly explain,

> [T]he bulk of government support for university research came not from [NSF and NIH] but from agencies pursuing particular missions and using university research as an instrument in that endeavor... the Department of Defense and the Atomic Energy Commission provided large scale research funding in fields of particular interest. And the support was not just for basic research. These agencies funded research that involved applied science and engineering departments in work at the forefront of technologies in materials and electronics. By the middle 1950s the American research universities clearly were ahead of those in the rest of the world in most fields.

Historians have documented the emergence over this period of the military industrial complex and the Cold War research university (e.g., Geiger 1993, Lowen 1997). As we show later, this pattern of DoD support is empirically visible in our data, especially in fields which were defense priorities, such as in physics, earth sciences, the emerging fields of computer science and materials science, and engineering. The logic behind military investments in science was borne of World War II and rested in the dual ideas that (i) military advantage required technological superiority and (ii) military technology depended on advances in science, making the pace of science, and the workforce producing it, key rate limiters for military performance. Some of this science was at the time too specific or immature to receive support from other sources, but more generally both Congress and the Defense Department appear to have interpreted this need broadly.

As a result, resources were distributed widely, and substantive progress in many of these fields could be attributed to DoD support. Through its research funding offices in service branches (Army, Navy, and Air Force) and through the newly-created Advanced Research Projects Agency (ARPA, established 1958), DoD was the leading patron in oceanography, seismology, atmospheric physics, radio astronomy, solid-state physics, electronic engineering, information theory and computing, applied mathematics, and operations research—in all cases due to their potential military relevance. Efforts to improve foreign nuclear test detection, ballistic missile defense, and the resilience of communications networks were examples of research programs at ARPA in this time which had significant scientific spillovers. Beyond the science, DoD was also a significant and stable source of support for large-scale scientific infrastructure, from computing centers and shared instrumentation facilities to observatories, field stations, and sea-faring research vessels.

2.1 The politics of military science

The military-university research partnership was ultimately dependent on congressional approval. Through the 1950s and early 1960s, bipartisan support for defense R&D was high, reflecting a shared view in Congress that science was important to national security. In the late 1960s, however, the political balance began to fracture. The Vietnam War intensified scrutiny of defense spending and prompted new demands for oversight and constraint (especially from Democrats), and universities became prominent sites of antiwar protest, complicating the relationship between universities, the military, and the military's Congressional supporters (especially Republicans). Both developments weakened the broad political coalition behind expansive defense sponsorship of university research during the early Cold War, putting this partnership under new strains.

This fracturing culminated in a fundamental change in how the Defense Department was authorized to spend money on R&D: reflecting concerns that DoD had become a "backdoor National Science Foundation" that was showering resources on university research without restraint, Congress added a rider to the 1970 military budget authorization act which prohibited funds from being used for research without "a direct and apparent relationship to a specific military function or operation"

(P.L. 91-121, §203). Known as the Mansfield Amendment (after its Congressional champion, Senate Majority Leader Mike Mansfield (D-MT)), this rider formalized a more restrictive interpretation of military relevance in university science and forced DoD to abandon its most permissive practices, which previously held that all fields of science and technology held the potential for military application and all research it funded was relevant to defense needs. As the House Armed Services Committee explained in approving its version of the bill, the language "military function or operation" was meant to be interpreted in its narrowest possible sense.

The Mansfield Amendment caused an immediate shift in the amount and types of science the Defense Department was willing to fund. Practically, the language of the Mansfield Amendment also created "a thicket of ambiguities" (Nichols 1971, p. 31) over how the relevance criterion should be applied. Barber Associates (1975, p. VIII-21) explain in contemporary writing that its effect was to "make mission-oriented agency bureaucrats much more conservative in supporting basic and applied research, biasing research support toward shorter-term efforts with obvious concrete applications and away from longer-term, less-constrained and potentially more innovative undertakings." Reflecting these constraints, military research contracts began including formal DoD relevance statements in 1970 (see example in Appendix Figure A.2), and ARPA became DARPA in 1972, formally adding "Defense" to its name.[3] To researchers at the time, this marked the "end of Eden": the end of a "trouble-free paradise for working, getting your ideas approved, getting funding for them" (Ed Feigenbaum, interviewed in Aspray 1989). Though the language of the Amendment was softened in 1971 and removed in 1972, contemporaries explain that its impacts continued to reverberate in the narrowing of what research DoD would fund.

Even then, the Mansfield Amendment was only one manifestation of the broader challenge that military research faced in the 1970s. As Senator Mansfield explained to Secretary of Defense Melvin Laird after its passage, his true intent was "to reduce [the] dependency by the scientific community on the Department of Defense" altogether and promote the responsibility of civilian agencies for the country's long-term basic research. Thus, at the same time as these constraints were imposed, Congress was also cutting DoD's R&D budget, with a particular target on university research. The fallout was swift. By mid-1970 alone, a number of major DoD sponsored university research programs had been downsized, shelved, spun out, or terminated altogether (Boffey 1970), and many more would follow over the next several years. Beyond the research itself, a corollary to these cuts was the loss of "independent university scientists knowledgeable enough about defense technologies,

[3]The then-Director of ARPA (Ed Rechtin) described the competing pressures of the Mansfield era, where university researchers "didn't dare stand up and say what they were working on was for purposes of defense" (due to student and faculty opposition), but if they claimed their DoD-funded work did not have military application, then "Whish. You get shot through the other temple [when] Congress says 'What the hell is Defense putting that money up for?'" (Ed Rechtin, quoted in Barber Associates 1975, p. VIII-10).

and about the strategic issues involved, to seriously debate national security policy" (Nichols 1971, p. 31), which had been abundant since the end of World War II.

The end result was that DoD investment in university research declined sharply over the first half of the 1970s, by our calculations falling 68% between 1969 and 1975 (based on military research contracts to universities). This decline is visible from multiple sources, which we present in Figure 1. Panel (A) shows total military research obligations at universities, by year, in 2025 USD. Panel (B) illustrates the relative magnitude of this decline in the university research enterprise, showing universities' average change in military research funding over time in proportion to total research expenditures in 1969; the blue line shows the straight average, and the red line weights by pre-1970 institution size. Panel (C) shows the share of STEM PhDs from U.S. universities who acknowledged DoD support in their dissertations falling by half over the next decade, and Panel (D) similarly shows the share of research articles in prominent general-interest scientific journals (Science, Nature, and PNAS) that acknowledge DoD support declining by over half.[4]

[Figure 1 about here]

2.2 Reinforcing and countervailing changes at other federal funders

The decline in defense science funding could have potentially been offset by changes elsewhere in the federal R&D portfolio. As Senator Thomas McIntyre (D-NH) explained, the intention of Mansfield and his supporters that the Amendment "would produce large scale reductions in Department of Defense research programs [that] would be offset by corresponding increases" at civilian agencies. However, outside of the transfer of a few institutional centers to NSF support (e.g., ARPA-funded materials science laboratories), this offset did not materialize. Obstacles included a Congress reluctant to rapidly expand the NSF, differences in NSF priorities and evaluation mechanisms that led to different funding patterns, and earmarks in NSF appropriations that limited how much its budget could be used to fund this work. The result, as McIntyre put it, was that "The academic community was saddled with most of the final burden ... [and] many academic investigators have found themselves cut off from the research support necessary" to continue their work. Contemporaries similarly observed that "Few of the cut projects have been supported by other agencies during this period of constrained federal R&D" (Nichols 1971, p. 30).

Beyond NSF, the broader funding environment was generally stagnant or contractionary. Though in the late 1960s, AEC and NASA were also large research sponsors in some defense funded fields,

[4] Further analysis indicates that beyond this overall decline in funding, the composition changed, with large awards giving way to smaller ones. Appendix Figure C.4 plots densities over the size distribution, which shifted substantially down after 1970, with the largest change at the $500,000 to $5 million range—suggesting that higher-dollar research infrastructure funding may have especially been a casualty of the Mansfield era.

both were linked to geopolitics and the national security state, and neither was expanded to offset the decline in defense research support. If anything, the end of NASA's Apollo program in the early 1970s (following the successful moon landing in 1969) contributed to a wider decline in research funding for would-be defense supported fields such as aerospace engineering, materials, electronics, or atmospheric sciences)—reversing an intense but ultimately short-lived surge in resources that the moonshot had created for university research in the late 1960s.[5]

By the 1980s, DoD was thus no longer the cornerstone of the university research system it once had been, and most of the fields exposed to these changes had not found substitute patrons of the same scale. Although the Reagan-era military buildup produced a modest recovery, the end of the Cold War in the early 1990s brought to a close the postwar era of large, open-ended military investments in science and research infrastructure, whose mission value eroded.

3 Data and Empirical Approach

3.1 Data on U.S. science and science funding

To evaluate the impacts of the U.S. military's retreat from science in the 1970s on the American scientific enterprise, we combine data from a constellation of sources, providing information on: (i) defense research funding, different universities' and fields' ex-ante exposure to funding cuts, and potential NSF offsets, (ii) universities' employment of scientists, PhD production, and individual scientists' careers, and (iii) university and nationwide scientific research (publications) and science-based invention (patents). To connect these data together, we manually crosswalk universities in each dataset to a common set of identifiers (IPEDS codes); we likewise crosswalk research subjects and fields to a common set of major fields (historical SED major fields); and, where relevant, we link individuals across datasets and over time.[6] Here we summarize these data sources and how we link them together. Further details are provided in Appendix B.

[5] We discuss the concurrence of defense research funding cuts in the 1970s with the termination of the Apollo program, and its implications for causal interpretations, in Section 3.3. Insofar as our goal is to evaluate the effects of large cuts to university research funding, coinciding declines in NASA support are more a matter of attribution than identification. Even so, multiple pieces of evidence will suggest that the results of this paper are more likely to be attributable to DoD than NASA, including their breadth, scale, timing.

[6] We use data from the U.S. Department of Education's Integrated Postsecondary Education Data System (IPEDS) for 1980 through 2021 to establish a base sample of institutions and manually link universities in our data sources to this set. Our analysis will ultimately restrict to research universities (Carnegie Classification R1/R2), as reported by IPEDS. Table B.4 lists the universities in our final sample. We use major fields reported in historical editions of the NSF Survey of Earned Doctorates (SED, an annual census of new PhD graduates from U.S. institutions) as a standardized measure of research space, restricting our focus to STEM fields (i.e., those in the life sciences, physical sciences, mathematical and computer sciences, and engineering), and manually link individuals and scientific publications to these fields. A list of the included fields is shown in Appendix Table B.5. For much of our analysis, we will combine engineering sciences into a single "Engineering" category.

3.1.1 Scale of and exposure to DoD funding cuts

We begin by documenting the funding shock itself. We measure DoD support for university research using administrative records of military research, development, test, and evaluation (RDT&E, henceforth R&D) contracts from 1966 to 1990, focusing on basic and applied research contracts (budget activity codes 6.1 and 6.2) made to universities.[7] We identify university contractors through organization type codes in these administrative records and manual evaluation of contractor names. Contract values are converted to constant (2025) dollars. As shown in Figure 1(A), DoD university research contracts declined sharply beginning in fiscal year 1970 and fell by roughly two-thirds in real terms by the mid-1970s. These cuts were distributed relatively evenly across universities, in proportion to existing levels of support: universities with the most pre-1970 funding saw the largest declines (Appendix Figure C.1). Using data from the U.S. government's Higher Education General Information Survey (HEGIS), which was administered to U.S. universities between 1969 to 1986, we measure universities' total research expenditures in 1969 as a benchmark for these declines, which on average amounted to roughly 10% of universities' overall pre-shock research budgets (Panel B). Since the affected fields comprised only a slice of university science, this figure implies a significantly higher decline in the fields DoD would have typically supported. To corroborate this shift, we collect data from other independent sources, including data on DoD-funded journal articles and PhD dissertations. In effect, we complement measures of the R&D input (spending) with measures of outputs (new discoveries and trainees). Because systematic measures of journal articles' sources of funding were not available for this period, we created them ourselves, extracting funder data from all articles published in three major cross-disciplinary journals between 1960 and 1990: Science, Nature, and the Proceedings of the National Academy of Sciences (PNAS). Similarly, since neither the U.S. government nor any other source has maintained data on which PhD graduates it has supported, we processed dissertations of STEM PhD graduates at U.S. universities between 1960 and 1990 (obtained from ProQuest) to extract funding sources (see Shvadron et al. 2025a). Both sources corroborate the patterns in Figure 1(A), with the DoD-funded share of graduates and articles declining by half to two-thirds during the 1970s (Panels C and D).

Exposure to the DoD funding cuts. The majority of our analysis will take place over university-fields—effectively, at the level of university departments. Because the R&D contract data do not consistently indicate the type of science they supported, and because observed funding cuts are

[7] In contrast to civilian science funders like the NSF and NIH, which issue grants, contracts were the primary mechanism through which DoD funded university science (and R&D more broadly) in the period we study. The Defense Department's use of grants or cooperative agreements for university research began to grow after the Federal Grant and Cooperative Agreement Act (P.L. 95-224) took effect in 1978. Even then, grants remained less common than contracts in defense research funding, for both operational and cultural reasons. To our knowledge there is no public, consolidated data source for DoD research grants prior to the 2000s.

potentially endogenous, our analysis will instead make use of information on pre-1970s DoD-funded investigators, and the concentration of such investigators across universities and departments. To do so, we turn to the National Register of Scientific and Technical Personnel (NRSTP), a biennial, NSF-administered survey of the country's scientists. The survey received high response rates and included information on a wide range of respondent characteristics, including demographics, education history, employer and area of specialization, and most importantly, whether their work was supported by each of about a dozen federal agencies. We use data from the final NRSTP survey wave, which was administered at the beginning of 1970 (shortly after the Mansfield Amendment was enacted, and before the austerity of the 1970s had taken effect).[8]

The share of NRSTP scientists reporting DoD funding in 1970 in different universities and fields serves as our principal measure of exposure to the 1970s funding cuts, capturing the intensity of a university's or field's dependence on defense support. Similar measures can be calculated for other agencies. To illustrate the variation in our data, Table 1 lists three prominent universities—MIT, Stanford, and Harvard—and the share of associated scientists in 1970 reporting (i) any federal agency support and (ii) support from each of four mission research funding agencies (DoD, AEC, NASA, and NIH). Though roughly 70% of scientists at each institution reported federal support, the composition varied substantially: over 25% of MIT scientists had defense funding, and only 15% NIH funding, reflecting MIT's ties to the defense sector; conversely, under 10% of Harvard scientists had DoD funding, and nearly 40% NIH funding, reflecting the size of the life sciences and the medical school. Stanford, across all measures, is in between. Beyond prima facie validation of the data (these patterns are consistent with our priors), Table 1 suggests meaningful variation in institutional exposure to declines in defense-funded research.

[Table 1 about here]

As these examples suggest, exposure varies considerably across institutions and across fields within institutions. Engineering, physics, computer science, and certain areas of mathematics had high rates of DoD support, whereas DoD support of biomedical and agricultural research was minimal, as these were the domain of other funders (the NIH and U.S. Department of Agriculture, or USDA). Table 2 lists the top 15 most exposed university-fields by this measure, where 45% or more of researchers were defense supported. As with Table 1, the contents of this list are consistent with our understanding of the contemporary research landscape and these universities' relationships to the

[8]We supplement the 1970 NRSTP with analogous data from the 1969 National Engineers Register (NER), a nearly identical NSF-run survey of engineers (including university engineering faculty), which had been included in early editions of the NRSTP but were split out to their own survey in the late 1960s. Henceforth we will refer to the NRSTP and NER samples and derived measures collectively as the NRSTP.

Defense Department (e.g., via the Applied Physics Laboratory at Johns Hopkins, the University of Dayton's links to the Air Force, the University of Utah's ARPA-funded computer science department, or MIT's broad engagement with defense research).

[Table 2 about here]

Additional evidence indicates that our NRSTP-based exposure measures are meaningful predictors of actual funding changes at the university level, where both can be measured. For each university, we calculate the change in total DoD R&D contracts between 1967-69 and 1975-77 (grouping up years to smooth annual fluctuations), and in Figure 2 we relate this change to exposure. Panel (A) shows that for the large majority of universities whose defense research funding declined, the scale of exposure predicts the scale of that decline. Panel (B) shows that for all universities (including the small number whose funding incidentally increased), our exposure measure predicts changes in funding as a share of pre-Mansfield (1969) research expenditure.

[Figure 2 about here]

We supplement these data with information on historical NSF grants between 1965 and 1980, which we use to evaluate whether defense research funding cuts may have been offset by countervailing increases in NSF funding. We obtain historical grant data by digitizing NSF's annual "Grants and Awards" publications listing grants made in the prior fiscal year, which were published from NSF's founding through the early 1980s, with information on the principal investigator, institution, title, value, and NSF division and program which issued the grant.[9]

3.1.2 Measures of the scientific workforce

One subset of our analysis will evaluate university employment, PhD production, and the evolution of scientific careers. To do so, we construct a panel of university-employed scientists from recent (post-2005) editions of American Men and Women of Science (AMWS). AMWS provides biographical profiles of active scientists, including complete education and employment histories, and covers a very large number of American scientists across all sectors.[10] From these records, we recover employment

[9]Though electronic records of NSF grants are available from NSF's website as early as the 1950s, prior to 1975 these files are missing essential fields for our analysis (such as PI or NSF program) and are missing grants that appear in the print volumes. We therefore prioritize the print records for our analysis.

[10]These AMWS editions we provide profiles of roughly 250,000 American scientists—nearly 200,000 with a PhD—including 70,000 who were granted their PhD before 1970. Though AMWS claims to sample prominent scientists, its catchment is broad, and it is to our knowledge the most comprehensive available resource for tracking individual scientists' careers over our study period. For the period we study (1960-1990), 2005+ is an opportune time to sample from AMWS, as this is when many scientists of this era are likely to be added to the publication (in/after the prime of their careers), at which point their full work history is then provided.

spells for scientists active during 1960-1990, classify employers into types (e.g., university, industry, government, hospital, non-profit, etc.), and link university employers to IPEDS. We additionally assign individuals to fields based on their self-described areas of expertise, and aggregating across individuals, we create a university-field-year panel of scientist employment. Using the AMWS employment histories, we also create an individual employment panel, where we observe career transitions between employers and across sectors.

We additionally measure universities' PhD production, using NSF's Survey of Earned Doctorates (SED), an annual census of PhD graduates from U.S. institutions which has been conducted since 1958 and which reports doctorates by university, field, and year. We augment the SED counts with similar measures constructed from ProQuest Dissertations and Theses Global (PQDT), an individual-level dissertation database which approximates the universe of U.S. STEM PhD graduates for the period we study and which has the added feature that it includes identifying information that we can use to link graduates forward into their careers.

To evaluate implications of defense research funding cuts for the defense sector specifically, we also develop new measures of PhD graduates who participate in the defense industrial base (DIB), operationalized as those who later publish research while employed at a DIB firm. To do so, we use annual lists of DoD's top 100 contractors to identify DIB firms, and a linkage from PQDT graduates to their future publications from Shvadron et al. (2025b).[11] Because the boundaries of the DIB are fuzzy, and top DoD contractors can range from traditional defense prime contractors (e.g., Lockheed or Boeing) to large civilian firms with only incidental defense business (e.g., General Motors), we develop two sets of firms which could plausibly be viewed as DIB: a more conservative set consisting of firms with significant defense business, and an expanded set adding firms which we view as borderline cases, in both cases dropping firms for which DoD was a relatively minor customer. In total, roughly 5% of the graduates in our sample enter the DIB (by either definition). The largest employers of these graduates are Texas Instruments, Lockheed Martin, Boeing, the Aerospace Corporation, SAIC, Hughes Aircraft, United Technologies, and Northrop Grumman—all of which were indeed cornerstones of the DIB in this era.

3.1.3 Publications and patenting

We measure university research output using publication data from OpenAlex, which we aggregate to the university-field-year level using authors' institutional affiliations and primary field that OpenAlex associates to each article.[12] In addition to the university-field panel, we also create a country x field

[11] We are grateful to Dror Shvadron for helping us match OpenAlex affiliations to DoD contractors.

[12] OpenAlex classifies articles to a proprietary hierarchical partitioning of research space, which it creates by clustering textually similar publications and labeling these clusters. Research fields in the OpenAlex classification system are straightforward to map to the SED major fields which are the basis for our analysis.

panel of national (U.S. and other country) scientific output, which supports an assessment of the effects of defense research funding cuts on national science, which we perform by comparing the growth of U.S. science against Germany, Japan, and the UK.

We additionally measure patenting activity at the individual, university, and national level, using information from multiple sources. The base layer consists of patent metadata from Google Patents, including inventors, assignees, and CPC codes. Individual patenting is measured at the AMWS scientist-year level, using the sample of linked patents described in Appendix B.4.3. Our measures of university patenting focus on inventions produced at universities with government funding, and make use of the Government Patent Register, an archival administrative (USPTO) record of government interest patents which we have collected in prior work (Gross and Sampat 2025a). Although many patents resulting from university research in the pre Bayh-Dole era were owned by the government and would not be identifiable as university-generated from the patent publication itself, these records report the research organization as well as the federal agency which supported the underlying research. Using this information, we create a university-year panel measuring patents produced with support from DoD and other federal mission agencies.

Finally, we construct a panel of nationwide patenting by U.S. inventors at the 4-digit CPC level, counting (i) total annual patents, (ii) DoD-funded patents (using the Government Patent Register), (iii) science-citing patents (measured as patents which reference scientific publications in their text; see Marx and Fuegi 2020, 2022, Bryan et al. 2020), and (iv) science-citing DoD-funded patents. We additionally measure CPC-level exposure to the 1970s funding cuts by (i) computing the share of patent citations to science in a given CPC that are made to publications in each field of science, (ii) computing the share of NRSTP scientists in each field in 1970 with DoD support, (iii) crossing them, and (iv) summing. The logic of this approach recognizes that different technologies are linked to different fields of science, and different fields of science are more or less heavily defense supported. The resulting measure is in effect a weighted average which captures the degree to which specific technological domains were downstream of DoD-supported science. Using this measure, we will evaluate cross-technology differences in patenting after 1970.

3.1.4 Linking these data sources together

Beyond data collection, additional infrastructure is needed to connect these datasets to each other. We undertake three linking efforts. The first is to connect universities across datasets (specifically, DoD contracts, HEGIS financials, NRSTP scientists, AMWS scientists, SED graduates, PQDT graduates, OpenAlex publications, NSF grants, and university patents) to a common set of identifiers. For all datasets other than AMWS, we manually link every university string to IPEDS codes; approximately 25,000 institution strings are reviewed in this manner. For AMWS we take a slightly different approach: given the roughly 185,000 unique employer strings in our AMWS sample, we manually process employers in descending order of associated person-years until we have processed 80% of all employment spells, manually linking those which we can to IPEDS codes. For the remainder, we develop a procedure that uses an ensemble of frontier large language models (LLMs) to link employer strings to IPEDS codes where possible, cross-validating links across models and retaining only high-confidence results (see Appendix B.4.1 for discussion).

The second linking we undertake is to link subjects and fields across data sources.[13] We crosswalk subjects and fields in each of our data sources to the aforementioned SED major fields (see Appendix Table B.5). As with universities, for all datasets other than AMWS we create comprehensive manual crosswalks, reviewing all values in the input datasets. For the 80,000 subjects in the AMWS data, we first classify them to roughly 200 topics and subtopics using an AMWS-provided hierarchical index and then manually crosswalk these topics to SED major fields.

The third linking exercise connects individual-level records across data sources. We begin with a sample of PhD scientists observed in the 1970 NRSTP, for whom we observe funding sources. Using information on their name and education history (e.g., PhD year, institution, and subject), we connect them to AMWS in order to retrieve employment histories. With these employment histories in hand, we then link scientists to NSF grants on name, employer, and year. We additionally link individuals to patents on inventor name and employer, using an ensemble of LLMs to match and cross-validate the scientist's employer in the patent filing year (from AMWS) to the patent assignee. We augment this sample using the Government Patent Register, which identifies the research organization even when the patent publication does not. In all cases, we drop candidate links with unrelated employers/assignees or which we are unable to disambiguate.

The final product of this data collection effort is an array of panel datasets at the (i) university-year, (ii) university-field-year, (iii) individual-year, (iv) field-year, and (v) technology-year, with the university panels restricted to R1 and R2 universities only. For each of these panels we measure (a) actual declines in DoD research funding and/or (b) pre-1970 dependence on defense support as an indicator of exposure to these declines, and (c) outcomes the military's retreat from science may have affected, including the scientific workforce, PhD production, career trajectories, and the growth of science and science-linked technological innovation.

[13]For example, NRSTP reports scientists' degree fields and research specialties (with a shared encoding), AMWS scientists have primary subjects, SED and PQDT report graduates' degree fields and subjects, OpenAlex publications have associated primary fields, and NSF grants are made by subject-oriented divisions and programs. To use these data together we seek to measure them in a common domain.

3.2 Empirical approach

Our analysis is purposefully broad, spanning a wide range of features of the U.S. scientific enterprise. Our empirical approach, however, will in each case exploit differences in pre-1970 reliance on DoD funding (across universities, fields, individuals, and technology areas).

The precise implementation varies somewhat for analysis at each of these levels. For example, for our analysis at the university-field level (approximating academic departments), though variation in exposure is continuous, measurement error with small denominators can make it both noisy and lumpy. To simplify measurement and interpretation, our primary specification will compare units with at least one DoD-funded scientist in 1970 to those with none, treating these as DoD departments; in robustness checks we separately estimate effects for units with high DoD exposure (based on the share of scientists in 1970 reporting DoD support).

Our workhorse regression for this first part of the analysis is a two-way fixed effects estimation of the following form, where i, j, and t index universities, fields, and years, and the sample runs from 1965 to 1990, with standard errors clustered at the university level:

$$Y_{ijt} = \sum_{t=1966}^{1990} \beta_t \cdot \mathbb{1}(\text{Any DoD exposure})_{ij} \cdot Year_t + X_{ijt}\gamma + \alpha_{ij} + \delta_{it} + \varepsilon_{ijt} \tag{1}$$

The unit is the university-field, which we measure in a balanced panel. Because larger units may be more likely to have at least one DoD-funded researcher, we control for differential trends by unit size, though doing so does not materially affect the results.[14] We will initially estimate specifications with different fixed effect (FE) assortments but will arrive at a preferred specification with university-field and university-year FEs, which will absorb permanent differences across institutions and fields as well as common time trends within institutions. The residual variation will effectively describe differential changes over time across fields with differential DoD exposure *within the same institution*. We use this specification to evaluate the impacts of the 1970s funding cuts on scientist employment, PhD production, and publication output in more heavily-exposed universities and fields. To simplify visual interpretations, regression tables will generally compare post-1970 outcomes to a 1965-1970 reference period, whereas figures will present estimated differences from 1960 onward, with 1969 as the (omitted) reference year. For most outcomes, pre-trends are either minimal or in the opposite direction of the effects we find—consistent with the historical context, as DoD-funded science was growing in the 1960s.

At the individual level, we estimate an analogous specification for early-career scientists (defined as

[14] We measure university-field size in 1970, based on the number of NRSTP respondents, and control for year-specific size gradients (i.e., we cross our continuous size measure with year fixed effects).

those who received their PhD between 1965 and 1969), interacting individual exposure (measured with an indicator for whether the scientist was DoD funded in 1970) with year dummies, conditional on research subject by year fixed effects, as follows:

$$Y_{ist} = \sum_{t=1966}^{1990} \beta_t \cdot \mathbb{1}(\text{DoD-funded in 1970})_i \cdot Year_t + \delta_{st} + \varepsilon_{it} \tag{2}$$

where i, s, and t index scientists, their primary subjects (fields), and years. This specification will be used to evaluate changes in scientists' employment sector over time; because our analysis will condition on pre-period employment sector, we omit individual fixed effects, which would otherwise be desirable for absorbing baseline differences in each outcome.

Where we study cross-country trends in national scientific output (Section 5), we estimate a similar specification to that in Equation (1), replacing the university index i with a country index c, and comparing trajectories across fields of science where DoD had a larger versus smaller presence (e.g., physics versus biology). Where we study changes over time in technological innovation downstream of science, we take a similar approach to that in Equation (2), where i indexes technology areas (CPC codes), and DoD exposure is measured as described above.

3.3 Interpretation and attribution

Our primary focus throughout this paper is on defense research funding specifically, and the impacts of post-1970 changes in defense R&D. The Mansfield Amendment, however, also coincided with the conclusion of NASA's Apollo program, after which NASA research investments dropped precipitously—following an equally precipitous and short-lived ascent in the latter part of the 1960s. The natural question these coinciding changes present is whether the effects we attribute to declining defense research funding may be partly driven by a shrinking post-Apollo NASA, particularly if they supported the same subjects or people. As an empirical matter, we find little correlation in DoD and NASA support at the individual level: researchers were typically DoD-funded or NASA-funded, but rarely both. At the university-field level, however, we see substantially greater correlation: those where a larger share of researchers were DoD-funded also had a larger share who were NASA-funded, ostensibly due to overlapping research priorities.

Insofar as the goal of this paper is to evaluate the effects of large research funding cuts, this is less a problem for identification than it is for attribution: whether the findings can be attributed to DoD alone, or changes in government R&D more broadly, is secondary to our goal of evaluating the effects of systemic contractions in research support. Reflecting this, in Appendix C.6 we reproduce our analysis with an alternative treatment measure calculated from the total set of NRSTP researchers in 1970 with (any of) DoD, AEC, or NASA support—effectively replacing our DoD exposure metric with a multi-agency exposure metric—and obtain quantitatively and statistically very similar results. This consistency may in part be because DoD was the largest of these agencies and accounts for the majority of the variation in this composite exposure measure.

Other pieces of evidence reinforce a DoD-driven interpretation. For example, pre-1970 trends in many of our outcomes mimic trends in DoD research funding more than NASA—with growth in the early 1960s giving way to stability later in the decade, when DoD research funding began to stagnate but NASA was explosively growing—suggesting a specifically-attributable causal relationship. At the university level, our DoD exposure measure predicts post-1970 military research funding declines, whereas agency exposure measures do not, suggesting other agencies' funding patterns are independent of realized DoD funding cuts (Appendix Table C.4). At the individual level, additional analysis indicates that DoD support in 1970 strongly predicts career transitions over the next decade, whereas other agency support only does weakly if at all.

Other potential confounds could include post-1970 changes in undergraduate enrollments, which influences faculty size and future PhD demand, or declining PhD enrollment due to the end of Vietnam War draft deferments for graduate students (Kantor et al. 2026), which began phasing out in 1967. These trends are in our view unlikely to be problematic under our empirical design: Equation (1) identifies off of cross-department differences within universities over time, and draft deferment policy would threaten identification only if its impacts likewise varied systematically across departments within the same university and were correlated with pre-1970 DoD funding exposure. Similarly, for our individual-level analysis in Equation (2), year fixed effects are likely to account for these aggregate phenomena when comparing the post-1970 evolution of individual scientists' postgraduate careers. Moreover, many of the outcomes our analysis will study (faculty hiring, publications, post-PhD career transitions) are not implicated by deferment policy specifically, but they will nevertheless be shown to vary with DoD exposure.

4 Main Results

We organize our main analysis into three sets of results. Section 4.1 evaluates impacts on institutional outcomes, namely scientist counts, new PhD graduates, and research output. Section 4.2 estimates differences in DoD-funded versus other academic scientists' post-1970 career trajectories, focusing on early-career scientists. Section 5 backs out to the aggregate level, comparing differential growth of U.S. and foreign science in the most exposed fields, and differential growth of U.S. technological innovation across more vs. less exposed technology areas.

4.1 Changes in the university research enterprise

We begin by examining the institutions at the center of the military-university research partnership: research universities themselves. Research funding ostensibly can influence most facets of university research; in this case, we measure scientist employment, PhD production, and publication activity. Following Equation (1), our analysis is conducted at the university-field (i.e., academic department) level, though results are similar for university-level analysis.

The core finding can be summarized as follows. After 1970, the universities and departments that had been more dependent on defense support pre-1970 began a slow but ultimately large contraction relative to their less-exposed counterparts—reducing researcher headcounts, training fewer PhDs, and publishing less science. Though this contraction exhibits some heterogeneity across fields, it was broad-based and persists to at least 1990—after which the more general post-Cold War decline in military R&D (Figure A.5) likely only exacerbated these differences.

4.1.1 University researchers and PhD trainees

Table 3 estimates variants of Equation (1) for department-level outcomes, evaluating changes in their number of research professionals and number of PhD graduates. We first evaluate headcounts under different fixed effect (FE) assortments, to see how they compare, before settling into our preferred specification with university-year FEs, which identifies differential post-1970 changes across fields with differential defense exposure *within the same university*. This design holds fixed any university-wide factors that may have varied over time, such as universities' size or fiscal condition; this choice is particularly useful because smaller universities tended to have lower DoD engagement but also grew faster than larger universities over the period we study (off of a smaller base). University-year FEs will account for these and other such factors.

[Table 3 about here]

Columns (1) to (3) report post-1970 changes in the (log) number of AMWS scientists, measured from AMWS-reported employment spells. We limit measurement to post-PhD employment years to ensure we do not conflate postgraduates with PhD students. In sequence, these columns include (1) university-field and year FEs, (2) university-field and university-year FEs, and (3) university-field and field-year FEs. All three columns show that departments with greater DoD exposure experienced slower growth in faculty size after 1970, with a persistent ∼10% relative decline emerging by the late 1970s, significant at the 1% level. These differences are similar across FE variants through 1980, though they diverge somewhat thereafter, when Columns (1) and (2) show a slightly intensifying difference and Column (3) a slightly attenuated difference.

In Columns (4) and (5) we estimate Equation (1) specifically for early-career scientists ($\leq$5 or $\leq$10 years post-PhD), which decline at higher rates (roughly 10% in the early 1970s, and 15-25% by the 1980s). The evidence is consistent with adjustments particularly taking place on the entry-level margin and foreshadows a recurring pattern across this paper, suggesting the largest consequences of large research funding declines fall on the pipeline of new scientists.

Columns (6) to (9) examine PhD production. Due to more frequent zeros in these outcomes, we transition from ordinary least squares to Poisson pseudo-maximum likelihood estimation. Columns (6) and (7) find that exposed departments experienced large relative reductions in their production of new PhD graduates (evaluating SED graduate counts and PQDT graduate counts, respectively), with a 15-25% long-run decline setting in by the early 1980s.[15] These reductions appear to apply to graduates of all types, but in Columns (8) and (9) we find that they are especially large for PhD graduates who eventually work in the defense industrial base, with long-run declines on the order of $\sim$50%, and modestly larger effects for our more conservative DIB definition. That the decline in PhD graduates (which becomes significant in the late 1970s) is slower to emerge than the decline in scientists may be because changes in faculty hiring are visible quickly, whereas changes in PhD enrollment become visible in graduations only after 4-5 years.

4.1.2 Research output

Figure 3 extends this evidence in a longer panel, showing annual differences between DoD-funded departments and others in their number of AMWS scientists (Panel A) and PQDT PhD graduates (Panel B). All differences are estimated relative to 1969 (the omitted category). In both charts, we see differential growth in the early 1960s (with point estimates rising), stability in the late 1960s (point estimates around zero), and a sustained decline after 1970. These patterns broadly match trends DoD research support over the same periods. As in Table 3, we also find evidence that the impacts on PhD production took roughly five years to manifest.

Panel (C) of Figure 3 performs this analysis for a third outcome: research output. Using OpenAlex publication data, which include author affiliations and publication fields, we measure departments' publication volume over time. Panel (C) finds a pattern similar to the other panels: defense-funded departments on average grew more quickly than their counterparts in publication output in the early 1960s, tracked in the late 1960s, and grew more slowly or contracted thereafter, with output eventually falling around 20-25% relative to other departments.

[Figure 3 about here]

[15]Marginal effects from the PPML results are computed as $100 \times \left(e^{\beta_t} - 1\right)$.

4.1.3 Additional evidence

In the appendix we present additional results. Appendix C.2 reproduces Figure 3 and Table 3 with field-year FEs in place of university-year FEs. Appendix C.3 reproduces these analyses measuring exposure to DoD funding cuts from 1968 NRSTP responses (rather than 1970). We arrive at the same results, suggesting that our findings are not contingent on the precise measure of exposure or set of individuals it is measured from: though NRSTP respondents and response rates varied year-to-year, aggregations are more stable, and lead to the same findings. In Appendix C.4 we extend this analysis to separately estimate differences across departments with no DoD-funded researchers in 1970, at least one such researcher, and many such researchers (operationalized as being in the top quintile of DoD support as a share of the 1970 NRSTP population, equivalent to having >10% of staff reporting DoD support). We find evidence of a dose response: across all outcomes, exposed departments contracted relative to unexposed departments, but more heavily exposed departments contracted at least as much and in most cases measurably more.

4.2 Impacts on individual scientists

We next study the careers of researchers whose work was supported by the military. We do so using our individual scientist panel, which is built up from employment spells in AMWS biographies. We focus our analysis on university scientists who were at the start of their careers at the time DoD began to withdraw from science, motivated by the intuition that young scholars may be relatively more vulnerable in a contractionary funding environment. To do so, we sample scientists who earned their PhDs between 1965 and 1969 and who (a) were employed continuously in the university sector from their PhD year to 1970 (according to AMWS) and (b) report university employment in the 1970 NRSTP. We then ask how their careers evolved post-1970 as a function of whether they were DoD-funded in 1970 (and thus exposed to post-1970 DoD funding cuts).

In Table 4 we evaluate individual scientists' employment sector over time (Equation 2). Because we restrict the sample to pre-1970 university scientists, we omit individual FEs, as our sampling already conditions out individual variation in the outcome in the base period; the post-1970 interactions will capture subsequent sectoral transitions. All columns include field-year FEs, such that we are comparing the career trajectories of initially DoD-funded scientists to others of the same generation (the 1965 to 1969 PhD cohort) and in the same discipline over time.

[Table 4 about here]

The patterns in Table 4 indicate that defense-funded early-career scientists were markedly more likely than their peers to leave the academy after 1970, and particularly to enter industry. Column

(1) shows defense-funded scientists left universities at roughly a 12 percentage point (p.p.) higher rate than peers by the 1980s, nearly double the base rate of roughly 14 p.p. Around one-third to one-half of those transitioners subsequently entered full-time industry employment (Column 2). Of the remainder, most are observed with multiple appointments (Column 4), most often in the university and industry sectors (Column 5), which includes consulting roles. We see little evidence of systematic transitions to government employment (Columns 3/6).[16]

Though the evidence in Table 4 is suggestive of changes taking place specifically in the wake of DoD funding cuts, a remaining possibility is that these are typical mobility patterns for defense-funded researchers for unobserved reasons. That the analysis conditions on research field alleviates this concern somewhat, as the result then cannot be attributed to DoD-funded scientists happening to be in more industry-relevant fields. But the possibility that DoD researchers are selected on other characteristics—including their specific research expertise—remains.

In Appendix C.5, we probe this possibility by studying different cohorts as comparative cases. Our first effort produces an analogous test for earlier and later cohorts of DoD-funded scientists: using our AMWS panel, we isolate the 1959-1963 PhD cohort, link it to the 1964 NRSTP, filter to graduates who were employed at universities continuously through 1964, and estimate the differential propensity of scientists who reported DoD funding in 1964 to transition out of the university sector and into other sectors by 1969 (up to the eve of DoD's withdrawal from research funding, to avoid contamination). For an apples-to-apples comparison, we perform the same analysis, using the same regressions, on our 1965-1969 PhD cohort linked to the 1970 NRSTP and filtered on the same conditions, estimating the differential propensity of scientists who reported DoD funding in 1970 to transition out of the university sector and into other sectors by 1975.[17] The two samples are designed for exact symmetry in the width of the PhD cohort, its timing relative to its observation in NRSTP, and the length of the subsequent observation window.

Appendix Table C.8 presents these difference-in-difference results, first for the 1959-1963 cohort (Panel A), then for the 1965-1969 cohort (Panel B). Whereas the earlier cohort shows no systematic differences in mobility for DoD-funded scientists and others, we confirm that DoD-funded scientists from the 1965-1969 cohort were substantially more likely than same-field peers to move to industrial employers. The results thus suggest against the possibility that our main result reflected general early-career industrial mobility patterns of DoD-funded scientists.

In Appendix Table C.9, we reproduce Table 4 for the next oldest cohort (PhD graduates from

[16]The evidence is broadly consistent with the findings of Babina et al. (2023), who show that university scientists whose fields face abrupt contractions in federal research support often pivot to private research funding. Because their study is based on university data, it is not as well suited to documenting scientist mobility out of the U.S. university sector in a changing funding environment, which is our focus here.

[17]This analysis should approximately reproduce the 1971-1975 parameters of Table 4).

1960-1964) to see if early-career scientists in 1970 were particularly adversely affected or if older scientists were similarly affected. As with the 1965-1969 PhD cohort, we condition to scientists who worked in the university sector continuously from the year of their PhD graduation to 1970. In contrast to our findings for the early-career cohort, we find few systematic post-1970 differences between DoD-funded scientists and other scientists from this older generation. These results point to an interpretation of early career scientists—who lack both an established track record and tenure—being particularly vulnerable to contractions in research support.

Changing research orientation Insofar as funding for basic research at universities declined and many scientists pivoted to industry employment or funding, one corollary may be a shift to more applied research. Babina et al. (2023), for example, show that academic researchers whose federal funding declines compensate by raising private funding, and their R&D output pivots somewhat away from (open) science towards (patented, appropriable) technology. This tendency is likely even larger among scientists who leave universities for the private sector: in our AMWS sample, industry scientists are 10 times more likely to patent in any given year than other scientists, and on average file roughly 4 to 5 times as many patents over their observable careers.

In Column (7) we examine the propensity for the early career university scientists in our sample to patent, estimating differences over time in the likelihood of filing at least one patent any given year. Though patenting is a rare event for nearly all scientists in our data—of scientists in our complete AMWS panel, 85% have no patents through 1990; of those in our estimation sample (i.e., scientists from the 1965-1969 PhD cohort working at universities in 1970), 95% never patent, and all but one have zero pre-1970 patents—the results suggest that defense-funded scientists became meaningfully more likely to produce patented inventions after 1970, with annual patenting propensity tripling off of the mean rate (up 1 p.p. on a base of 0.5 p.p., significant at the 5% or 10% level, depending on the year) by the late 1970s and throughout the 1980s.

5 Repercussions for Science and Technology

How did the decline in university science affect scientific progress or downstream technology development? We take on this question next, asking whether the effects we found in earlier sections add up to a long-run impact on science and technology at the national level. The level of DoD's pre-1970 research funding in target fields, and scale of its post-1970 cuts, together raise the possibility of significant aggregate impacts in affected research areas—both in scientific research, and in the development of new technology that draws on that science.

5.1 National research output

To assess national science, we compare the growth of U.S. publication output over time against that of the United Kingdom, Germany, and Japan, in fields which were more versus less heavily defense-supported before 1970. This triple-difference design (differencing across countries, fields, and time) will thus identify the post-1970 differential growth or decline of research output in (would-be) defense-supported subjects in the U.S. relative to other countries.

We implement this test by comparing national publication output in the eight major fields which we measure consistently across the essential data sources (namely, NRSTP scientists and Open-Alex publications): agricultural sciences, biological/biomedical sciences, chemistry, earth sciences, physics and astronomy, mathematics, computer science, and engineering. In light of historical context and the frequency of DoD support in the 1970 NSRTP, we group physics as its own treatment class (based on its historical relationship to the military) and mathematics, computer science, earth sciences, and engineering as a second treatment class (based on their also having substantial DoD support). We then estimate the following specification, comparing the trajectory of U.S. and foreign publication activity in these treatment classes from 1960 to 2000:

$$\begin{aligned} Ln(Publications)_{ijt} = \sum_{t=1961}^{2000} & [\beta_{1t} \cdot (\text{Country } i = \text{US}) \cdot (\text{Field } j \in \text{class 1}) \\ & + \beta_{2t} \cdot (\text{Country } i = \text{US}) \cdot (\text{Field } j \in \text{class 2})] + \alpha_{ij} + \delta_t + \varepsilon_{ijt} \end{aligned} \tag{3}$$

where i, j, and t index countries (grouped up to U.S. vs. foreign), fields (grouped up to treatment classes), and years. To reduce visual congestion we plot results with parameters in five year intervals, with robust standard errors (as sample size precludes clustering).

Figure 4 presents the results. From 1960 to the early 1970s, U.S. and foreign output in the affected fields—physics and the other defense-supported sciences—evolved in parallel with others, without any differential pre-trends. From the late 1970s onward, however, U.S. research output declined in these fields relative to foreign counterparts, with the gap largest in physics ($\downarrow$ 30% relative to counterparts for most of the post-period), still large and statistically significant in other DoD fields ($\downarrow$ 10%), and in both cases widening through the end of the century.

[Figure 4 about here]

Science was growing over this period in all countries and fields, such that the results should be read as evidence of post-1970 foreign catch-up in previously DoD-supported fields, more so than contractions in U.S. research output in the absolute. We caution against attributing the entirety of this convergence to the defense drawdown, as the postwar decades saw a broad rebuilding of European and Japanese science—though the absence of pre-trends, and the differentially slow post-1970 growth of American science in the fields the U.S. military once funded, is consistent with a causal interpretation. The results should nevertheless be read cautiously for a different reason: the focus on a small number of advanced economies with research-intensive innovation sectors and the high level of aggregation at which we measure research subjects results in a sample of only 32 country-fields (4 countries x 8 fields) observed over 41 years (1960-2000). The size of this sample arguably limits the degree to which broad inferences should be drawn, even as the results are suggestive of aggregate effects of DoD's withdrawal from science.

5.2 Technological innovation

The second question is whether the DoD-driven contraction in science propagated into technology. To evaluate this question, we study changes in U.S. patenting across technology areas (4-digit CPC codes) with differential exposure to post-1970 declines in DoD-funded science, measured as weighted average DoD intensity of the fields of science each CPC draws on, weighted by the CPC's relation to each field.[18] We then divide the sample into above- and below-median exposure CPCs, and separately into terciles of exposure, and we estimate differential changes in patenting over time across these exposure quantiles q using the following specification:

$$Ln(Patents)_{jt} = \sum_{q} \sum_{t=1961}^{2000} \beta_{qt} \cdot \mathbb{1}\left(\text{CPC } j \in \text{quantile } q\right) + \alpha_j + \delta_t + \varepsilon_{jt} \tag{4}$$

where j and t index CPCs and years, and standard errors are clustered by CPC. In order to evaluate impacts on U.S. technology specifically, we restrict our measurement to patents with U.S.-based first inventors, which indicates domestically-developed innovation.

Results are presented in Table 5, where we evaluate post-1970 changes in total patents (Column 1), DoD-funded patents (Column 2), science-citing patents (Column 3), and DoD-funded, science-citing patents (Column 5) in CPCs with above versus below median DoD exposure.[19] Column (4) evaluates differential changes in the breadth of cited science, measured as the number of unique publications cited by patents in a given CPC. As in previous tables, we collapse the specification to five-year block parameters for more parsimonious presentation.

[18] Concretely, we construct exposure by crossing (i) the share of patent citations made by patents in a given CPC to different fields of science by (ii) the share of scientists in each field with DoD support in 1970, and (iii) summing to the CPC level. The result is a weighted average exposure metric.

[19] We measure DoD-funded patents using the Government Patent Register (Gross and Sampat 2025a), and science-citing patents using the Reliance on Science dataset (Marx and Fuegi 2020, 2022, counting only in-text citations to science that are measured with high confidence; see Appendix B.3 for further discussion).

[Table 5 about here]

The results draw a clear line between general patenting and science-linked patenting. Total patenting and defense patenting in more exposed CPCs show no evidence of differential post-1970 changes (Columns 1 and 2). Science-citing patents, however, experienced substantially slower growth (relative decline) in more exposed CPCs, lagging less-exposed CPCs by roughly 50% by the late 1980s and 70% by the late 1990s (Column 3). The range of science cited by these patents accordingly declined substantially, and at an even faster rate, indicating a consolidation of science-linked technology around an increasingly narrow research base (Column 4).

Figure 5 presents the annual variant of Equation (4), estimated over 1960 to 2000, where we can evaluate the dynamics of these changes. Panel (A) presents estimates for science-citing patents (corresponding to Column 3) and Panel (B) for the breadth of science cited. Both began a sustained, gradual, long-term decline in more exposed CPCs after 1970, with flat pre-trends in the decade prior to the initiation of the 1970s defense research funding cuts—suggesting that science-linked invention in these technology areas kept pace with other fields until 1970, after which a slowdown in related science may have potentially stifled continued progress. When estimated across terciles of DoD exposure (rather than an above/below median cut), we additionally find evidence of a dose response, consistent with patterns in prior sections (e.g., Figure 4).

[Figure 5 about here]

These systemic effects present a contrast to the individual-level evidence in Table 4, which found that previously DoD-funded early career scientists individually grew more likely to patent—offering a reminder that the aggregate effects of declining public investment in science can potentially be substantially different than the localized (individual) effects.

6 Assessing mission impacts of military R&D

Our analysis thus far has mainly focused on evaluating the impacts of the 1970s funding cuts on science and technology broadly, in keeping with the economic tradition that motivates public R&D on the basis of broad economic returns to innovation (e.g., Solow 1956, Griliches 1979) and market failures in private R&D investment (vis-à-vis private markets' tendency to underinvest in R&D at collectively desirable levels, following Nelson 1959, Arrow 1962).

Although these are widely-accepted arguments for public R&D, the military is guided by a specific and different set of goals which are at most only loosely related to economic performance (Mowery

2009): its R&D investment is instead motivated by the value of frontier science and technology to national defense.[20] Whereas there are established approaches—and a substantial body of evidence—relating public R&D to economic outcomes, there is by comparison far less evidence of how public R&D affects military performance or other national security outcomes, nor a consensus on how to go about generating it. The challenges are several, including ambiguity over what are appropriate endpoints for assessing military performance, and how they can be systematically measured (modern militaries are large, complex organizations with multiple goals, active conflicts are rare, and deterrence is a valuable but empirically invisible result), and difficulties linking specific scientific discoveries to those outcomes. Despite these challenges, one can imagine a variety of surrogate endpoints, such as scientific knowledge incorporated in military systems, or science-linked technologies that transition into acquisition programs of record.

We focus on two metrics. The first is human capital: as Nice (2025) explains, the national security innovation base is heavily reliant on high-skill human capital. The importance of a high-quality technical workforce to defense innovation is in part what motivated our analysis of PhD graduates entering the defense industrial base in Section 4.1. Consistent with this intuition, although a 1960s DoD study of military weapons systems (Project HINDSIGHT) found it difficult to identify specific impacts of basic research on these systems, it concluded that "The greater payoff of undirected basic research in science identified in HINDSIGHT studies has been observed in [other] forms ... In terms of numbers, the gain has been in the training of scientists and engineers who performed the directed research in basic science or in technology that led to the new weapon systems" (Project Hindsight final report; Isenson 1969, pp. 96-97). HINDSIGHT further emphasized "how valuable university-trained scientists have been to the Department of Defense, [especially] those trained in universities that had defense-oriented research programs" (ibid., p. 97).

Taken at face value, this argument suggests that human capital may be among the most important channels through which public investments in science affect military capabilities. If so, one of the most consequential legacies of DoD's withdrawal from science may have been a depleted stock of future scientists available to advance defense science and technology (Table 3). Even then, our analysis remains incomplete: our measurement is limited to PhD graduates, but insofar as reductions in defense research support also reduced training opportunities for master's students and other technical workers—who comprise the majority of the military-industrial complex's technical workforce—the consequences might have been even more substantial.

[20] Despite the dominance of the market failure rationale for public R&D in economic studies, this is not the motivation for the majority of government R&D in the United States, most of which is funded by mission agencies with specific and typically non-economic goals (Mowery 2009). In a mission context, economic impacts of public R&D are often only an incidental byproduct of innovation policies that exist for other reasons.

The second metric we examine is science-linked defense innovation. Table 5, Column (5) estimates differential changes in this type of patenting over time in technology areas most exposed to defense research funding cuts. Here we find that science-citing defense patents initially rose in the more exposed technology areas after 1970, before fading to a statistical equivalence by the 1980s and falling below the reference group trend in the 1990s. This non-monotonic trajectory is consistent with a short-term lift to defense patenting, as scientific labor reallocated to industry (Section 4.2), and a long-term decline, as the supply of new science and new scientists thinned over the following decades, leaving the defense sector with less new knowledge and a smaller pool of high-skill workers to generate science-based defense technologies around and with.

7 Concluding Remarks

In this paper, we study the impacts of the largest systemic contraction in science funding in U.S. history: the U.S. military's retreat from university research in the 1970s. For the first 25 years after World War II, the Department of Defense was the country's leading patron of the physical sciences and engineering, comparable in scale to NIH's position in the life sciences. In the early 1970s, however, amid the political turbulence of the Vietnam era, Congress reduced this support in both scale and scope, and DoD's university research funding fell by roughly two-thirds and never recovered. Comparing universities, departments, and individual scientists with pre-1970 defense support against others, we trace the long-run imprint of this withdrawal across the American research system. The evidence suggests that in exposed universities and fields, the scientific workforce thinned, PhD production fell, and publishing declined. Early career scientists reliant on defense support disproportionately left the academy for industry, where some became more likely to patent, but these gains did not offset the broader retrenchment: nationally, U.S. leadership in global science compressed in the fields DoD had traditionally funded, and science-linked innovation slowed in technology areas most exposed to these (formerly) DoD-driven fields.

At the time of writing, U.S. university research is once again confronting large cuts in public funding. Whether these changes will have similar effects to those 50 years ago is an open question, and one we anticipate more evidence will become available on in the coming years. At its essence, the core pattern which presents itself throughout this paper is that when research funding declines, the scientific enterprise is likely to contract along with it, as might some science-linked technological innovation. Declining research capacity may be difficult to recover quickly, in part because key assets like scientific human capital and infrastructure take substantial time and investment to rebuild. It is also important to emphasize that our shock was specifically to university research funding, and our results primarily reflect a contraction of university (not industrial) science, though the impacts on patenting we find are economy-wide, and other research has shown that industrial science was also declining over the period we study (Arora et al. 2018).

Alongside these results, we also find evidence of scientific talent reallocating to the private sector, and indications of an increased propensity to produce patented inventions. This evidence raises a question of whether university research funding steers R&D workers into science and away from industrial R&D. Though distortionary, traditional economic arguments suggest that such a policy-induced reallocation would be market-correcting (Nelson 1959). But one can also imagine what university scientists might do in the private sector, and vivid examples are available from the 1970s era, such as advances in user computing at Xerox PARC, which employed several formerly military-funded computer science faculty and students (see, e.g., Kay 2006, Spicer 2008). However, we also note that although reductions in university research funding may have drawn one generation of scientists out of the university and into industry, boosting some innovation in the short-run, they also reduced the production of new science and scientists, at the risk of choking off future science-based innovation—evidence of which is also visible in this paper.

Beyond these particular themes, this paper also explores the national security rationale for innovation policy. Though U.S. research policy is grounded in the belief that science can deliver benefits for national defense, health, and economic prosperity (Bush 1945), empirical studies of innovation policy have almost exclusively studied health and economic outcomes. What the impacts of research on national security are—and even before that, what the relevant endpoints are, and how can they be measured—are major questions which have proved vexing to scholars and military planners alike. Though we engage with two approaches—measuring the defense industrial workforce and defense patenting—these are at most intermediate links, and further research on national security impacts is needed to fully understand the public returns to science.

References

Arora, Ashish, Sharon Belenzon, and Andrea Patacconi. 2018. "The decline of science in corporate R&D." *Strategic Management Journal* **39**(1):3-32.

Arrow, Kenneth. 1962. "Economic welfare and the allocation of resources for invention." In *The Rate and Direction of Inventive Activity: Economic and Social Factors*, pp. 609-626. Princeton: Princeton University Press.

Aspray, William. 1989. *Oral History: Edward Feigenbaum*. Available at https://hdl.handle.net/11299/107282.

Azoulay, Pierre, Matthew Clancy, Danielle Li, and Bhaven N Sampat. 2025. "What if NIH had been 40% smaller?" *Science* **389**(6767):1303-1305.

Azoulay, Pierre, Joshua S. Graff Zivin, Danielle Li, and Bhaven N. Sampat. 2019. "Public R&D investments and private-sector patenting: Evidence from NIH funding rules." *Review of Economic Studies* **86**(1):117-152.

Azoulay, Pierre, Joshua S Graff Zivin, and Jialan Wang. 2010. "Superstar extinction." *The Quarterly Journal of Economics* **125**(2):549-589.

Babina, Tania, Alex Xi He, Sabrina T Howell, Elisabeth Ruth Perlman, and Joseph Staudt. 2023. "Cutting the innovation engine: how federal funding shocks affect university patenting, entrepreneurship, and publications." *The Quarterly Journal of Economics* **138**(2):895-954.

Barber Associates. 1975. "The Advanced Research Projects Agency, 1958-1974." Technical report, available at https://apps.dtic.mil/sti/citations/ADA154363.

Baruffaldi, Stefano and Fabian Gaessler. 2026. "The returns to physical capital in knowledge production: Evidence from lab disasters." *American Economic Journal: Applied Economics* **18**(1):248-285.

Boffey, Philip M. 1970. "Mansfield Amendment Curb on Basic Research May Spread." *Science* **167**(3924):1473.

Bryan, Kevin A, Yasin Ozcan, and Bhaven Sampat. 2020. "In-text patent citations: A user's guide." *Research Policy* **49**(4):103946.

Bush, Vannevar. 1945. *Science, the Endless Frontier: A report to the President*. Washington: Government Printing Office.

Draca, Mirko. 2013. *Reagan's innovation dividend? Technological impacts of the 1980s US defense build-up*. Working paper.

Geiger, Roger L. 1993. *Research and relevant knowledge: American research universities since World War II*. Oxford: Oxford University Press.

Griliches, Zvi. 1979. "Issues in assessing the contribution of research and development to productivity growth." *The Bell Journal of Economics* pp. 92-116.

Gross, Daniel P. and Maria P. Roche. 2025. *Coordinated R&D Programs and the Creation of New Industries*. Working paper.

Gross, Daniel P. and Bhaven N. Sampat. 2023a. "America, jump-started: World War II R&D and the takeoff of the US innovation system." *American Economic Review* **113**(12):3323-3356.

Gross, Daniel P. and Bhaven N. Sampat. 2023b. "The World War II crisis innovation model: What was it, and where does it apply?" *Research Policy* **52**(9):104845.

Gross, Daniel P and Bhaven N Sampat. 2025a. "The Government Patent Register: A new resource for measuring U.S. government-funded patenting." *Research Policy* **54**(1):105142.

Gross, Daniel P. and Bhaven N. Sampat. 2025b. *The Therapeutic Consequences of the War: World War II and the 20th-Century Expansion of Biomedicine*. NBER working paper no. 33447.

Hart, David M. 1998. *Forged consensus: Science, technology, and economic policy in the United States, 1921-1953*. Princeton: Princeton University Press.

Howell, Sabrina T. 2017. "Financing innovation: Evidence from R&D grants." *American Economic Review* **107**(4):1136-64.

Ilzetzki, Ethan. 2024. "Learning by necessity: Government demand, capacity constraints, and productivity growth." *American Economic Review* **114**(8):2436-2471.

Isenson, Raymond S. 1969. "Project HINDSIGHT." Final report, Office of the Director of Defense Research and Engineering, U.S. Department of Defense, Washington DC.

Kantor, Shawn, Arthur Novaes De Amorim, and Alexander Whalley. 2026. *Researchers, Ideas, and Economic Growth: Evidence from Vietnam War Draft Avoidance*. Working paper.

Kantor, Shawn and Alexander Whalley. 2025. "Moonshot: Public R&D and growth." *American Economic Review* **115**(9):2891-2925.

Kay, Alan. 2006. *Oral History: Butler Lampson*. Available at https://www.computerhistory.org/collections/catalog/102658024/.

Kevles, Daniel J. 1977. "The National Science Foundation and the debate over postwar research policy, 1942-1945: A political interpretation of Science–The Endless Frontier." *Isis* **68**(1):5-26.

Kleinman, Daniel Lee. 1995. *Politics on the endless frontier: Postwar research policy in the United States*. Durham: Duke University Press.

Leslie, Stuart W. 1993. *The Cold War and American science: The military-industrial-academic complex at MIT and Stanford*. New York: Columbia University Press.

Lowen, Rebecca S. 1997. *Creating the Cold War university: The transformation of Stanford*. Berkeley: University of California Press.

Marx, Matt and Aaron Fuegi. 2020. "Reliance on Science: Worldwide Front-page Patent Citations to Scientific Articles." *Strategic Management Journal* **41**(9):1572-1594.

Marx, Matt and Aaron Fuegi. 2022. "Reliance on science by inventors: Hybrid extraction of in-text patent-to-article citations." *Journal of Economics & Management Strategy* **31**(2):369-392.

Moretti, Enrico, Claudia Steinwender, and John Van Reenen. 2025. "The intellectual spoils of war? Defense R&D, productivity, and international spillovers." *Review of Economics and Statistics* **107**(1):14-27.

Mowery, David C. 2009. "What does economic theory tell us about mission-oriented R&D?" In *The new economics of technology policy*, edited by Dominique Foray. Northampton: Edward Elgar.

Myers, Kyle R. 2020. "The elasticity of science." *American Economic Journal: Applied Economics* **12**(4):103-34.

Nelson, Richard R. 1959. "The simple economics of basic scientific research." *Journal of Political Economy* **67**(3):297-306.

Nelson, Richard R. 1993. *National Innovation Systems*. New York: Oxford University Press.

Nelson, Richard R and Gavin Wright. 1992. "The rise and fall of American technological leadership: The postwar era in historical perspective." *Journal of Economic Literature* **30**(4):1931-1964.

Nice, Amy. 2025. "Meeting US Defense Science and Engineering Workforce Needs: A Progress Report." In *Entrepreneurship and Innovation Policy and the Economy*, edited by Benjamin F. Jones and Josh Lerner, volume 4, pp. 179–215. University of Chicago Press.

Nichols, Rodney W. 1971. "Mission-Oriented R&D: Senator Mansfield's questions sharpen congressional uncertainties about federal R&D patterns." *Science* **172**(3978):29-37.

Rogerson, William P. 1994. "Economic incentives and the defense procurement process." *Journal of Economic Perspectives* **8**(4):65-90.

Romer, Paul M. 1990. "Endogenous technological change." *Journal of Political Economy* **98**(5, Part 2):S71-S102.

Scotchmer, Suzanne. 1991. "Standing on the shoulders of giants: Cumulative research and the patent law." *Journal of Economic Perspectives* **5**(1):29-41.

Shvadron, Dror, Hansen Zhang, Lee Fleming, and Daniel P Gross. 2025a. *Measuring the Production of Scientific Human Capital: New Data, Methods, and Evidence on the U.S. Scientific Training Ecosystem*. NBER working paper no. 33944.

Shvadron, Dror, Hansen Zhang, Lee Fleming, and Daniel P Gross. 2025b. "A Quarter of US-Trained Scientists Eventually Leave. Is the US Giving Away Its Edge?" *arXiv preprint arXiv:2512.11146* .

Solow, Robert M. 1956. "A contribution to the theory of economic growth." *Quarterly Journal of Economics* **70**(1):65-94.

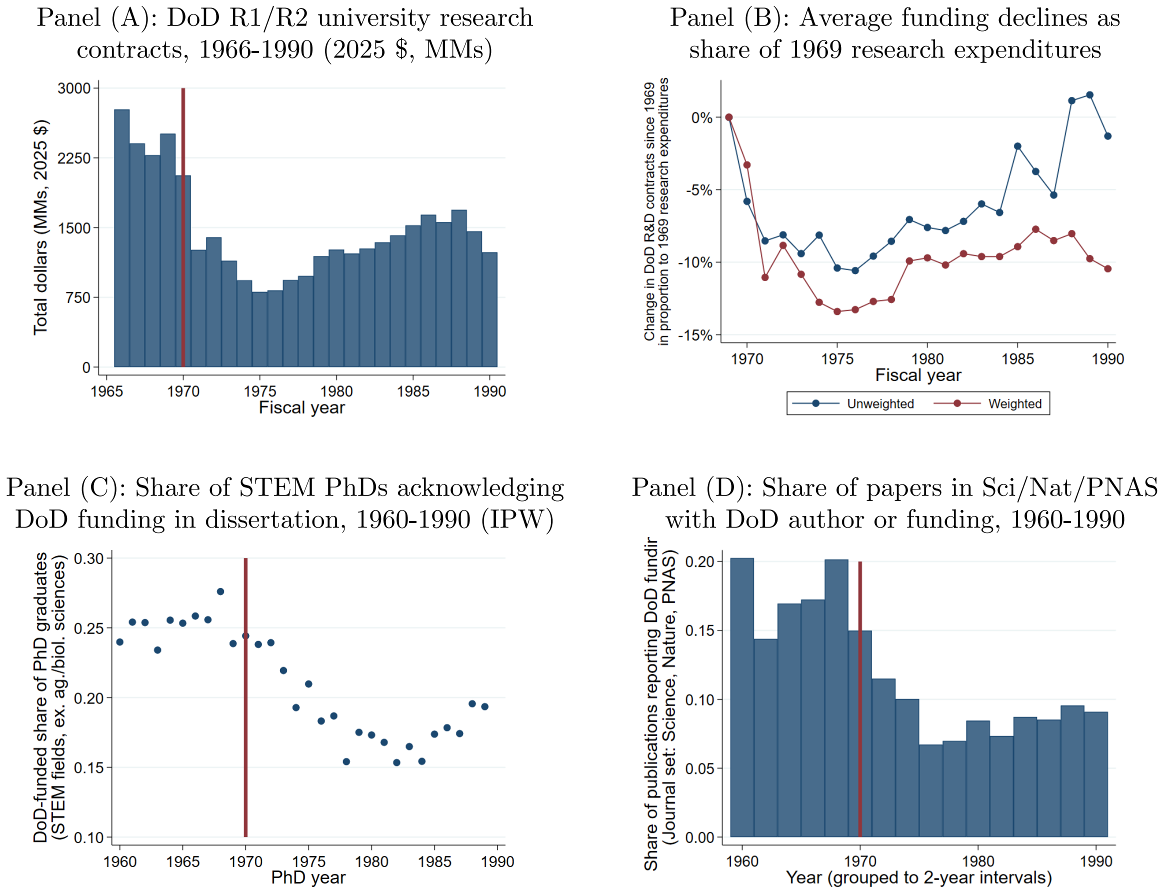
Spicer, Dag. 2008. *Oral History: Alan Kay*. Available at https://www.computerhistory.org/collections/catalog/102658340/.

Tham, Wei Yang, Joseph Staudt, Elisabeth Ruth Perlman, and Stephanie D Cheng. 2024. *Scientific talent leaks out of funding gaps*. arXiv preprint arXiv:2402.07235.

Waldinger, Fabian. 2016. "Bombs, brains, and science: The role of human and physical capital for the creation of scientific knowledge." *Review of Economics and Statistics* **98**(5):811-831.

Zerhouni, Elias A. 2006. "NIH in the post-doubling era: Realities and strategies." *Science* **314**(5802):1088-1090.

Figure 1: Sharp drop in DoD funding for scientific research broadly visible in the data

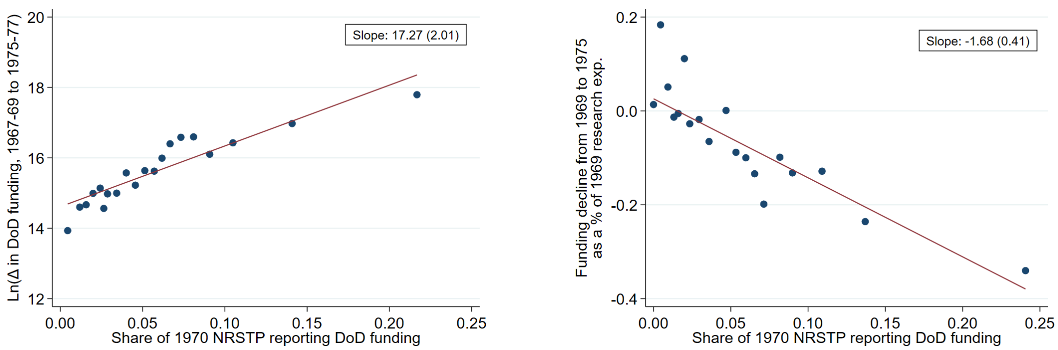


Notes: Figure provides four different views of the 1970s defense research funding cuts. Panel (A) shows total annual military funding for university basic or applied research (budget categories 6.1-6.2) from 1966 to 1990, computed from military prime contract files (available 1966+), inflation adjusted to 2025 USD. Panel (B) shows the average percent decline in universities' DoD research funding relative to their 1969 research spending (as reported in HEGIS). The blue line shows the unweighted average, and the red line weights by institution size. Panel (C) shows the share of US STEM PhDs between 1960 and 1990 who acknowledge DoD support in their thesis, using inverse propensity weights to adjust for graduates' underreporting (data from Shvadron et al. 2025a; patterns are directionally similar in the unweighted raw data but shifted downward). Panel (D) shows the share of articles published in Science, Nature, and PNAS between 1960 and 1990 which either have a DoD-affiliated author or acknowledge DoD funding (we bin the data into two-year intervals to smooth noise). The red vertical line in all figures marks 1970.

Figure 2: Universities' funding changes correlate with share of 1970 scientists with DoD support

Panel (A): Ln(Decline in funding) vs. NRSTP DoD share (university level)

Panel (B): Change as a share of 1969 research expenditure vs. NRSTP DoD share



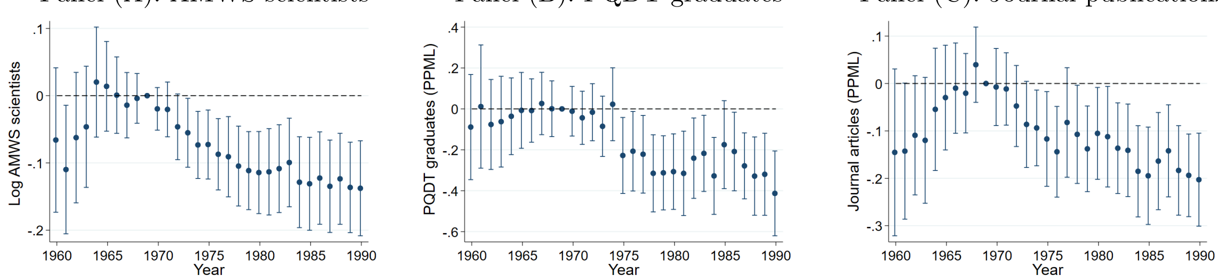
Notes: Figure provides binned scatterplots correlating measures of universities' observed funding changes in the 1970s with the share of 1970 NRSTP respondents with DoD support. Panel (A) relates log declines in funding between 1967-1969 and 1975-1977 to this exposure measure (restricting to universities with funding declines, with larger values indicating larger declines). Panel (B) relates the change in funding from 1967-1969 to 1975-77 as a share of 1969 research expenditure to this exposure measure. The evidence indicates that universities where a larger share of researchers were DoD supported experienced larger declines in research funding.

Figure 3: Scientists, PhD grads, and pubs at more vs. less exposed university fields, 1960-1990

Panel (A): AMWS scientists

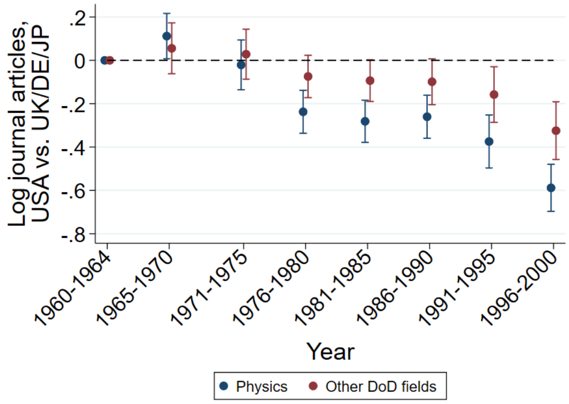
Panel (B): PQDT graduates

Panel (C): Journal publications



Notes: Figure shows estimated differences over time in AMWS scientists, PQDT PhD graduates, and journal articles at/from university-fields with versus without exposure to DoD funding cuts (Panels A to C, respectively). Underlying regression estimates differences in log scientists by OLS and PhD graduates and publication counts by Poisson pseudo-maximum likelihood (PPML). All regressions control for university-field and university-year fixed effects. Journal articles are fractionally associated to each listed author and their affiliated institution. All estimates are relative to 1969 (the omitted category). Error bars represent 95% confidence intervals, computed from standard errors clustered at the university level.

Figure 4: Differences in total US vs. foreign publications in affected fields, 1960-2000

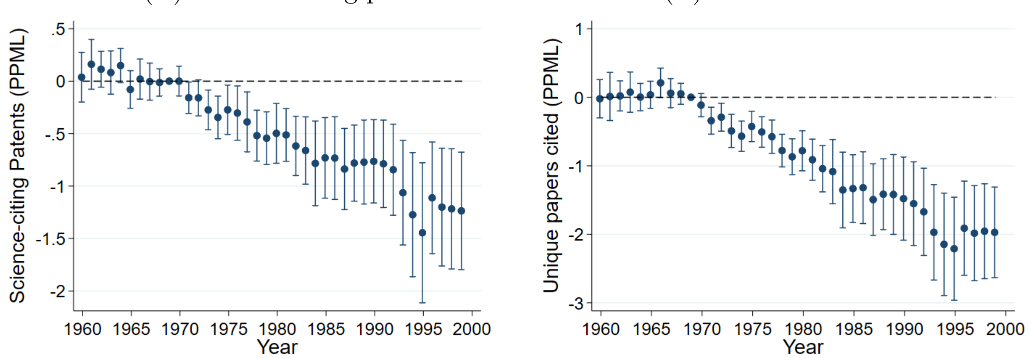


Notes: Figure shows estimated differences over time in log journal articles published by US vs. British, German, and Japanese authors in more vs. less heavily DoD-supported fields. Underlying regression is estimated off a country-field-year sample, with 5-year averages shown to smooth annual fluctuations. We separately estimate differences in the growth of national science for physics (the most DoD-intensive field; shown in blue) and for geosciences, mathematics, computer science, and engineering (other DoD-intensive fields; shown in red). Journal articles are fractionally associated to each listed author and their affiliation country. All estimates are relative to the 1965-1970 period (the omitted category). Error bars represent 95% confidence intervals, computed from robust standard errors.

Figure 5: Patenting in technology areas with differential exposure to DoD-funded science

Panel (A): Science-citing patents

Panel (B): Breadth of science cited



Notes: Figure shows estimated differences over time in US patenting in technology areas (CPC subclasses, henceforth CPC) with higher (vs. lower) exposure to DoD funding cuts. CPC-level exposure is calculated by (i) beginning with a dataset of patents filed by US inventors and merging in their in-text citations to scientific publications, (ii) calculating the distribution of scientific fields of these cited publications, (iii) calculating the share of researchers in each of these fields that was DoD-supported in 1970, and (iv) crossing the two to get a weighted average exposure measure. Subclasses where most scientific citations are to papers in subjects with heavy DoD support will thus be measured as more exposed. We restrict the sample to patents filed by US inventors and associate patents to their primary inventive CPC. We then divide CPCs into terciles of exposure and measure assorted outcomes at the CPC x year level. Panel (A) shows estimated differences in more vs. less exposed CPCs' number of science-citing patents, and Panel (B) shows differences in the breadth of science they cite (number of unique papers cited each year). Underlying regression estimated by Poisson pseudo-maximum likelihood (PPML) and controls for CPC and year fixed effects. All estimates are relative to 1969 (the omitted category). Error bars represent 95% confidence intervals, computed from standard errors clustered at the CPC level.

Table 1: Share of NRSTP scientists at MIT, Stanford, and Harvard in 1970 with federal funding

University	NRSTP scientists	Any govt. funding?	Funding agency DOD	AEC	NASA	NIH
Massachusetts Institute of Technology	1045	70%	27%	12%	12%	15%
Stanford University	878	70%	17%	11%	9%	27%
Harvard University	1137	65%	7%	4%	5%	38%

Notes: Table illustrates variation in the sample among even the most elite US research universities in their exposure to DoD research funding cuts. Although 65-70% of NRSTP scientists at each of Harvard, MIT, and Stanford reported government support in 1970, MIT was significantly engaged in DoD-funded research (27%), Harvard disengaged (7%), and Stanford in between (17%). These patterns are similar with respect to other research sponsors close to the defense mission (AEC, NASA) and inverted for biomedical research funding (NIH).

Table 2: Top 15 university-fields by share of scientists in 1970 with DoD support

University	Department	NRSTP personnel in 1970 survey	Pct. of NRSTP with DoD support
Johns Hopkins University	Engineering	18	83.3%
University of Dayton	Chemistry	20	65.0%
University of Dayton	Engineering	16	56.3%
Brown University	Engineering	11	54.5%
University of Dayton	Physics and astronomy	22	54.5%
University of Utah	Computer sciences	11	54.5%
University of Utah	Engineering	11	54.5%
University of New Mexico-Main Campus	Engineering	15	53.3%
Illinois Institute of Technology	Engineering	17	52.9%
Massachusetts Institute of Technology	Engineering	101	52.5%
Massachusetts Institute of Technology	Computer sciences	100	51.0%
Stevens Institute of Technology	Engineering	10	50.0%
Carnegie Mellon University	Computer sciences	27	48.1%
Georgetown University	Physics and astronomy	17	47.1%
University of Rochester	Mathematics and statistics	71	46.5%

Notes: Table lists the top 15 university-fields (in essence, departments) by their share of NRSTP scientists with DoD support in 1970, restricting to departments with at least 10 reporting NRSTP scientists (to reduce noise). The list is consistent with contextual understanding of the research landscape at the time (e.g., Johns Hopkins' Applied Physics Laboratory, Carnegie Mellon's and University of Utah's heavily ARPA-funded computer science departments, University of Dayton and New Mexico's relationships to national security installations like Wright Field or Los Alamos, or MIT's many defense research labs).

Table 3: University-field scientist headcount and PhD production over time, 1965-1990

	AMWS scientists					PhD graduates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	All	All	≤5y in	≤10y in	SED PhDs	PQDT PhDs	Def. base	Def. base
Any DoD exposure * 1(1971-1975)	-0.079***	-0.051**	-0.050**	-0.100**	-0.114***	0.009	-0.067	-0.483**	-0.631*
	(0.020)	(0.022)	(0.020)	(0.040)	(0.036)	(0.051)	(0.052)	(0.216)	(0.334)
Any DoD exposure * 1(1976-1980)	-0.121***	-0.099***	-0.072***	-0.117**	-0.216***	-0.127*	-0.272***	-0.710***	-0.944***
	(0.026)	(0.028)	(0.025)	(0.050)	(0.051)	(0.070)	(0.068)	(0.206)	(0.292)
Any DoD exposure * 1(1981-1985)	-0.114***	-0.113***	-0.056*	-0.135**	-0.240***	-0.160**	-0.252***	-0.860***	-0.909***
	(0.031)	(0.033)	(0.030)	(0.052)	(0.056)	(0.082)	(0.073)	(0.253)	(0.310)
Any DoD exposure * 1(1986-1990)	-0.106***	-0.128***	-0.047	-0.175***	-0.217***	-0.188**	-0.313***	-0.662***	-0.682**
	(0.034)	(0.035)	(0.032)	(0.055)	(0.056)	(0.089)	(0.078)	(0.238)	(0.318)
N	36514	36438	36514	25245	31547	28793	30289	13945	11253
R^2	0.95	0.97	0.95	0.83	0.88				
Y mean	2.219	2.223	2.219	1.105	1.510	9.883	9.601	0.611	0.491
Method	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Inst x Field FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y								
Inst x Year FEs		Y		Y	Y	Y	Y	Y	Y
Field x Year FEs			Y						

Notes: Table estimates differences over time in the number of PhD scientists employed at and PhDs graduating from university-fields with versus without exposure to DoD funding cuts. Scientists are measured using biographical listings in American Men and Women of Science (AMWS) from 2005 onward, from which we can extract listed scientists' previous employers and years of employment, and using these, count up scientists at the university-field-year level. We separately evaluate post-1970 changes in total AMWS scientists (Columns 1 to 3) and early-career scientists (Columns 4 and 5), which we alternatively define as researchers less than five or ten years into their careers. PhD graduates are independently measured in the SED and from PQDT (Columns 6 and 7). The final columns report changes in the number of PhD graduates produced who later enter the defense industrial base, using a more liberal (Column 8) and conservative (Column 9) definition of its boundaries (see text for details). Columns (1) to (5) estimate log outcomes by OLS and Columns (6) to (9) count outcomes by Poisson pseudo-maximum likelihood, reflecting the nature of the variation in each outcome. Columns (1) to (3) control for university-field fixed effects (FEs) and (1) year FEs, (2) university-year FEs, and (3) field-year FEs. Columns (4) to (9) control for university-field and university-year fixed effects. All columns include controls for time-varying differences by units' size (measured by a university-field's 1970 NRSTP respondents) and are estimated relative to 1965-1970 (the omitted category). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by university in parentheses.

Table 4: Early career researchers (PhD in 1965-1969): Employment sector over time

	(1) University	(2) Industry	(3) Government	(4) Multiple	(5) Univ-Ind	(6) Univ-Gov	(7) Any Pats.
DoD-funded in 1970 * 1(1971-1975)	-0.068***	0.035***	0.015*	0.011	0.005	0.007	0.003
	(0.020)	(0.013)	(0.009)	(0.013)	(0.007)	(0.009)	(0.003)
DoD-funded in 1970 * 1(1976-1980)	-0.118***	0.030*	0.011	0.062***	0.042***	-0.001	0.010*
	(0.029)	(0.016)	(0.012)	(0.020)	(0.014)	(0.011)	(0.005)
DoD-funded in 1970 * 1(1981-1985)	-0.115***	0.038**	-0.001	0.070***	0.036**	0.006	0.011**
	(0.031)	(0.018)	(0.011)	(0.024)	(0.015)	(0.013)	(0.005)
DoD-funded in 1970 * 1(1986-1990)	-0.115***	0.049**	-0.002	0.064**	0.033**	0.007	0.012*
	(0.032)	(0.020)	(0.011)	(0.025)	(0.016)	(0.014)	(0.007)
N	105371	105371	105371	105371	105371	105371	105502
R^2	0.08	0.02	0.01	0.04	0.01	0.02	0.01
Y mean	0.856	0.028	0.018	0.077	0.018	0.030	0.005
Field-Year FEs	Y	Y	Y	Y	Y	Y	Y

Notes: Table estimates propensity for AMWS-listed, early career university scientists to work in assorted sectors over time, as a function of whether they had DoD support in 1970. Sample restricted to scientists who received their PhD in 1965-1969 and worked at universities until at least 1970. Outcomes indicate employment in the university, industry, or government sectors (Columns 1 to 3) or a mixture of sectors (i.e., individuals with either multiple affiliations in a given year or who are transitioning between sectors, Columns 4 to 6). The final outcome (Column 7) measures patenting, as an indicator for whether the given scientists filed one or more patents in a given year. All columns control for field-year fixed effects and present estimates relative to 1965-1970 (the omitted category); because the sample is conditioned to pre-1970 university scientists, all post-1970 outcomes should be interpreted as a transition away from university employment (and similarly for patenting, of which there was almost none in this population prior to 1970). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by individual in parentheses.

Table 5: US patenting in technology areas with differential exposure, 1965-2000

	(1) Patents	(2) DoD pats.	(3) PCS pats.	(4) Uniq. cites	(5) DoD-PCS pats.
Above-median exposure * 1(1971-1975)	-0.011	0.040	-0.234***	-0.466***	0.371*
	(0.030)	(0.066)	(0.087)	(0.080)	(0.204)
Above-median exposure * 1(1976-1980)	-0.019	0.041	-0.444***	-0.757***	0.534**
	(0.048)	(0.105)	(0.131)	(0.112)	(0.214)
Above-median exposure * 1(1981-1985)	-0.008	0.130	-0.658***	-1.212***	-0.095
	(0.064)	(0.104)	(0.178)	(0.230)	(0.228)
Above-median exposure * 1(1986-1990)	-0.039	-0.099	-0.765***	-1.464***	-0.340
	(0.084)	(0.144)	(0.213)	(0.290)	(0.226)
Above-median exposure * 1(1991-1995)	-0.049	-0.062	-1.147***	-2.049***	-0.443
	(0.133)	(0.157)	(0.299)	(0.371)	(0.328)
Above-median exposure * 1(1996-2000)	0.140	-0.111	-1.192***	-1.972***	-0.853***
	(0.184)	(0.194)	(0.296)	(0.352)	(0.281)
N	22968	18036	21096	21312	10548
Y mean	81.893	2.487	10.560	79.589	0.766
Method	PPML	PPML	PPML	PPML	PPML
CPC FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y

Notes: Table shows estimated differences over time in US patenting in technology areas (CPC subclasses, henceforth CPC) with higher (vs. lower) exposure to DoD funding cuts. CPC-level exposure is calculated by (i) beginning with a dataset of patents filed by US inventors and merging in their in-text citations to scientific publications, (ii) calculating the distribution of scientific fields of these cited publications, (iii) calculating the share of researchers in each of these fields that was DoD-supported in 1970, and (iv) crossing the two to get a weighted average exposure measure. Subclasses where most scientific citations are to papers in subjects with heavy DoD support will thus be measured as more exposed. We restrict the sample to patents filed by US inventors and associate patents to their primary inventive CPC. We then divide CPCs into above and below median exposure and measure assorted outcomes at the CPC x year level. Column (1) evaluates total patents; Column (2), defense patents (measured as DoD-funded patents; Gross and Sampat 2025a); Column (3), science-citing patents; Column (4), the breadth of science cited (number of unique papers cited each year); and Column (5), science-citing defense patents. All columns control for CPC and year fixed effects. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by CPC in parentheses.

Online Appendix

Retreating from Science: The Long-Run Effects of the 1970s U.S. Military Disinvestment from University Research

Daniel P. Gross, Bhaven N. Sampat, and Hansen Zhang

Table of Contents

A Historical Appendix

A.1 Mansfield Amendment: Policy background

On July 3rd, 1969, Senate Majority Leader Mike Mansfield (D-MT) proposed an amendment to the FY 1970 Military Authorization bill disallowing Department of Defense funding of research that lacked "a direct and apparent relationship to a specific military function or operation." The bill passed the Senate on September 18th and was agreed to in the House on October 3rd. It was eventually enshrined in Public Law No. 91-121 on November 19th, 1969.

In this appendix we provide a more extended account of the Mansfield Amendment, including its legislative history, contemporary reactions, and questions of impacts.[1]

A.1.1 Contextual factors: War and public distrust of government

The Mansfield Amendment came into being during the Vietnam War—arguably the most unpopular war in American history. Due to advances in photography and television, the sights and sounds of the war were brought into American living rooms for the first time, putting service member and civilian casualties under direct public scrutiny. Public opinion turned on the conflict as a result. In 1964, two-thirds of Americans said they paid "little or no attention to developments in South Vietnam," but by 1969, more than 80% of Americans thought U.S. involvement in Vietnam was a "mistake" (Lunch and Sperlich 1979). Protests became common across the country, but anti-war activism manifested itself particularly strongly on university campuses.

Universities saw opposition to the Vietnam war by their student bodies from the beginning of the conflict. Protests at colleges increased in frequency and scale throughout the 1960s as students objected not only to what they considered to be an immoral war but also the presence of the military on their campus. Many demanded the elimination of the Reserve Officers Training Corps at their school, saying the program's continuation represented an institutional endorsement of U.S. participation in the Vietnam War. Others protested on-campus research funded by and performed for the military. At the University of Michigan, for example, protesters condemned the university's connection to Willow Run, an Army research lab, and the >$66 million in military contracts awarded to the university in relation to it. With the election of President Richard Nixon in 1968, end of draft deferment in 1969, and assassination of student protesters at Kent State University in 1970, the protest movement reached a fever pitch—leading to demonstrations by "over four million students at nearly 1,350 campuses" and "nine hundred colleges [being] shut down on account of student strikes; 169 bombs exploded on campuses, and 35,000 National Guardsmen called up to end on-campus riots" (The Akron Beacon Journal 1970, pp. 19-23).

Beyond the Vietnam War, the 1960s produced a significant decline in public confidence in the U.S. government as a steward of the American public and the American taxpayer. In 1964, according

[1] Portions of this section are adapted from a policy memo written for us by Mark McDonough.

to a survey from the Pew Research Center, 77% of Americans believed that they could trust the government "always" or "most of the time"; by 1970, the share with this view had fallen to just above 50% (Pew Research Center 2015). Some of the declining confidence could likely be attributed to the progression of the Vietnam War, but some also reflected growing perceptions of extravagance and waste: in the same survey, 46% of respondents in 1964 agreed that the government "wasted money a lot", and 57% and 68% agreed in 1968 and 1970 (Miller 1974).

A.1.2 Proposition and debate around Mansfield Amendment

At the dawn of the 1970s, defense-funded university science thus found itself squeezed between the one half of Congress which was skeptical of the military, the other half which was put off by student protest movement, and increasing pressures of austerity on both sides. It is in this context that Mansfield's restrictions on military research funding were proposed. Senator Mansfield was a prominent anti-war Congressman who advocated for withdrawal from Vietnam. Military research was only one domain where the senator sought to rein in the Department of Defense: for example, just one day before the Mansfield Amendment was formally proposed (July 3, 1969), the Senate discussed DoD missile programs, after Mansfield was quoted by the New York Times claiming that America had "wasted $23 billion in the past decade" on missile projects (Finney 1969)—an estimate which others in the Senate argued was for many reasons an exaggeration, as it included successful projects and did not take seriously the ex-ante uncertainty of R&D.

A few days after the 1970 military authorization bill was presented to the Senate with the Mansfield Amendment in it, Mansfield expressed his reasoning in a dialogue about anti-ballistic missile (ABM) systems. He initially targeted the Hudson Institute, a research center that worked closely with the U.S. government, saying "I am wondering how much the Hudson Institute has received over the past decade or more, and I wonder how much it has produced in return." Mansfield then expanded his scope to colleges, universities, and other research groups, questioning how much of DOD's $8 billion dollar research budget "was siphoned off" to these institutions and what the money tangibly produced. Senator Ted Kennedy (D-MA) echoed Mansfield's argument.

Amid this falling out, other Senators came to the defense of research institutions. Senator Barry Goldwater (R-AZ) responded to Mansfield's remarks, saying he would feel "remiss" if he were to let the record imply that there was some sort of wrongdoing on behalf of the Hudson Institute—a point to which Mansfield agreed. Goldwater then followed up by asserting that the future of the military would continue to rely heavily on the academic sector and, rather than cut out all funding, Congress has the prerogative to help set guidelines to structure their involvement. Senator Peter Dominick (R-CO) took a harder stance, warning about the danger of letting anti-war sentiments define policy that could leave the country unprepared for future conflict.

With regards to university research specifically, Mansfield harbored a firm belief that basic research should be supported by civilian agencies like the NSF, rather than the Pentagon. The Mansfield Amendment was in effect an effort "to reduce the research community's dependence on the Department of Defense" (Nature Washington Correspondent 1970, p. 1291). As Charles Ferris, a Mansfield advisor, explained, DoD's influence on science had grown excessive: "We felt the scientific community had exposed itself to charges that it had prostituted itself by taking DOD money while simultaneously claiming that none of the research had any relation to the Defense Department and that the Congress had exposed itself to charges that it was not sufficiently mature, because it failed to recognize that basic research should be supported for its own sake, not just when it was being requested under a veil of national security" (Ferris, as quoted in Lubkin 1971, p. 61). Mansfield noted in congressional remarks that in his view, "DoD funding of academic research [should be] no more than 25 percent of that funded by the National Science Foundation" by the end of 1971, and if the Nixon administration were to reduce the overall level of science funding in its next budget request, "that would not be a national calamity."

The Mansfield Amendment was merely one (significant) manifestation of this broader battle. Once introduced, Senate discussion of the Mansfield Amendment and wasteful military spending continued throughout the summer of 1969 until the military authorization bill passed on September 18, with the amendment in it. The House of Representatives then passed its own version of the military authorization bill on October 3. Though these bills had yet to be reconciled and no section yet directly mirrored Mansfield's amendment to the Senate bill, several provisions of the House bill limited research—particularly at universities—which led to heated debate on the House floor. Representative Donald Fraser (D-MN) called into question a section that required universities to provide "a statement summarizing the record of the school, college, or university with regard to cooperation on military matters" before DoD would write a research contract, attracting rebuke from Representative Lucius Rivers (D-SC), who defended the measure and said the U.S. government should not "reward a college [that was not] supporting our military."

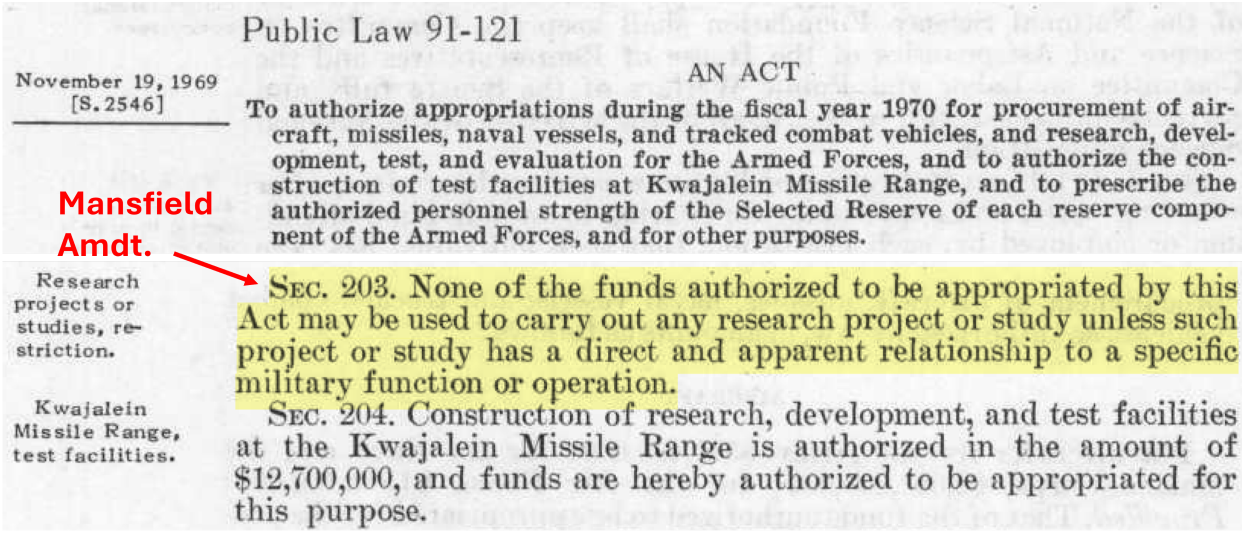
Away from Capitol Hill, the Mansfield Amendment generated regular discussion in the news and editorial sections of scientific journals, which updated readers on this policy change. Some observers in the general media also took notice of the Mansfield Amendment, including some syndicated, widely-circulated reporting on Mansfield's attempts to "clamp down on Pentagon research," which included a quote from Mansfield that "The days of just asking and receiving are in the past" (Mears 1969). More often, however, general media merely reported on Mansfield's broader battle against the Defense Department, of which the amendment was just one front.

The Mansfield Amendment was formally written into law as Section 203 of Public Law 91-121 on November 19th, when the military authorization for fiscal year 1970 was enacted. Figure A.1 shows the text of the one-sentence amendment in its final form.

A.1.3 Enactment, enforcement, and adaptation

The Mansfield Amendment triggered immediate changes in contracting practices at DoD, where new contracts, and existing contract renewals, began to received greater scrutiny with regards to their mission relevance and began to incorporate relevance statements. We have found evidence of

Figure A.1: Mansfield Amendment (FY 1970): Legislative Text and Specific Requirements



Public Law 91-121

November 19, 1969
[S. 2546]

AN ACT

To authorize appropriations during the fiscal year 1970 for procurement of aircraft, missiles, naval vessels, and tracked combat vehicles, and research, development, test, and evaluation for the Armed Forces, and to authorize the construction of test facilities at Kwajalein Missile Range, and to prescribe the authorized personnel strength of the Selected Reserve of each reserve component of the Armed Forces, and for other purposes.

Research projects or studies, restriction.

SEC. 203. None of the funds authorized to be appropriated by this Act may be used to carry out any research project or study unless such project or study has a direct and apparent relationship to a specific military function or operation.

Kwajalein Missile Range, test facilities.

SEC. 204. Construction of research, development, and test facilities at the Kwajalein Missile Range is authorized in the amount of $12,700,000, and funds are hereby authorized to be appropriated for this purpose.

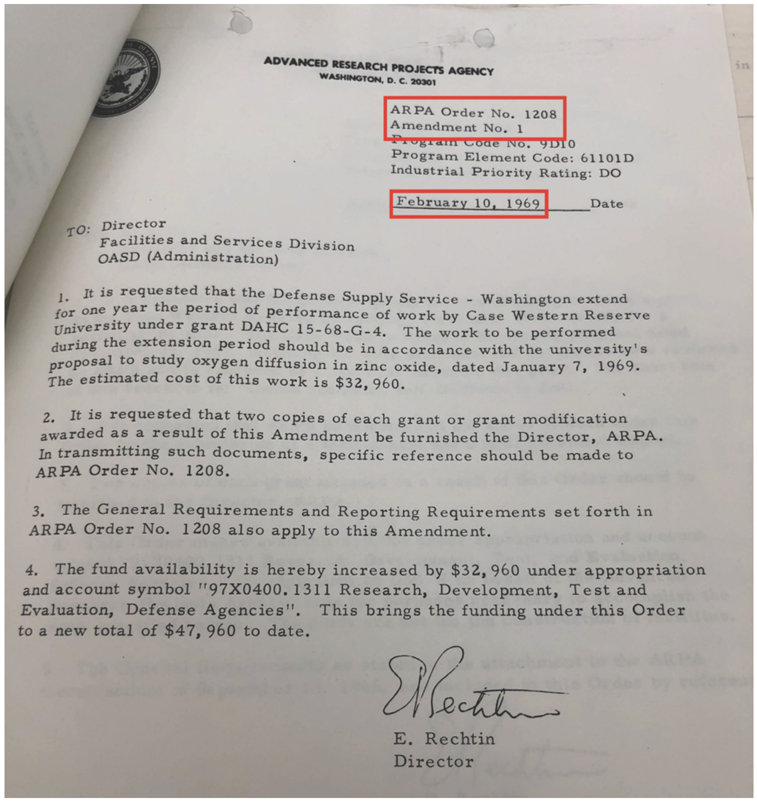
this ourselves in archival contract records: Figures A.2 to A.4 show the evolution of an example ARPA research contract, across three sequential amendments from 1969 to 1971, as the Mansfield Amendment's requirements on DoD-funded research began to take effect, with relevance statements being added in 1970 and extended in 1971. Other contracts are similar.

Shortly after the amendment was enacted, Mansfield wrote to Deputy Secretary of Defense David Packard and leaders at other research funding agencies to notify them that "Section 203 expresses a fundamental change in Federal funding for research. In essence, it emphasizes the responsibility of the civilian agencies for long term, basic research" (Nichols 1971, p. 30). At Mansfield's request, DoD proceeded to undertake a complete review of its research portfolio (over 15,000 projects) to assure itself and Congress that its projects were compliant with the relevance requirement. Roughly 400 projects, with $10 million in annual funding, were terminated as a result of this review, though as Nichols (1971) observes, "this budget reduction was swamped by the $64 million budget cut imposed by Congress on DoD's planned FY 1970 program."

Despite their aggressive posture, Mansfield and his supporters claimed they did not wish for important research abandoned, only transitioned to civilian support—even if, as Mansfield acknowledged, change could be costly in the short run. To this end, Mansfield's Senate allies on the NSF appropriations subcommittee proposed a substantial (20%) increase in NSF's budget for fiscal year 1971 to counteract defense research cuts. However, due to resistance in the House, this increase was only enacted a year later, and much of that increase was earmarked for applied research programs that would not be able to fund the same research the Defense Department was leaving behind. Resource constraints, priority differences, and the exposure of civilian research to congressional budget cycles all meant that NSF was unlikely to be a comparable substitute for DoD as a research funder, especially in long-range science and research infrastructure.

The challenges of transitioning research from DoD to NSF support, and the political landmines it

Figure A.2: Example ARPA contract (AO 1208), Amendment 1, February 1969



ADVANCED RESEARCH PROJECTS AGENCY
WASHINGTON, D. C. 20301

ARPA Order No. 1208
Amendment No. 1
Program Code No. 9D10
Program Element Code: 61101D
Industrial Priority Rating: DO

February 10, 1969 Date

TO: Director
Facilities and Services Division
OASD (Administration)

1. It is requested that the Defense Supply Service - Washington extend for one year the period of performance of work by Case Western Reserve University under grant DAHC 15-68-G-4. The work to be performed during the extension period should be in accordance with the university's proposal to study oxygen diffusion in zinc oxide, dated January 7, 1969. The estimated cost of this work is $32,960.

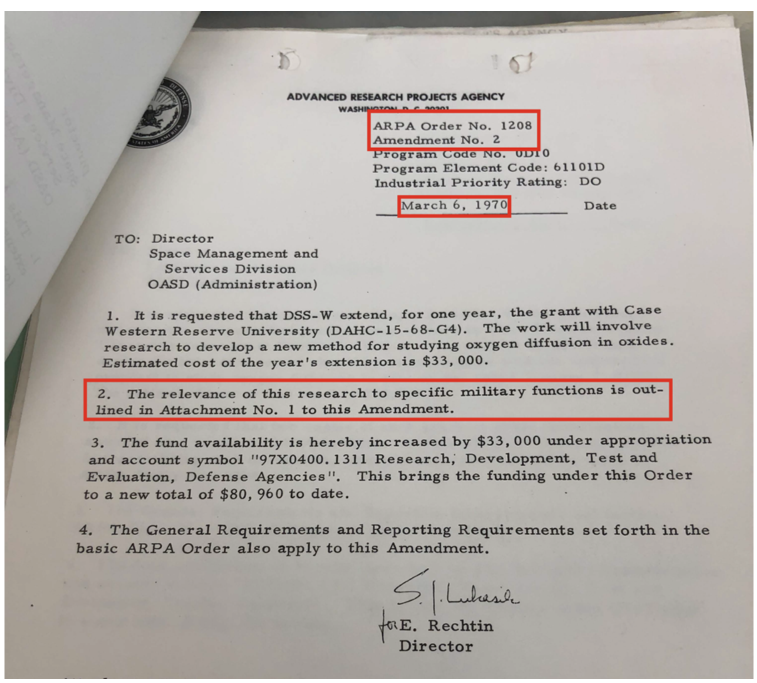
2. It is requested that two copies of each grant or grant modification awarded as a result of this Amendment be furnished the Director, ARPA. In transmitting such documents, specific reference should be made to ARPA Order No. 1208.

3. The General Requirements and Reporting Requirements set forth in ARPA Order No. 1208 also apply to this Amendment.

4. The fund availability is hereby increased by $32,960 under appropriation and account symbol "97X0400.1311 Research, Development, Test and Evaluation, Defense Agencies". This brings the funding under this Order to a new total of $47,960 to date.

E. Rechtin
Director

Figure A.3: Example ARPA contract (AO 1208), Amendment 2, March 1970



ADVANCED RESEARCH PROJECTS AGENCY
WASHINGTON, D. C. 20301

ARPA Order No. 1208
Amendment No. 2
Program Code No. 0D10
Program Element Code: 61101D
Industrial Priority Rating: DO

March 6, 1970 Date

TO: Director
Space Management and
Services Division
OASD (Administration)

1. It is requested that DSS-W extend, for one year, the grant with Case Western Reserve University (DAHC-15-68-G4). The work will involve research to develop a new method for studying oxygen diffusion in oxides. Estimated cost of the year's extension is $33,000.

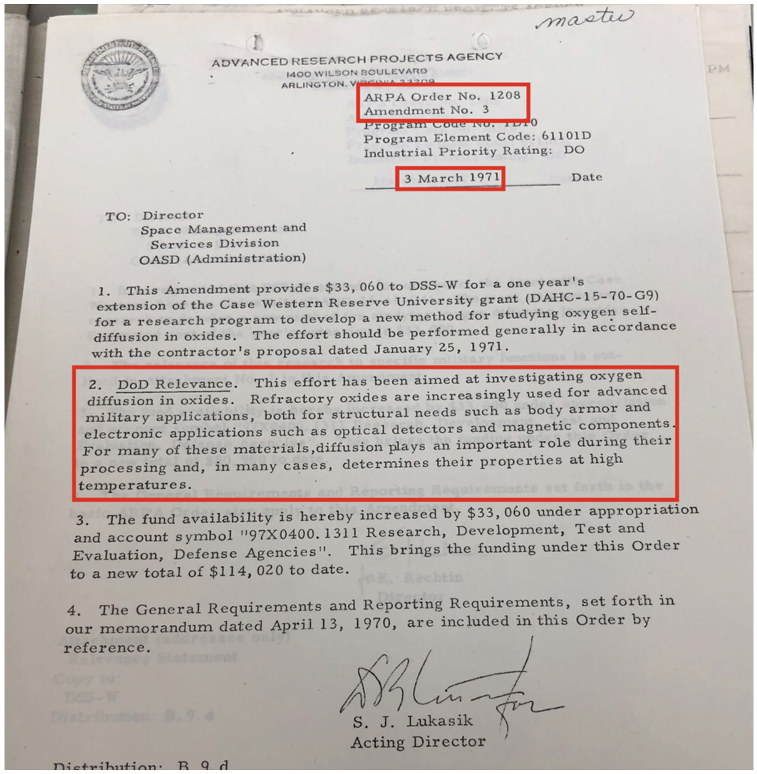
2. The relevance of this research to specific military functions is outlined in Attachment No. 1 to this Amendment.

3. The fund availability is hereby increased by $33,000 under appropriation and account symbol "97X0400.1311 Research, Development, Test and Evaluation, Defense Agencies". This brings the funding under this Order to a new total of $80,960 to date.

4. The General Requirements and Reporting Requirements set forth in the basic ARPA Order also apply to this Amendment.

S. J. Lukasik
for E. Rechtin
Director

Figure A.4: Example ARPA contract (AO 1208), Amendment 3, March 1971



master

ADVANCED RESEARCH PROJECTS AGENCY
1400 WILSON BOULEVARD
ARLINGTON, V

ARPA Order No. 1208
Amendment No. 3
Program Code No. ..10
Program Element Code: 61101D
Industrial Priority Rating: DO

3 March 1971 Date

TO: Director
Space Management and
Services Division
OASD (Administration)

1. This Amendment provides $33,060 to DSS-W for a one year's extension of the Case Western Reserve University grant (DAHC-15-70-G9) for a research program to develop a new method for studying oxygen self-diffusion in oxides. The effort should be performed generally in accordance with the contractor's proposal dated January 25, 1971.

2. DoD Relevance. This effort has been aimed at investigating oxygen diffusion in oxides. Refractory oxides are increasingly used for advanced military applications, both for structural needs such as body armor and electronic applications such as optical detectors and magnetic components. For many of these materials, diffusion plays an important role during their processing and, in many cases, determines their properties at high temperatures.

3. The fund availability is hereby increased by $33,060 under appropriation and account symbol "97X0400.1311 Research, Development, Test and Evaluation, Defense Agencies". This brings the funding under this Order to a new total of $114,020 to date.

4. The General Requirements and Reporting Requirements, set forth in our memorandum dated April 13, 1970, are included in this Order by reference.

S. J. Lukasik
Acting Director

Distribution: B.9.d

created, were further evident in a contentious exchange between Mansfield and presidential science advisor Lee A. DuBridge in July 1970. After DuBridge explained that "If DoD had been working only under budgetary restrictions, it would have cut out what it believed to be the less productive ... research activities that it was supporting, [b]ut with the Mansfield Amendment it had to cut out some of our ... most valuable projects to the country because they could not prove their relevance to specific military purposes", Boffey (1970a, p. 356) reports that

> He [Mansfield] called DuBridge's assertion that the defense agencies had cut some of their most productive research projects while continuing to fund less productive projects "a shocking statement," arguing that if nonproductive research remains in the Defense Department, then it should be eliminated, and that if DoD had been forced to cut high-quality work because it has no relation to defense matters, then such work should be supported by the National Science Foundation. Mansfield went on to argue that "if high quality work is going down the drain, it is largely DuBridge's fault for failing to assure that the work is transferred to NSF.

A.1.4 Alleged impacts of the Mansfield Amendment

Within six months, evidence of the effects of the Mansfield Amendment and the broader austerity surrounding it had begun to build. Boffey (1970) reported in March 1970 that Representative Emilio Q. Daddario (D-CT), the chairman of the House Subcommittee on Science, Research, and Development, had announced in a press conference $50 million in research that DoD was slated to cancel. Among the scheduled terminations were a particle accelerator at Florida State University, the National Magnet Laboratory and Haystack Radio Telescope at MIT, and quantum physics research at the University of Illinois. Reflecting their own constraints, Daddario also noted NASA-, and AEC-, and NIH-funded projects which were also on the chopping block. Some, but not all, of these programs were later funded by NSF, albeit at different levels.

A report from the Research Management Advisory Panel (RMAP)—an advisory group to the House Subcommittee on Science, Research, and Development created in 1963—expressed a concern that the United States "recently won leadership in science" was at risk as "Government support for university research has become unstable and unpredictable [and] is actually decreasing in several fields of science" (RMAP 1970, p. 2). At its essence, the RMAP argued, the U.S. government was "treating university basic research as a luxury it can no longer afford," contradicting the rationale behind national science policy since World War II, under which science was "central to stability, economic progress, and security" (RMAP 1970, pp. 1-2).

In congressional debate and contemporary newspaper articles about the Mansfield Amendment, the discussion of the measure focused on the principles of the provision and the past events that led to its inclusion in the military authorization bill, than of its potential effects. Only scientific journals engaged with the potential impacts of Mansfield's amendment (e.g., Laitinen 1970, Nichols 1971, Lubkin 1971). Of the journalists, editors, and op-ed contributors at these outlets who commented on the new restrictions, many expressed concern about its consequences for American science, with some simply claiming that the policy was short-sighted, and others presenting more dramatic assessments that "the entire post-World War II institutional machinery and rhetoric for R&D are now in disarray" and require a rethinking "to restore the public confidence necessary for adequate support of science and technology" (Nichols 1971, pp. 36-37).

Despite the heated rhetoric, little systematic evidence was available at the time regarding the effects of the Mansfield Amendment or the broader changes in defense research it was emblematic of.[2] That proponents of the Mansfield measure could claim success at the same time as opponents could claim great damage was being wrought reflects the complexity of the fragmented science policy landscape, which meant there were multiple potential funders for some research; empirical ambiguity given the limited available data; and the difficulty of assessing counterfactuals. In some ways, this paper is an effort to address this gap 50 years later.

[2] Oral histories with researchers from this era later provided more color. Several ARPA-funded computer scientists, for example, described how the research environment changed, with one future Turing Award winner (Edward Feigenbaum) calling it the "end of Eden" (Feigenbaum, in Aspray 1989) "ARPA up until the Mansfield Amendment was [a] trouble-free paradise for working, getting your ideas approved, getting funding for them." Another ARPA-funded future Turing Award winner (Alan Kay) left the academy to join Xerox PARC in 1970, amid this turbulence in research support, and ascribed its growth in the 1970s to the Mansfield Amendment and the ex-university scientists it recruited—claiming "PARC wouldn't have happened without [it]" (Kay 2006).

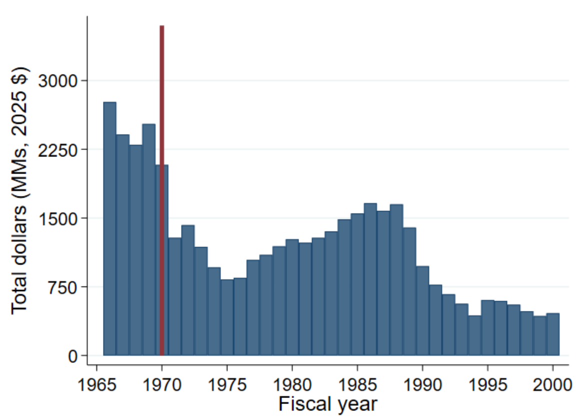
A.1.5 Rescission and reverberations

Because the Mansfield Amendment was a provision in a military authorization bill, it was effectively subject to annual Congressional renewal. Mansfield succeeded in attaching a similar measure to the 1971 fiscal year military authorization act, albeit with softer language, reducing the requirement that funded research have a "direct and apparent relationship to a specific military function or operation" to "a potential relationship". This change not only seemingly expanded the scope of what research was permitted, but also allowed more discretion. Mansfield Amendment provisions were removed from the 1972 military authorization act, making it appear outwardly that the Mansfield era was a short-lived interlude in defense science policy.

The spirit of the Mansfield Amendment, however, had a much greater and longer-lived impact than its statutory requirements would suggest, as it appears to have permanently altered the culture of defense research policy from open-ended to more conservative and focused investments in science, driven by the view that this was what Congress expected and a continued congressional emphasis on accountability. Beyond the relevance criteria, it also ushered in an era of declining defense R&D budgets, especially for university science. Though part of the cost was borne by the researchers, and research projects, whose funding was interrupted, a greater portion was arguably borne by researchers and research which would not be funded thereafter.

As Deitchman (1976) explained, the Mansfield Amendment "marked a turning point in national support for scientific research and the beginning of a leveling off and downturn in federal budgeting for such research" from which universities and the scientific community would be slow to recover. Figure A.5 suggests that military R&D funding of university science never did: measured in constant dollars (2025 USD), by the end of the 20th century, defense research contracts to universities were (by value) less than 20% of what they had been in the late 1960s.

Figure A.5: DoD funding for university research, 1966-2000, all universities



Notes: Figure shows total university basic and applied research funding from DoD (budget categories 6.1-6.2), from 1966 to 2000, inflation adjusted to 2025 USD. Data from military prime contract files (available 1966+) and filtered to university contractor type codes.

B Data Appendix

B.1 Exposure to DoD research funding cuts

B.1.1 Military research contract records (1966+)

We measure Department of Defense (DoD) research contracts between 1966 and 2000 using DoD's Military Prime Contract Files (MPCF, covering FY 1966-1975) and its successor database, the Defense Contract Action Data System (DCADS, FY 1976-2000). Both data series are obtained from the U.S. National Archives (NARA).[3] The MPCF contains the earliest record of defense contracting that we have been able to find in any format (paper or electronic). The unit of observation in these data is a contract action, with each entry consisting of encoded fields from a filed DD Form 350 (a contract action report form). Figure B.1 shows an example.

The set of fields reported on these forms, and the response options, changed somewhat over time. To build a longitudinally consistent dataset, we focus on fields which are consistently reported and standardize the coding scheme over time. We make use of information on the contracting department (Army, Navy, Air Force, or Defense Logistics Agency); the federal supply code (FSC, indicating what was procured); the contractor name, location, and organization type; and the contract action date and contract value. these contract files include records of all procurement (of all types of goods and services). We filter the data to research, development, test, and engineering (RDTE) contracts, which are identifiable from the FSC code, and further code these into the DoD's six RDTE budget categories (Table B.1). We standardize contractor names using a set of name cleaning rules, identify potential university contractors based on organization type codes, and manually crosswalk these contractors by name and location to IPEDS (see Section B.4). Because organization types are occasionally miscoded in the raw data, we then apply this crosswalk to all RDTE contracts. In our analysis we use the resulting data on university-based basic (6.1) and applied (6.2) research contracting to evaluate changes to DoD university research funding in the 1970s.[4] Contract value is inflated to constant (2025) USD.

Table B.1: RDTE budget categories definitions, 1970s and today

Activity code	Nomenclature, 1970s	Nomenclature, today
6.1	Research	Basic research
6.2	Exploratory development	Applied research
6.3	Advanced development	Advanced technology development
6.4	Engineering development	Advanced component development
6.5	Operational systems dev.	System development & demonstration
6.6	Management and support	RDTE management support

[3]The MPCF can be obtained from the NARA online catalog at https://catalog.archives.gov/id/606901. The DCADS data can be obtained from NARA at https://catalog.archives.gov/id/578589.

[4]Though research contracts were the prevailing mechanism for funding research (including at universities) in the period we study, grants-in-aid were also issued to university researchers in this era. However, to our knowledge there is no consolidated data source for DoD research grants for the period we study.

Figure B.1: Example DD Form 350 (Contract Action Report), from mid-1980s

INDIVIDUAL CONTRACTING ACTION REPORT *(OVER $25,000)* — REPORT CONTROL SYMBOL DD - DR & E (M) 1014

PART A
A1. TYPE OF REPORT — 0 Original; 1 Cancel; 2 Correcting
A2. REPORT NO.
A3. CONTRACTING OFFICE CODE
A4. NAME OF CONTRACTING OFFICE

PART B
B1. CONTRACT NUMBER
B2. MOD. ORDER OR OTHER ID NUMBER
B3. ACTION DATE *(YYMMDD)*

B4. CONTRACTOR IDENTIFICATION INFORMATION
B4A. DUNS NUMBER
B4B. CONTRACTOR NAME AND DIVISION NAME
B4C. CONTRACTOR ADDRESS *(Street, City, State, Zip Code)*

B5. PRINCIPAL PLACE OF PERFORMANCE
B5A. CITY OR PLACE CODE
B5B. STATE OR COUNTRY CODE
B5C. CITY *(place)* STATE *(country)* NAMES

B6. TYPE OBLIGATION — 1 Obligation; 2 Deobligation; 3 Unfunded
B7. TOTAL DOLLARS *(Obligated or Deobligated) (Enter whole dollars only)*
B8. PRINCIPAL PRODUCT OR SERVICE
B8A. FSC OR SERVICE CODE
B8B. DOD CLAIMANT PROG. NO.
B8C. SYSTEM OR EQUIP CODE
B9. CONSULTING SVCS CONTRACT — 1 Yes 2 No
B10. MULTI-YEAR CONTRACT — 1 Yes 2 No
B11. TOTAL MULTI-YEAR VALUE *(Enter whole dollars only)*
B8D. NAME / DESCRIPTION
B12. FOREIGN MILITARY SALE — 1 Yes; 2 No

B13. KIND OF CONTRACTING ACTION *(Make one selection from 1 - 8 or A - G)*
1 Initial Letter Contract
2 Definitive Contract Superseding Letter Contract
3 Definitive Contract
4 Order Under DoD BOA
5 Order Under DoD Contract
6 Order Under Mandatory GSA Federal Supply Schedule
7 Action with Another Agency
8 Order Under Optional GSA Schedule

MODIFICATION
A Additional Work *(new agreement)*
B Additional Work *(other)*
C Funding Action
D Change Order
E Termination for Default
F Termination for Convenience
G Cancellation

PART C ***(Do Not Complete This Part If Item B12 Above is Coded 1)***

C1. SYNOPSIS — 1 Yes; 2 No
C2. REASON NOT SYNOPSIZED *(Enter appropriate reason code from instructions)*
C3. METHOD OF CONTRACTING — 1 Formal Advertising/ Sealed Bidding; 2 Negotiated
C4. NEGOTIATION AUTHORITY *(Enter appropriate reason code from instructions)*
C5. EXTENT OF COMPETITION
1 Price Competition
2 Design Technical Competition
3 Follow on After Price Competition
4 Follow on After Design/Technical Competition
5 Other Non-Competition
6 Catalog or Market Price
7 Not Applicable

C6. TYPE OF CONTRACT
A Fixed Price Redetermination, Type A
B Fixed Price Redetermination, Type B
J Firm Fixed Price
K Fixed Price Economic Price Adjustment
L Fixed Price Incentive *(W/Perf. Incentive)*
M Fixed Price Incentive *(W/O Perf. Incentive)*
R Cost Plus Award Fee
S Cost Contract
T Cost Sharing
U Cost Plus Fixed Fee
V CPIF *(W/Perf. Incentive)*
W CPIF *(W/O Perf.Incentive)*
Y Time and Materials
Z Labor Hour

C7. NUMBER OF OFFERORS SOLICITED — 1 One; 2 More than one
C8. NUMBER OF OFFERS RECEIVED — 1 One; 2 More than one

C9. SOLICITATION PROCEDURES
A Full & Open Competition-Sealed Bid
B Full & Open Competition-Competitive Proposal
C Full & Open Competition-Combination
D Architect-Engineer
E Basic Research
F Multiple Award Schedule
G Alternate Source-Reduced Cost
H Alternate Source-Mobilization
J Alternate Source-Eng/R&D Capability
K Set Aside
L 8(a) Program
M Otherwise Authorized by Statute
N Other than Full & Open Competition

C10. AUTHORITY FOR OTHER THAN FULL & OPEN COMPETITION
1A Unique Source
1B Follow-on Contract
1C Unsolicited Research Prop
1D Patent/Data Rights
1E Utilities
1F Standardization
1G Only One Source - Other
2A Urgency
3A Mobilization
3B Essential R & D Capability
4A International Agreement/ FMS
5A Authorized by Statute
5B Authorized Resale
6A National Security
7A Public Interest

PART D ***(Do Not Complete This Part If Item B12 Above is Coded 1 or If Item B13 is Coded 6, 7 or 8)***

D1. TYPE OF BUSINESS *(Make one selection from 1 - 4 or A - E)*
1 Large Business Performing in the U.S.
2 Small Business Performing in the U.S.
3 Foreign Concern
4 Domestic Firm Performing Work Outside the U.S.
NONPROFIT INSTITUTION
A Education
B Hospital
C Workshop for the Blind or Other Severely Handicapped from Procurement List
D Workshop for the Blind or Other Severely Handicapped - Other Optional Placement
E Other Nonprofit

D2. REASON NOT AWARDED TO SMALL BUSINESS
1 No Known Small Business Source
2 Small Business Not Solicited
3 Small Business Solicited - No Offer
4 Small Business Solicited - Offer Was Not Low
5 Other Reason

D3. SMALL DISADVANTAGED BUSINESS
1 Not a Small Disadvantaged Business
2 SBA 8(a) Award
3 Other Award to Small Disadvantaged Business

D4. REASON NOT AWARDED TO SMALL DISADVANTAGED BUSINESS *(SDB)*
1 No Known SDB Source
2 SDB Not Solicited
3 SDB Solicited. No Offer
4 SDB Solicited. Offer Was Not Low
5 Other Reason

D5. WOMEN OWNED SMALL BUSINESS — 1 No; 2 Yes; 3 Did Not Certify

D6. SMALL BUSINESS SET-ASIDE PREFERENCE
1 Not Set-Aside for Small Business
2 Total Small Business Set-Aside
3 Partial Small Business Set-Aside

D7. SUBCONTRACTING PLAN - SMALL & SMALL DISADVANTAGED BUSINESS
1 Plan Not Included Because Subcontracting Possibilities Non Existent
2 Plan Not Required
3 Plan Required, Incentive Not Included
4 Plan Required, Incentive Included

D8. SMALL BUSINESS INNOVATION RESEARCH (SBIR) PROGRAM
1 Not a SBIR Program Action
2 SBIR Program Phase I Action
3 SBIR Program Phase II Action

D9. LABOR SURPLUS AREA *(LSA)* PREFERENCE
1 Not an LSA Preference
2 Combined Small Business LSA Set-Aside
3 Partial Set-Aside for LSA Firms
4 Tie Bid LSA Preference
5 Total LSA Set-Aside
6 Total Small Business LSA Set-Aside

D10. SUBJECT TO LABOR STANDARDS STATUTES
1 Walsh-Healey Act, Manufacturer
2 Walsh - Healey Act, Regular Dealer
3 Service Contract Act
4 Davis - Bacon Act
5 Not Subject to Walsh - Healey, Davis - Bacon or Service Contract Act

D11. CERTIFICATE OF CURRENT COST OR PRICING DATA — 1 Obtained; 2 Not Obtained; 3 Waived

D12. TRADE DATA RELATING TO PRODUCTS OR COMPONENTS NOT MANUFACTURED IN THE U.S. OR SERVICES PERFORMED BY FOREIGN CONCERNS
D12A. NUMBER OF OFFERORS
D12B. BUY AMERICAN ACT PERCENT DIFFERENCE
D12C. COUNTRY OF ORIGIN CODE

D13. CONTRACT FINANCING *(Progress Payments (PP) and Advance Payments (AP))*
1 Contains FAR Clause 52.232-16
2 Contains DFARS Clause 52.232-7004
3 Provides Percentage of Completion PP
4 Contains Unusual PP or AP
5 None of the Above

PART E *(RESERVED FOR OSD USE)* — *(FOR DEPARTMENTAL USE)*
E1
E2
E3
E4

PART F
F1. NAME OF CONTRACTING OFFICER OR REPRESENTATIVE *(Last, First, MI)*
F2. SIGNATURE
F3. TELEPHONE NO.
F4. DATE*(YYMMDD)*

NARA Reference Page #8

DD Form 350, MAY 85 — *Previous editions are obsolete.*

B.1.2 University financial data (1969+)

We obtain information on annual university finances from the U.S. government's Higher Education General Information Survey (HEGIS), the predecessor to the modern IPEDS (Integrated Post-secondary Education Data System). HEGIS was administered by the Department of Education and its predecessors until the late 1980s, when IPEDS began. Financial statistics were one of several survey modules: from FY 1969 onwards, universities were required to report information on their revenues by category (e.g., tuition and fees, federal/state/local government appropriations, federal/state/local sponsored research, endowment revenue, gifts, product sales, hospital revenue, etc.), costs (instruction, research, operations, maintenance, scholarships, hospitals, etc.), assets (land, building, equipment), debt, and more. We obtained data files, codebooks, original questionnaires, and documentation for the 1969-1986 surveys from ICPSR.

We used the HEGIS data to attempt to create a university panel with annual financial statistics. However, a combination of factors makes it difficult to produce reliable measures: changes in the questionnaire (response fields and definitions), the complexity of university accounting (e.g., how to allocate costs of joint activities or overhead; Azoulay et al. 2025), and the reliability of the data (due to misreporting, under-reporting, and values being imputed by HEGIS when not reported) can all challenge the fidelity of comparisons, both cross-sectionally and especially over time as the response variables changed.[5] These challenges were sometimes visible in internal inconsistencies (components not adding to totals) and sometimes visible in aggregate time series charts, many of which had more year-to-year variability than we would expect.

Based on a close reading of the annual questionnaires and their instructions to respondents, we attempted to reassign and/or group reported measures to the narrowest time-consistent definitions. This was often difficult or ambiguous, and even after doing so, only measures of total revenue and costs, tuition revenue, educational costs, and research costs change smoothly over time in the aggregate. In the end, we do not use these data broadly, in part due to the short pre-1970 panel and in part because we did not have enough confidence in the data to make longitudinal comparisons. We instead use 1969 research expenditures (inflated to 2025 USD) as a benchmark for evaluating the relative scale of post-1970 changes in DoD funding.

B.1.3 Pre-1970s DoD-supported researchers and institutions (1970)

We obtain information on researchers' pre-Mansfield sources of support from the National Register of Scientific and Technical Personnel (NRSTP). The NRSTP was an NSF-led effort in the 1950s and 1960s to catalog U.S. scientific personnel, in biennial surveys.[6] The NRSTP was compiled

[5] Imputation rates vary across variables and over time, but can be large in some cases (up to 20%). More mundane challenges in data processing also include distinguishing missing values, high-frequency low values ("10" is common), and zeros from each other. Independent of data quality, the survey start date (1969) also gives us a very short pre-treatment panel, with some variables (e.g., assets and debt) not reported until after 1970.

[6] The NRSTP was a statutory requirement of the NSF Act of 1950, which directed the NSF to "maintain a register of scientific and technical personnel and in other ways provide a central clearinghouse for information covering all scientific and technical personnel in the United States" (P.L. 81-507 §3(a)(8)).

through an NSF-designed survey which was administered by scientific professional societies (e.g., the American Institute of Physics, American Chemical Society, and so on) to their members, which included both PhD-holders and non-PhDs (with the latter making up the majority of the sample).[7] The NRSTP was discontinued after 1970, after which point NSF claimed the U.S. no longer had a shortage of technical talent and further cataloging was unnecessary.

Electronic data files for all NRSTP survey waves (1954-1970) are available from NARA, along with the questionnaires, codebooks, and documentation.[8] Among characteristics germane to this paper, the NRSTP measures individuals' name, education, field, employer (name and type), employment function, and—importantly—whether their work was funded by each of 14 different federal agencies.[9] One of these 14 agencies is the Department of Defense (DoD). For this paper, we use the 1970 NRSTP (which was mailed on February 1) to identify individuals reporting DoD (and other agency) support right as the Mansfield Amendment took effect.We additionally (i) clean and standardize individual and employer names; (ii) manually link all degree institutions and university employers to IPEDS; and (iii) manually crosswalk all degree and employment fields to a standard set of SED major fields. Using these data, we can measure exposure at the university-field level as the share of scientists who reported DoD funding at the start of 1970.

Though engineers were included in early editions of the NRSTP, by the mid-1960s the engineering population had been split off into a similar but independent survey, the National Engineers Register (NER). The NER was conducted in 1964, 1967, and 1969, and collected mostly the same information as the NRSTP, including the essential fields for our analysis. We thus supplement our 1970 NRSTP data with analogous data from the 1969 NER survey. Throughout the paper and this appendix we refer to these two sources collectively as the NRSTP for simplicity.

B.1.4 DoD-supported PhD graduates (1960-1990)

In parallel work, a subset of this author team has processed the text of roughly one million STEM PhD dissertations from U.S. universities since 1950, using data obtained from ProQuest Dissertations and Theses Global (PQDT), to extract acknowledgments and measure graduates' sources of support (Shvadron et al. 2025a). For each graduate, we additionally measure their PhD institution, degree subject, and year, which we crosswalk universities to IPEDS and subjects to SED major fields and which allows us to count graduates by university-field-year. As Shvadron et al. (2025a) explain, the PQDT sample approximates the universe of STEM PhD graduates from U.S. universities over this time period. However, pre-1990, dissertation text is only available for around 45% of graduates, due to the indexing methods used at the time (the undermeasurement appears to be unrelated to any economic phenomena). We use this sample to construct measures of the share of graduates in each

[7]Participation was voluntary; accompanying documentation describes an average response rate of 65%, but response rates were likely substantially higher among the PhD-holding population specifically.

[8]The NRSTP can be obtained from the NARA online catalog at https://catalog.archives.gov/id/622629. Additional details available in the associated NSF publication series *American Science Manpower*.

[9]The NRSTP reports many more individual characteristics, including place and date of birth, sex, home and work locations, work experience, employment status, and foreign language proficiency.

university-field with DoD support over time.

B.1.5 DoD-supported Science/Nature/PNAS articles (1960-1990)

Although research articles have for many decades acknowledged authors' sources of support, the databases which provide this information for modern research (e.g., Dimensions) have poor coverage for the period we study (especially its early years). Though we do not endeavor to fully fill this gap with this project, to get insight into the level of DoD support across different fields over time, we develop independent measures from research articles which published between 1960 and 1990 in three general interest journals: *Science*, *Nature*, and *PNAS* (SNP).

This effort begins with acquiring PDF files of the target research articles, which we sourced from institutional repositories and journal websites.[10] Extracting acknowledgments from these articles is in principle feasible (as Shvadron et al. 2025a have shown) but in practice complicated by the intersection of two patterns in some journals and years: acknowledgments can appear at the beginning or end of the article, and one article begin on the same page where the previous article ends. Because two articles may appear on the same page, attributing an acknowledgment printed anywhere on that page to the right article becomes more difficult.

In order to accurately assign acknowledgments, we first need to segment articles, which in most cases was done by matching a given article's and next article's titles and specific layout features (font size, style), using exact matching as a first pass and fuzzy matching thereafter. We then process the text of each article to identify acknowledgment sentences, using a list of funding-related keywords (e.g., "funded", "supported", "grant", etc., including variants to account for alternative spellings or OCR-induced errors). Upon detecting a target keyword in a sentence, we extract a context window of two sentences preceding and up to three sentences following the identified sentence. These expanded snippets were then carefully reviewed, deduplicated, consolidated, and submitted one-by-one to an LLM (OpenAI's `gpt-4o-mini` model), which was prompted to return organization names mentioned in the input. We matched the resulting output by name to a reference list of research offices at DoD, the names of which we obtain from the Research Organization Registry (ROR, a public global registry of research organizations, which includes relationships between organizations that enable us to identify all of DoD's subsidiaries).

In parallel, we also measure whether authors of these articles were DoD-affiliated. To do so, we link our SNP sample to OpenAlex publications on their DOI, and we retrieve author affiliations from OpenAlex. We similarly match these affiliations to DoD research organizations found in ROR. We use these measures to produce an indicator of whether each article in our SNP sample has (i) a

[10] We specifically focus on research articles, omitting other publication types (such as news, commentary, book reviews, etc.) At *Nature*, we specifically collected articles categorized as "Article" or "Letter"; articles in *Nature* represent substantial original reports with significant implications, whereas letters are concise original research reports with broad scientific appeal. Similarly, at *Science*, we exclusively sampled "Reports"—which correspond to peer-reviewed research articles—omitting other types such as categories such as "News & Comments", "Book Reviews", "Technical Comments", and "Editorials". At *PNAS*, we sampled all publications. Most of these are already OCRed; for PDFs without an existing text layer, we OCRed the images before proceeding.

DoD-affiliated author, (ii) acknowledgment of DoD support, or (iii) either. We additionally retrieve each article's primary field (as measured by OpenAlex), which we crosswalk to SED major fields. Though our sample is large (with ≈100,000 SNP articles between 1960 and 1990), publications are too sparse at the university-field-year level for systematic analysis. We instead use these data to evaluate in the aggregate the share of SNP articles over time with DoD support, overall and by field, in providing evidence of a 1970s shift in the rate of support.

B.1.6 NSF research grants (1964-1983)

Because the National Science Foundation was the principal alternative source of funding for research in many of the fields DoD supported, we collect data on NSF grants issued over our study period. Our primary reference is the NSF publication "Grants and Awards for the Fiscal Year Ended [Month] [Day], [Year]", which was published every year from 1964 to 1983 and listed all grants and contracts the NSF had made that year, including complete information on the principal investigator (PI), institution, title, value, grant number, and other features.[11] Electronic records of NSF grants are also available from the NSF website for this period, but at the original time of retrieval (in 2022), these records were less complete than the print records in both the set of grants included and the information provided.[12] Most importantly, electronic files before 1975 are missing information about the issuing NSF division and program, which we need to assign grants to scientific fields, and about the PI, which we need to link grants to individuals.

We therefore extracted data on roughly 150,000 grants between 1964 and 1983 from print records, which we subsequently cleaned and regularized (e.g., standardizing PI name formatting, institution names, division and program labels, etc.). It appears that after 1983, the NSF stopped producing this publication (transitioning fully to electronic records), as we have not been able to identify later editions. In the paper, we limit our analysis of NSF funding to the 1965-1980 period, bounding it more closely around the Mansfield Amendment and implementation of the 1970s defense research funding cuts, in part because this is the relevant period to study and in part to maintain internal consistency in the data provenance across the analysis sample.

[11] We obtain copies of these publications from Hathitrust. Although it is possible NSF published similar records pre-1964, we have been unable to find any copies.
[12] See https://www.nsf.gov/awardsearch/download-awards.

B.2 Personnel, careers, and graduate training

B.2.1 AMWS: Data on scientist employment and individual careers (1960-1990)

We also seek to measure universities' employment of scientists over time and individual scientists' career trajectories. Because there are no administrative data which can do so systematically across the U.S. scientific enterprise, we turn to American Men and Women of Science (AMWS) as a data source.[13] AMWS is a biographical directory of American scientists which is periodically updated and re-published, and which reports individual scientists' education history, employment history, area of expertise, professional memberships and awards, and contact information. AMWS has been published since 1906 (at that time, titled American Men of Science, or AMoS) and currently profiles living scientists in the physical and biological sciences, as well as public health scientists, engineers, mathematicians, statisticians, and computer scientists.[14]

Though AMWS officially samples prominent scientists, the AMWS population in modern editions is large (up to 200,000 individuals per edition). We focus our data collection on individuals included in annual AMWS editions between 2005 and 2021. Conveniently—and in contrast to studies which require digitizing historical editions—these years have native electronic data (XML files). Because our target study period is 1960-1990, and the AMWS sample intrinsically trends older (listing scientists who are advanced enough to be included), this sampling frame is also the most attractive one for our specific needs: graduates between 1960 and 1990 will be in the prime of their careers in 2005-2021, which is when they are likely to enter AMWS, and once they do, AMWS will provide a full career history, including the 1960-1990 study period.

The AMWS data require substantial effort to make them analytically useful. Some of these challenges are created by our effort to combine data from multiple editions. In particular once a scientist is added, their entry typically appears in all subsequent editions until their death, at which point the record is removed. Though we wish to use multiple editions to expand our population to include scientists who enter or exit the AMWS sample over time, we also seek to avoid double counting. We therefore link individuals across editions, retaining for each individual the most recent profile available. Table B.2 list the AMWS editions used in this paper, the number of biographical entries in each, and the number of individuals each edition contributes to our final sample, after disambiguation. In total, we collect data on roughly 250,000 unique scientists which appear in at least one AMWS edition in this sampling period (2005-2021).

[13] Since the final NRSTP survey in 1970 and a follow-up Employment Survey of Scientists and Engineers (ESSE) in 1971, the U.S. government has not conducted systematic surveys of complete U.S. scientific workforce. The modern surveys that NCSES administers generally focus on specific subpopulations (such as graduate students, postdocs, or U.S. doctoral degree recipients; in the latter case, only a small share of degree recipients are contacted in each survey wave, and response rates are low and non-representative).

[14] Select editions have been used to study the U.S. scientist population in a growing body of scholarship—including the historical data used by Kim and Moser (2025), Moser et al. (2025), Lubczyk and Moser (2025a,b), Airoldi and Moser (2024) and more recent editions used by Arora et al. (2023).

Table B.2: AMWS Editions and Sample Construction

AMWS Edition	Year	Scientists profiled	Contribution to the final sample
22	2005	132,812	4,732
23	2007	133,372	606
24	2008	132,312	2,056
25	2008	132,642	2,740
26	2009	131,880	2,949
27	2010	131,024	661
28	2010	131,024	3,217
29	2011	135,790	2,230
30	2012	140,502	1,424
31	2013	145,439	1,184
32	2014	151,083	4,815
33	2015	158,884	595
34	2016	166,583	2,965
35	2017	169,048	6,943
36	2018	184,912	1,240
37	2019	180,225	878
38	2020	198,172	2,181
39	2021	203,272	201,042
Final sample			242,458

Listing B.1 illustrates a sample profile in AMWS. Each entry is presented as a compact paragraph and typically lists a scientist's education, professional positions, memberships, and research statement in free text. To transform this unstructured text into analyzable data, we developed a data processing pipeline to extract professional experience, area of expertise, and education history, using pattern matching to separate fields and large language models to extract and standardize employer names, expand abbreviations, and assign employers to categories.

Listing B.1: Sample AMWS (2021) scientist profile: Scheck, Rebecca A

```
CHEMICAL BIOLOGY. Education: Columbia Univ, BS, 2004; Univ Calif, Berkeley
    , PhD (chem), 2008. Professional Experience: Grad biomed sci mem, Cell,
     Molecular & Develop Biol Prog, Tufts Univ, as of 2023; prin investr,
    Scheck Res Group, Dept Chem, Tufts Univ, as of 2023; ASSOC PROF,
    GENETICS, MOLECULAR & CELLULAR BIOL PROG, CELL, MOLECULAR & DEVELOP
    BIOL PROG, REBECCA SCHECK LAB, TUFTS UNIV, as of 2023; ASSOC PROF, DEPT
     CHEM, SCH ARTS & SCI, TUFTS UNIV, 2022- ; asst prof, Dept Chem, Tufts
    Univ, 2013-2022; NIH Ruth I Kirschstein postdoctoral fel, Yale Univ,
    2008-2011; postdoctoral training, Dept Chem & Chem Biol, Yale Univ,
    2008-2013. Memberships: Am Chem Soc. Research Statement & Publications:
     Development of new chemical methods that are used to study complex
    posttranslational modification networks; study of native and unnatural
    posttranslational modifications to provide valuable chemical and
    synthetic biology tools. Mailing Address: Dept Chem, Sch Arts & Sci,
    Tufts Univ, 62 Talbot Ave, PO Box 100X, Medford, MA 02155. Fax:
    617-627-3443. E-Mail: rebecca.scheck@tufts.edu
```

Extracting professional experience The "Professional Experience" section of an AMWS profile reports individuals' prior employment spells. Our infrastructure will identify a professional experience section, extract each employment spell in it, and separate these spells into three components, based on delimiters: the job title (e.g., "assoc prof," "dir," "staff scientist"), the employer (e.g., "Tufts Univ," "NASA," "Bell Labs"), and the years of employment (e.g., "1970–1972," "beginning 1971," "ending 2008"). Table B.3 illustrates the result of this parsing procedure for Rebecca A. Scheck (Listing B.1), where each of her professional roles has been separated into a distinct observation with its associated employer and years of service.

Table B.3: Example extracted professional experience: Rebecca A. Scheck

Job title	Institution	Years of service
grad biomed sci mem, cell, molecular, develop biol prog	Tufts Univ	as of 2023
prin investr, scheck res group, dept chem	Tufts Univ	as of 2023
assoc prof, genetics, molecular & cellular biol prog, cell, molecular & develop biol prog, Rebecca Scheck lab	Tufts Univ	as of 2023
assoc prof, dept chem, sch arts & sci	Tufts Univ	2022-
asst prof, dept chem	Tufts Univ	2013-2022
NIH Ruth I Kirschstein postdoctoral fel	Yale Univ	2008-2011
postdoctoral training, dept chem & chem biol	Yale Univ	2008-2013

A key difficulty is that AMWS records employer names often heavily abbreviated or in inconsistent formats (e.g., "Univ Minn," "Calif Inst Technol," "U Tex Hlth Sci Ctr"), often embedded within department or program descriptors. This requires not only extracting the employer name but also mapping it into a canonical form that can be consistently classified. To address this challenge, each extracted segment is processed using the large language model `gpt-4o-mini`, which is prompted first to extract the employer name from the broader text and then to map that employer into a standardized, canonical form. At the same time, the model assigns the institution to one of six mutually exclusive categories (university, company, government, hospital, non-profit, or other). The prompt instructs the model to extract the core institution name (excluding programs or departments), expand abbreviated forms into full names, and classify the institution into one of these six mutually exclusive categories, while ignoring non-essential tokens such as job titles, disciplinary fields, and years. When multiple institutions are mentioned in a single line, the model is instructed to return all employers. As an example, the input *grad biomed sci mem, cell, molecular & develop biol program, tufts univ, as of 2023* returns the extracted employer *Tufts Univ*, which is then standardized to *Tufts University* and classified to the *university* type.

A further complication arises because AMWS often omits repeated institution names when listing multiple sequential positions at the same organization. To address this exception, additional processing was required. For example, an academic career might be recorded as "assistant professor, associate professor, professor, dean" with the university name appearing only once at the beginning of the string. Industry careers follow a similar pattern, with job progressions such as "research scientist, director, vice president" where the company name is only provided at the front of the string. Although these entries are correctly separated by semicolons, the missing institution names would lead to incomplete records if left unaddressed. To resolve this issue, we developed a continuous employment imputation algorithm. Whenever an institution name is missing, the algorithm inherits the institution from the closest preceding segment.

This processing pipeline was applied to the full collection of professional experience records, covering 1.36 million raw employment spells. After standardization, these contain 286,000 unique employer strings, and 183,000 for employment spells within our target period for these data (1960-2000). We then undertake two additional efforts with this list: (i) classifying employer strings to sectors, and (ii) linking and consolidating them to a canonical set of identifiers.

To classify entities to sectors, we develop a hybrid procedure that leverages an ensemble of frontier large language models (LLMs). This procedure first submits each entity independently to Anthropic's Claude Sonnet 4.6 and OpenAI's GPT 5.4 and asks each to classify the entity into one of nine categories: "University", "Industry", "Government", "FFRDC", "Hospital", "Non-profit", "Professional Society", "Consulting/Self-employed", or "Unknown/Unclassifiable". In the majority (89%) of cases, the two models agree. For cases where they disagree, we send the entity to Google's Gemini 3.1 Pro to adjudicate and determine which of these labels is appropriate, or—in a small number of cases—apply a third label. Manual review suggests this procedure is very effective, including for boundary cases; where it varies the most is with university medical centers, which can reasonably be categorized as universities or hospitals. We additionally cross-validate much of the list through our entity linking procedure, which connects employer strings to external identifiers (e.g., PERMNOs, IPEDS UnitIDs, and custom identifiers for specific government agencies and national labs) and is described further in Appendix B.4. We manually supersede the LLM ensemble's sector classification with corrections where our links indicate such changes should be made (e.g., if an entity links to an IPEDS UnitID, we reclassify it as a university).

Extracting professional expertise AMWS encodes a scientist's research area in two distinct ways. First, the opening capitalized words of each profile, such as *CHEMICAL BIOLOGY* or *AREA-EFFICIENT COMPUTATION, VLSI DESIGN*, indicate the scientist's area of expertise. We extract these terms verbatim to construct a controlled vocabulary of disciplinary expertise. Second, each profile contains a "Research Statement & Publications" section, where scientists provide free-text descriptions of their research agenda. For example, Rebecca A. Scheck's profile reports research on: *Development of new chemical methods that are used to study complex posttranslational modification networks; study of native and unnatural posttranslational modifications to provide valuable chemical and synthetic biology tools.* We extract these research areas and descriptions to build a text-based record of research expertise that can form the basis for subsequent linkage to other datasets in this project, which we address further in Appendix B.4.

Extracting educational history We process the complete education histories of all 242,458 scientists to extract all degree records, including undergraduate, master's, doctoral, and professional degrees. This extraction yields nearly 650,000 degree records, the most frequent of which are BS (211,208 records), PhD (202,462), and MS (137,098) degrees, followed by MD, BA, MA, and a long tail of other professional and specialized credentials. In total, AMWS records contain more than 800 distinct degree names, reflecting the diversity in educational qualifications present in this sample. After identifying degree types, we then focus on identifying PhD (and PhD-equivalent) degrees, using a custom dictionary of doctoral degree indicating strings (e.g., PhD, DPhil, DEng, ScD, DSc, etc.). For individuals with doctoral degrees, we retrieve the associated institution names, identifying roughly 13,000 institutions (unique strings) that have at least one PhD (or equivalent) degree issued to a scientist in our sample. Degree information will also be used for linking AMWS to other datasets in this project, as we discuss in Appendix B.4.

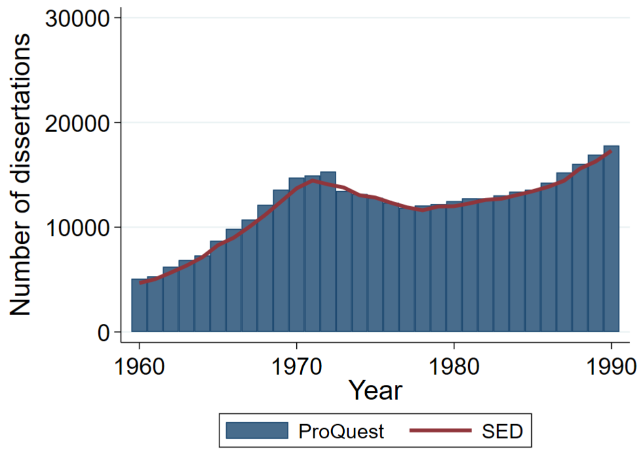
B.2.2 SED: Administrative data on PhD graduates (1960-1990)

We measure PhD graduates by university, field, and year using data from the U.S. Survey of Earned Doctorates (SED). The SED is a survey which the National Center for Science and Engineering Statistics (NCSES, an office of the NSF) has administered to all graduating PhD candidates at U.S. universities since 1958, and with response rates 90-95% comprises an approximate census of annual PhD graduates. The SED public data reporting tool makes publicly available annual counts of graduates at the institution x major field level, where major fields are at the level of areas such as the "biological sciences" or "computer and information sciences".

B.2.3 PQDT: Dissertation-derived data on PhD graduates (1960-1990)

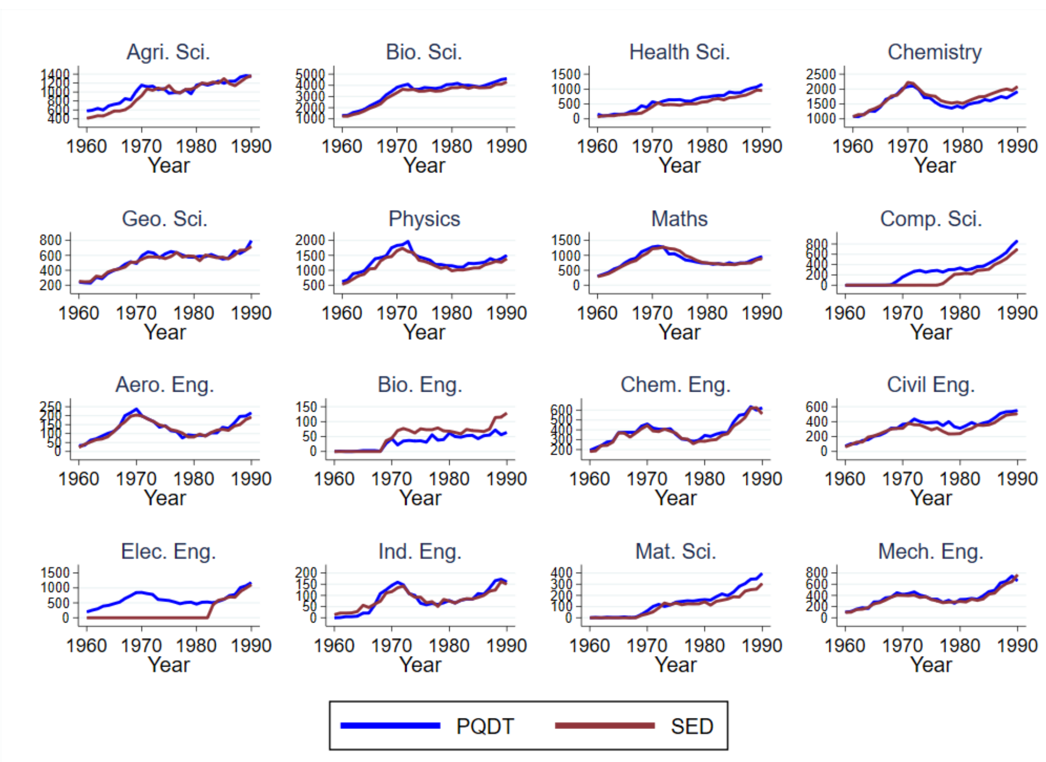
A complementary resource for measuring the U.S. PhD graduate population is ProQuest Dissertations & Theses Global (PQDT). For nearly a century, ProQuest has been acquiring, indexing, and re-publishing the dissertations of U.S. PhD graduates. PQDT provides both metadata and dissertation text for each graduate in its sample, which we use to measure PhD graduates and features of their dissertation research. The PQDT metadata include information on both the graduate and the dissertation, including author, advisor(s), institution, degree name, dissertation title, dissertation abstract, principal subject, and more. In Shvadron et al. (2025a), we used these data to produce a curated subsample of the PQDT database consisting of STEM PhDs from U.S. institutions, using degree names and subjects to identify PhDs (and PhD-equivalents) in the natural sciences and engineering. Figures B.2 and B.3 show that PQDT approximates the U.S. STEM PhD population reported by the SED over the period we study, both overall and by field, with the only notable divergence being in two fields which we can detect in PQDT but which the SED did not separately report until the 1980s (computer science and electrical engineering). A second data source on PhD graduates to the SED is potentially useful as a check, but given their close relation, unlikely to add much new information on its own. The motivation for incorporating PQDT data into this project is twofold: (i) it enables an assessment of DoD-funded graduates, using the measures produced from these graduates' dissertation text by Shvadron et al. (2025a), previously discussed in Appendix B.1, and (ii) it can be used to link graduates forward into their scientific careers via the publication record, as we have previously done in Shvadron et al. (2025b). We refer readers to these two papers for further details on this sampling, measurement, and linking.

Figure B.2: ProQuest vs. SED graduates in STEM fields, by year



Notes: Figure shows annual PQDT graduate counts in the natural sciences and engineering (blue bars) and SED counts (red line) for comparison, from 1960 to 1990. Data from Shvadron et al. (2025a).

Figure B.3: ProQuest vs. SED graduates in STEM fields, by field and year



Notes: Figure shows annual PQDT graduate counts in the natural sciences and engineering (blue line) and SED counts (red line), from 1960 and 1990, disaggregated across 16 SED major fields. Note that the SED did not begin reporting computer science and electrical engineering PhDs until the 1980s. Data from Shvadron et al. (2025a).

Identifying PhDs graduates working in the defense industrial base We also desire to evaluate the degree to which PhD graduates of the universities in our sample worked in the defense industrial base (DIB). Measuring this behavior requires first establishing a definition of the DIB, and identifying which firms (and other organizations) belong in it.

Our measurement of the DIB begins with a list of the top 100 Department of Defense contractors, which DoD published annually from 1958 to 1997, and which we obtain from the Defense Technical Information Center (DTIC). These lists effectively reproduce information available in the MPCF contract records (Appendix B.1), but are preferred because provide an official list and consolidate contractors to canonical names. We digitize these lists, standardize names across years, and build a list of all unique entities. Many of these entities are clearly dedicated, defense-first (or defense-only) firms (e.g., Lockheed Martin), but many others are large civilian firms with some defense business (e.g., General Motors) or diversified conglomerates (e.g., General Electric). And whereas these examples are of large/prominent firms, the top 100 lists also include smaller/less prominent firms at lower ranks, and some universities (e.g., MIT) and non-profit institutions (e.g., RAND Corporation, Battelle Memorial Institute), especially those that administer military-funded FFRDCs. The boundaries of the DIB are thus fuzzy, and if our goal is to identify PhD graduates who work in the DIB, some of these entities would be misleading indicators: even if a large number of PhDs work at GE or MIT, most of them will not be doing any defense-related work.

The first task is thus to develop filters for defining the subset of organizations we can reasonably consider defense-first contributors to the DIB for the purposes of this exercise. We produce two subsamples, which we consider more liberal and conservative. With the interactive assistance of Claude Cowork (using Opus 4.7) plus manual review, we attempted to classify and score the 550 unique contractors in these data on their defense relatedness and defense specificity. We first categorized contractors into the following groups: core aerospace and defense firms ($\sim$100), defense services/IT firms (20), FFRDC operators (10), military construction and shipbuilders (20), removing all other firms in these lists from further analysis. For those that remained, we then gave the agent context on the task and asked it to score each organization on a scale of 1-5 on whether it should be considered part of the DIB for the purposes of identifying PhD graduates who entered the DIB, and provide reasoning. We manually reviewed the results, and using contextual knowledge plus manual research assigned firms into three categories:

1. Those that were important defense contractors (generally, scores $\geq$4; those scored 5 were key A&D contractors, like Lockheed, Raytheon, or Thomson Ramo Wooldridge, and those scored 4 had significant defense and civilian businesses, like Texas Instruments)

2. Those that were borderline cases (generally, scored 3; these include organizations like General Electric, RCA, Varian Associates, or the Rand Corporation)

3. Those for which were large suppliers but for which DoD was a relatively minor customer (generally, scored $\leq$2; e.g., Ford Motor, Eastman Kodak, Halliburton)

We treat the first group (scores 4+) as a conservative sample, and the first + second groups (scores 3+) as a more liberal sample. Universities are excluded in both cases.

With these firms in hand, we then turn to OpenAlex data on scientific publications (see Appendix B.3 for a description). We first load the PQDT-OpenAlex person-to-publication links developed in Shvadron et al. (2025b). For linked publications, we retrieve raw affiliation strings from OpenAlex, and match affiliations to the firms in our top 100 defense contractor lists, using embedding-based similarity measures to identify matches (following the same procedures used in Shvadron et al. 2025b). This yields a person-publication-affiliation dataset, with top 100 contractor firm names merged in. Finally, for each PQDT graduate, we generate two indicator for whether that graduate was ever observed at a DIB employer: one for the broader DIB catchment, and one for the narrower catchment. Among STEM PhD graduates from U.S. universities between 1960 and 1990 in the PQDT sample, 5.1% meet the broad filter, and 4.2% the narrower filter. The largest contributors to the conservative sample are Texas Instruments, Lockheed Martin, Boeing, the Aerospace Corporation, SAIC, Hughes Aircraft, United Technologies, and Northrop Grumman—all examples of firms which we would (subjectively) consider contributors to the DIB.

It is important to recognize that this methodology identifies PhD graduates who published at a DIB organization, and not all graduates who worked at one. Nevertheless, publication is an indication of both employment and scientific production—the intersection of which is scientifically and technologically meaningful. Another approach to measuring universities' production of PhDs who later work in the DIB could begin with the AMWS population, where we observe both education histories and later-in-life employment, but would yield a differently-selected sample (selected on inclusion in AMWS). The AMWS sample is unlikely to be as broad or as representative our PQDT-OpenAlex linked sample: for example, whereas nearly 1,200 graduates in our PQDT sample between 1960 and 2000 can be linked to a publication with an affiliation at Lockheed Martin, only 500 scientists in our AMWS sample received PhD degrees during the same period and have employment histories that include an employment spell Lockheed Martin. This evidence, alongside our understanding of each sample, leads us to prefer the PQDT-based measurement approach.

B.3 Research outputs: Publications & patents

B.3.1 OpenAlex: Publications by country, institution, field, and year (1960-2000)

We use OpenAlex (Priem et al. 2022) to measure scientific output over time at national and subnational levels. OpenAlex is to our knowledge the most complete bibliometric database available, especially historically, and provides article-level metadata, including publication year, publication type, journal, authors lists, institutional affiliations, topic classifications, and many other features. Using OpenAlex's bulk data, we construct two panels for use in this project: a country-field-year dataset, and a university-field-year dataset, in each case counting associated publications (and in the case of universities, additional publication features) over time.

To measure the evolution of national scientific output across fields, we first filter the OpenAlex population to research articles which published between 1960 and 1990 with at least one listed author and one associated topic. We identify each article's primary topic (highest-scoring associated topic, as defined and determined by OpenAlex) and retrieve the associated (more aggregated) field. We associate each article fractionally to the countries of its authors (based on their affiliations), and count up articles at the country-field-year level to measure national research output by field. In a secondary measure we also assign papers to countries in whole (not fractional) units and compute similar totals, though our results are similar with either measure.

We measure university-level scientific output in a similar manner. We first filter to research articles published during the same window and associate these publications fractionally to the authors' institutions, identifying institutions with OpenAlex-provided ROR codes.[15] We then count articles at the institution-field-year level, and link these observations to other datasets by crosswalking RORs and OpenAlex fields to a canonical set of identifiers used throughout the project (see Appendix B.4). In a secondary measure, we again repeat these counts with whole assignments (rather than fractional), though our results are similar for either construction.

B.3.2 GPR: Government-funded patents (1960-2000)

In addition to university scholarship, we also measure university patenting. To do so we use the records underlying the Government Patent Register Gross and Sampat (2025a), a recent dataset developed by a subset of this paper's authors that identifies patents produced from government-funded research using a mix of archival USPTO records, the modern USPTO Patent Assignment Dataset, observed patent assignees, and government interest statements in patent text. The archival records collected in the course of that project were the official (administrative) register of patents to which the U.S. government had title or license (for having funded the work) from the 1920s until the USPTO converted fully to electronic records in the early 1990s (see Gross and Sampat 2025a for a fuller discussion). The historical records include information not otherwise available from

[15] OpenAlex assigns ROR codes to authors based on their affiliation strings and their own matching algorithms; though these ROR IDs can be imperfect, they reduce the dimensionality of our problem substantially, are commonly used in research, and we think are high-enough quality for our aims.

public patent data for the period we study, including the research organization: most government interest patents at this time that resulted from sponsored university research were assigned to the U.S. government or to the inventor, and it is only in these records that one can observe the research contractor or grantee institution as the assignor of the title or license. Using this information, we are able to identify patents which were produced at specific universities with government funding, as well as the agency that funded the work. We use these data to construct a university-year panel with government-funded patent counts, by funding agency.

B.3.3 USPTO: Patents filed by US inventors (1960-2000)

We additionally create a panel dataset of patenting at the technology class x year level. The base layer for this panel is the universe of patents filed at the USPTO from 1960 to 1990 and issued by 2015, which we obtain from Google Patents (via Google BigQuery). We filter this sample to patents with a U.S. first inventor, using inventor locations from Gross and Sampat (2023a) for patents issued through 1979 and from PatentsView for patents issued after 1980.[16] For every patent, we retrieve a primary (inventive) CPC code, and we use these to create two panels at the 3- and 4-character CPC code x year level (henceforth, CPC-3 and CPC-4 x year panels).

We measure several features in these panels. The first is the (nationwide) number of patent filings with U.S. inventors. Using the Government Patent Register (described above), we measure DoD-funded patents by CPC-year. We then use the Marx and Fuegi Reliance on Science dataset (Marx and Fuegi 2020, 2022) to count science-citing patents. In doing so, we restrict these data in-text patent citations to science (PCS)—which Bryan et al. (2020) argue may be a better measure of an invention's knowledge inputs than "front-page" citations to non-patent literature (NPL), whose legal purpose is identifying prior art against which claims are evaluated—and to PCS with a confidence score of 8 (of 10) or higher. In addition to counting the number of science-citing patents in each CPC-year, we also count the breadth of science cited, measured as the number of unique publications (OpenAlex IDs) cited by patents in a given CPC-year.

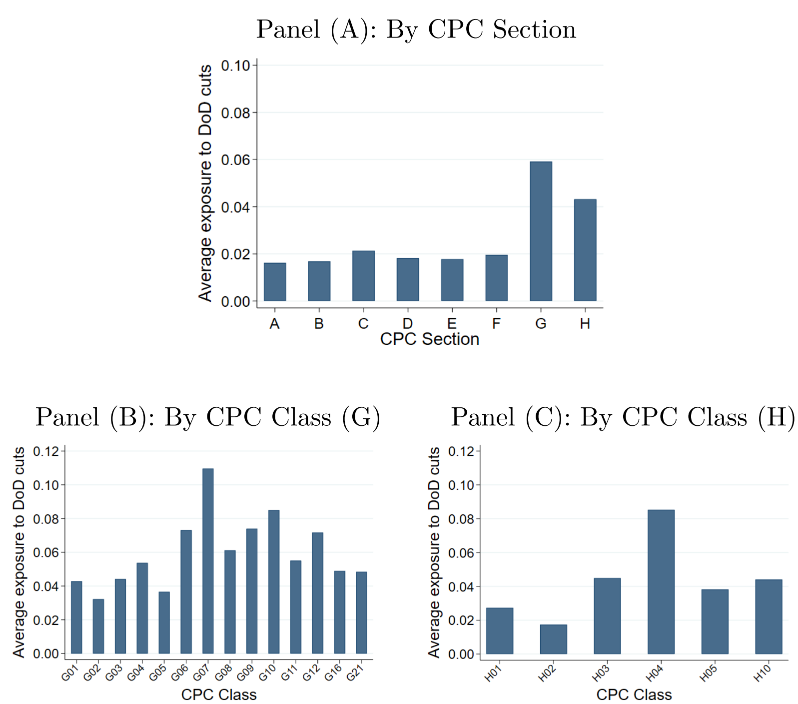
Thus far we have described outcomes. We also develop measures of each CPC's exposure to DoD-funded science. To do so, we adapt shift-share logic. We begin with the premise that individual technology areas have differential exposure to science broadly (vis-à-vis the share of patents which cite science), and to individual fields of science specifically (vis-à-vis which fields of science patents in those areas cite). For example, pharmaceutical innovation is close to biological sciences, whereas electronic innovation may be closer to electrical engineering and physics, and computer innovation closer to mathematical and computer sciences. We additionally recognize that each of these fields had differential exposure to DoD's research funding cuts in the 1970s, based on the relative rate at which they were (and are) DoD supported, reflecting DoD priorities.

[16] The inventor locations used by Gross and Sampat (2023a) are measured by triangulating across three historical patent datasets which report locations: HistPat (Petralia et al. 2016), CUSP (Berkes 2018), and PatentCity (Bergeaud and Verluise 2024). As we report in the data appendix to Gross and Sampat (2023a), each of these sources is individually subject to some error, but cross-validation can substantially reduce this error.

We combine these two observations to create a CPC-level measures of exposure to the 1970s research funding cuts. To measure individual CPCs' relation to different fields of science, we return to the Marx and Fuegi PCS data, but now expand the PCS sample to include both in-text and front-page (NPL) citations, as NPL citations usefully indicate proximity of an inventive area to a particular type of science. For each citation to a scientific publication that meets our confidence screen, we retrieve the primary field of that publication from OpenAlex, crosswalk these fields to our canonical set (see Appendix B.4), and measure the share of PCS in each CPC that are made to each of our focal scientific fields. For each of these fields, we then use the 1970 NRSTP data (see Appendix B.1) to measure the share of scientists in each of those fields in 1970 who were DoD supported—which is our field-level measure of exposure to the 1970s funding cuts. Crossing the two and summing, we obtain a CPC level weighted average exposure to DoD research funding, weighted by the given CPC's relative proximity to each of our focal scientific fields.

To illustrate the variation in the resulting exposure measure, Figure B.4 shows average CPC-4 level values, first plotting these averages by CPC section (A to H; Panel A) and then plotting average within CPC-3 classes for select sections (G and H; Panels B and C). Intuitively, CPC exposure to DoD research funding is highest in Sections G and H, which represent inventive areas like physics, optics, control systems, and computing (G) and electrical engineering and electronics (H). Other branches of the CPC tree, covering other invention categories such as medical, agricultural, chemical, textile, construction, mining, etc. are less exposed.

Figure B.4: Average CPC subclass (CPC-4) exposure to DoD research funding, by CPC section and CPC class (CPC-3)



B.4 Linking universities across data sources

B.4.1 Linking universities across all data sources

Additional infrastructure is needed to connect these datasets to each other. The centerpoint of our linking effort is in connecting universities across these datasets (DoD contracts, HEGIS financials, NRSTP scientists, AMWS scientists, SED graduates, PQDT graduates, OpenAlex publications, NSF grants, and GPR patents) to a common set of identifiers.

We use IPEDS (the U.S. Department of Education's Integrated Postsecondary Education Data System) to create a reference list of potential institutions to which our data could be matched. Our base layer is the 2021 IPEDS directory, which lists approximately 6,000 higher education institutions in the U.S. of all kinds, from small vocational training and junior colleges to elite research universities, which are only a small share of IPEDS. Though we will later filter to R1 and R2 universities only, our catchment is initially broad. For each of the universities in the individual datasets entering this project, we link them by name to IPEDS to retrieve its IPEDS code (a persistent identifier). Some historical institutions in our data closed, merged with others, or reorganized and received a new IPEDS identifier prior to 2021; to handle these cases, we search for institutions that we cannot match to the 2021 data in 1980, 1990, 2000, and 2010 IPEDS directories, aiming to obtain codes for as many institutions as possible.[17]

This linking to IPEDS often required significant historical understanding of the U.S. higher education system and benefited significantly from experience, and was therefore performed by the authors. Due to the presence of distinct same-named institutions in the data (e.g., there are three Loyola Universities in the U.S.), we used geographic information to disambiguate as available and as needed.[18] In the case of the HEGIS and SED data, linking is straightforward, as the IPEDS directories include institutions earlier HEGIS FICE codes, which we can merge on, and the SED data include IPEDS codes. We use the LinkTransformer python package (Arora and Dell 2023) to assist in our linking in all other cases, though we manually review all non-exact matches. In total we reviewed roughly 25,000 institution names. Non-matches typically fell into one of five categories: non-university institutions, foreign institutions, defunct institutions, institutions we could not match, and institutions we could not unambiguously match. Where links could not be easily made and it was not immediately obvious why, we manually researched institutional histories in order to identify whether there was an appropriate link to make. Our search is comprehensive: with a few exceptions (discussed in more depth below), we either identify an IPEDS code for every institution in a dataset or code a reason why we were unable to do so.

[17] Though IPEDS began in 1986, replacing HEGIS (see Section B.1), the IPEDS bulk data download website includes university directories as far back as 1980. The pre-1986 data are likely repackaged from HEGIS, but with IPEDS codes appended where they exist and with universities otherwise identified by their HEGIS FICE (Federal Interagency Committee on Education) code, which we use in such cases.

[18] This becomes especially useful for state university systems when the institution name does not specify the campus, which we can infer from the location. The DoD, NRSTP, HEGIS, NSF, and GPR/patent data include geographic information at the state or city level which can be used to this end.

Non-university institutions enter many of our datasets for a mix of reasons. In many cases, this is because non-university educational institutions were included in the data source (e.g., DoD contract data identify educational institutions, not universities per se; NSF grantees include non-university institutions; some sources misclassify some research institutions like Woods Hole Oceanographic Institution as universities; etc.). Foreign institutions enter our data for similar reasons. Defunct and unmatched institutions are typically small and unimportant, both economically and to the research enterprise, and would not pass our upcoming R1/R2 university screen. The more complex cases are universities with disambiguation challenges. These typically consist of state university system names without an explicit campus and where either (i) we lacked location data to disambiguate or (ii) location data was not sufficient to disambiguate. For example, "Univ Cal" and "University of California" cannot be resolved without campus information. Fortunately, in all datasets, state universities can be disambiguated with a campus or location in most cases. We will ultimately omit universities for which we are unable to make a high-confidence link.

A few more comments on specific data sources are as follows. To link OpenAlex publications to IPEDS, we rely on OpenAlex's measurement of authors' affiliation ROR IDs, and we link them to IPEDS codes through these ROR IDs. OpenAlex assigns ROR codes to authors based on their affiliation strings and their own matching algorithms; though these ROR IDs can be imperfect, they reduce the dimensionality of our problem substantially, are commonly used in research, and we think are high-enough quality for our aims. The crosswalk we make is thus from ROR to IPEDS. In making this crosswalk, we first filter to ROR IDs with at least one associated publication in the OpenAlex data in our sample period. We then merge in ROR variables for these IDs, including institution name and type. We review all institutions which ROR categorizes into the "education" type, as well as all ROR institutions which are not assigned the "education" type but have words like "University" or "College" in the name. Other ROR institutions classified as a company, facility, government, non-profit, or healthcare institution are not evaluated.

Insofar as we apply this approach to AMWS data, we do so for AMWS degree institutions only. Due to the sheer volume of individuals, employment spells, and variants on employer spellings in AMWS employment data, a similar but slightly different approach was taken. For AMWS employers—of which there are 183,000 unique strings in our sample—we manually process employers in descending order of associated individual-years to link them to IPEDS codes until we have processed 80% of all employment spells, as well as any additional employer strings beyond this threshold that we have linked to IPEDS in other datasets and merge exactly. For the remaining set of AMWS employer strings, including non-university employer strings, we develop a hybrid approach that leverages an ensemble of LLMs, similar to the ensemble used for sector classification (see Appendix B.2). For the remaining tail of university employers, we fuzzy match these strings to the IPEDS university list to obtain a set of candidate matches for each, retaining candidates with a match score above a modest threshold. We then send these candidates to Claude Sonnet 4.6 and GPT 5.4 to identify which of the candidates is the correct link, or else to identify the entity as ambiguous (e.g., "State University of New York" or "University of California", without specifying campus), foreign, defunct, or otherwise unable to be matched. For cases where Claude and GPT disagree, we send the entity to Google's Gemini 3.1 Pro to adjudicate. The final output is a list of university employer strings and their associated IPEDS UnitIDs (if they can be matched), along with a confidence score out of 10. Manual review indicates that links with confidence scores $\geq$6 account for 90% of these strings and are reliable, and we restrict these links to those where the LLM confidence score is above this threshold. The remaining cases ($\sim$2,000 out of 30,000 university entities, but generally very low count ones) we treat as cases lacking sufficient information to match.

Though we do not leverage information on specific government or industry (or other sector) employers in this paper, for completeness we undertake a similar linking procedure to connect government and industry entities to (i) a (manually-created) canonical set of roughly 40 federal agency codes, as well as indicators for other federal agencies, foreign government offices, state/local government offices, and uncertain cases, and (ii) CRSP's historical list of PERMNOs, which identify publicly-listed companies. For the industry employer strings, we reproduce the IPEDS linking methodology almost exactly, replacing the input IPEDS university list with a list of firm names (COMNAMs) and their PERMNOs, and asking our ensemble to classify entities to one of the firms in a fuzzy-matched shortlist or to identify it as ambiguous, foreign, domestic but private, or otherwise unable to be matched. As with universities, we retained links with a final confidence score $\geq$6, which in this case accounted for 65% of industry entities, and presumed the remainder were unmatchable. For the government employer strings, we asked our ensemble to classify entities to one of our manually-created government agency categories, using the same methods for resolving disagreements. Based on manual review of the results, here we retained links with either (a) a confidence score of $\geq$6 (93% of cases) or (b) with lower confidence scores but where Claude and GPT agreed, which collectively account for 99% of government entities. We undertake one further linking effort on the AMWS employer string list: we crosswalk entities which are government-funded, privately-run FFRDCs (e.g., national labs, NSF-sponsored observatories, etc.) to (i) their funding agency, and (ii) a canonical list of names. We perform this linking manually based on keyword filters (e.g., "Los Alamos" or "Jet Propulsion Laboratory") and substantial manual review, in many cases redirecting previous classifications and links away from original results (e.g. from Government/DOE to FFRDC/Los Alamos National Lab, or from University/CalTech to FFRDC/JPL).

Our analysis ultimately filters the IPEDS universe—and the very wide range of institutions in our various data sources which we linked to IPEDS—to the 258 universities with an R1 or R2 Carnegie Classification in 2000 ("very high" and "high" research activity doctoral institutions, respectively). Table B.4 lists these universities with their location and Carnegie classification, as well as indicators for whether they appear at least once in each of our data sources.

Table B.4: R1/R2 university sample and presence in each data source

					Present in source										
								AMWS							
IPEDS	University	City	State	Carnegie	DOD	HEGIS	NRSTP	Empl.	Deg.	SED	PQDT	ROR	NSF	GPR	Total
188429	Adelphi U.	Garden City	NY	16	1	1	1	1	1	1	1	1	1	0	9
100654	Alabama A&M U.	Normal	AL	16	1	1	1	1	1	1	0	1	1	0	8
131159	American U.	Washington	DC	15	1	1	1	1	1	1	1	1	1	1	10
168740	Andrews U.	Berrien Springs	MI	16	1	1	1	1	1	1	0	1	1	0	8
137148	Argosy U.	Sarasota	FL	16	0	1	0	0	0	1	0	0	0	0	2
104151	Arizona State U.	Tempe	AZ	15	1	1	1	1	1	1	1	1	1	1	10
100858	Auburn U.	Auburn	AL	15	1	1	1	1	1	1	1	1	1	1	10
150136	Ball State U.	Muncie	IN	16	1	1	1	1	1	1	1	1	1	0	9
223232	Baylor U.	Waco	TX	16	1	1	1	1	1	1	1	1	1	0	9
196079	Binghamton U.	Vestal	NY	15	1	1	1	1	1	1	1	1	1	0	9
110097	Biola U.	La Mirada	CA	16	0	1	1	1	1	1	0	1	0	0	6
164924	Boston Coll.	Chestnut Hill	MA	15	1	1	1	1	1	1	1	1	1	0	9
164988	Boston U.	Boston	MA	15	1	1	1	1	1	1	1	1	1	1	10
201441	Bowling Green State U.	Bowling Green	OH	16	1	1	1	1	1	1	1	1	1	0	9
165015	Brandeis U.	Waltham	MA	15	1	1	1	1	1	1	1	1	1	1	10
230038	Brigham Young U.	Provo	UT	15	1	1	1	1	1	1	1	1	1	1	10
217156	Brown U.	Providence	RI	15	1	1	1	1	1	1	1	1	1	1	10
110404	California Inst. of Tech.	Pasadena	CA	15	1	1	1	1	1	1	1	1	1	1	10
211440	Carnegie Mellon U.	Pittsburgh	PA	15	1	1	1	1	1	1	1	1	1	1	10
201645	Case Western Reserve U.	Cleveland	OH	15	1	1	1	1	1	1	1	1	1	1	10
169248	Central Michigan U.	Mount Pleasant	MI	16	1	1	1	1	1	1	0	1	1	0	8
112251	Claremont Graduate U.	Claremont	CA	15	1	1	1	1	1	1	1	1	1	0	9
138947	Clark Atlanta U.	Atlanta	GA	16	1	1	1	1	1	1	1	1	1	0	9
165334	Clark U.	Worcester	MA	16	1	1	1	1	1	1	1	1	1	0	9
190044	Clarkson U.	Potsdam	NY	16	1	1	1	1	1	1	1	1	1	0	9
217882	Clemson U.	Clemson	SC	15	1	1	1	1	1	1	1	1	1	0	9
202134	Cleveland State U.	Cleveland	OH	16	1	1	1	1	1	1	1	1	1	0	9
126818	Colorado State U.	Fort Collins	CO	15	1	1	1	1	1	1	1	1	1	1	10
190150	Columbia U.	New York	NY	15	1	1	1	1	1	1	1	1	1	1	10
190415	Cornell U.	Ithaca	NY	15	1	1	1	1	1	1	1	1	1	1	10
190576	CUNY Graduate School	New York	NY	15	0	1	0	1	1	1	1	1	1	0	7
182670	Dartmouth Coll.	Hanover	NH	16	1	1	1	1	1	1	1	1	1	1	10
144740	DePaul U.	Chicago	IL	16	0	1	1	1	1	1	1	1	1	0	8
212054	Drexel U.	Philadelphia	PA	16	1	1	1	1	1	1	1	1	1	0	9
198419	Duke U.	Durham	NC	15	1	1	1	1	1	1	1	1	1	1	10
212106	Duquesne U.	Pittsburgh	PA	16	0	1	1	1	1	1	1	1	1	0	8
198464	East Carolina U.	Greenville	NC	16	1	1	1	1	1	1	1	1	1	0	9
220075	East Tennessee State U.	Johnson City	TN	16	1	1	1	1	1	1	1	1	1	0	9
139658	Emory U.	Atlanta	GA	15	1	1	1	1	1	1	1	1	1	1	10
133669	Florida Atlantic U.	Boca Raton	FL	16	1	1	1	1	1	1	0	1	1	0	8
133881	Florida Inst. of Tech.	Melbourne	FL	16	1	1	1	1	1	1	1	1	1	0	9
133951	Florida International U.	Miami	FL	15	1	1	0	1	1	1	0	1	1	0	7
134097	Florida State U.	Tallahassee	FL	15	1	1	1	1	1	1	1	1	1	1	10
191241	Fordham U.	Bronx	NY	15	1	1	1	1	1	1	1	1	1	0	9
232186	George Mason U.	Fairfax	VA	16	1	1	1	1	1	1	0	1	1	0	8

Table B.4: R1/R2 university sample and presence in each data source (continued)

					Present in source										
								AMWS							
IPEDS	University	City	State	Carnegie	DOD	HEGIS	NRSTP	Empl.	Deg.	SED	PQDT	ROR	NSF	GPR	Total
131469	George Washington U.	Washington	DC	15	1	1	1	1	1	1	1	1	1	1	10
131496	Georgetown U.	Washington	DC	15	1	1	1	1	1	1	1	1	1	1	10
139755	Georgia Inst. of Tech.	Atlanta	GA	15	1	1	1	1	1	1	1	1	1	1	10
139940	Georgia State U.	Atlanta	GA	15	1	1	1	1	1	1	1	1	1	0	9
166027	Harvard U.	Cambridge	MA	15	1	1	1	1	1	1	1	1	1	1	10
191649	Hofstra U.	Hempstead	NY	16	0	1	1	1	1	1	1	1	1	0	8
131520	Howard U.	Washington	DC	15	1	1	1	1	1	1	1	1	1	0	9
142276	Idaho State U.	Pocatello	ID	16	0	1	1	1	1	1	1	1	1	0	8
145725	Illinois Inst. of Tech.	Chicago	IL	16	1	1	1	1	1	1	1	1	1	1	10
145813	Illinois State U.	Normal	IL	16	1	1	1	1	1	1	1	1	1	0	9
151324	Indiana State U.	Terre Haute	IN	16	1	1	1	1	1	1	1	1	1	0	9
213020	Indiana U. of Pennsylvania	Indiana	PA	16	0	1	1	1	1	1	0	1	1	0	7
151351	Indiana U.-Bloomington	Bloomington	IN	15	1	1	1	1	1	1	1	1	1	0	9
151111	Indiana U.-Indianapolis	Indianapolis	IN	16	1	1	1	1	1	1	1	1	1	1	10
153603	Iowa State U.	Ames	IA	15	1	1	1	1	1	1	1	1	1	1	10
175856	Jackson State U.	Jackson	MS	16	1	1	1	1	1	1	0	1	1	0	8
162928	Johns Hopkins U.	Baltimore	MD	15	1	1	1	1	1	1	1	1	1	1	10
155399	Kansas State U.	Manhattan	KS	15	1	1	1	1	1	1	1	1	1	1	10
203517	Kent State U.	Kent	OH	15	1	1	1	1	1	1	1	1	1	0	9
213543	Lehigh U.	Bethlehem	PA	15	1	1	1	1	1	1	1	1	1	1	10
117636	Loma Linda U.	Loma Linda	CA	16	1	1	1	1	1	1	1	1	1	0	9
159391	Louisiana State U.	Baton Rouge	LA	15	1	1	1	1	1	1	1	1	1	1	10
159647	Louisiana Tech U.	Ruston	LA	16	1	1	1	1	1	1	1	1	1	0	9
146719	Loyola U. Chicago	Chicago	IL	15	1	1	1	1	1	1	1	1	1	0	9
239105	Marquette U.	Milwaukee	WI	15	1	1	1	1	1	1	1	1	1	0	9
166683	Massachusetts Inst. of Tech.	Cambridge	MA	15	1	1	1	1	1	1	1	1	1	1	10
212841	MCP Hahnemann U.	Philadelphia	PA	16	1	1	1	1	1	1	1	0	1	0	8
204024	Miami U.	Oxford	OH	16	1	1	1	1	1	1	1	1	1	0	9
171100	Michigan State U.	East Lansing	MI	15	1	1	1	1	1	1	1	1	1	1	10
171128	Michigan Technological U.	Houghton	MI	16	1	1	1	1	1	1	1	1	1	1	10
220978	Middle Tennessee State U.	Murfreesboro	TN	16	0	1	1	1	1	1	1	1	1	0	8
176080	Mississippi State U.	Mississippi State	MS	15	1	1	1	1	1	1	1	1	1	0	9
178411	Missouri U. of Science & Tech.	Rolla	MO	16	1	1	1	1	1	1	1	1	1	1	10
180461	Montana State U.	Bozeman	MT	16	1	1	1	1	1	1	1	1	1	1	10
147536	National Louis U.	Chicago	IL	16	0	0	0	1	1	1	0	1	0	0	4
185828	New Jersey Inst. of Tech.	Newark	NJ	16	1	1	1	1	1	1	1	1	1	0	9
187967	New Mexico Inst. of Mining & Tech.	Socorro	NM	16	1	1	1	1	1	1	1	1	1	1	10
188030	New Mexico State U.	Las Cruces	NM	15	1	1	1	1	1	1	1	1	1	1	10
193900	New York U.	New York	NY	15	1	1	1	1	1	1	1	1	1	1	10
199193	North Carolina State U.	Raleigh	NC	15	1	1	1	1	1	1	1	1	1	1	10
200332	North Dakota State U.	Fargo	ND	16	1	1	1	1	1	1	1	1	1	0	9
167358	Northeastern U.	Boston	MA	15	1	1	1	1	1	1	1	1	1	1	10
105330	Northern Arizona U.	Flagstaff	AZ	16	1	1	1	1	1	1	1	1	1	0	9
147703	Northern Illinois U.	Dekalb	IL	15	1	1	1	1	1	1	1	1	1	0	9

Table B.4: R1/R2 university sample and presence in each data source (continued)

					Present in source										
								AMWS							
IPEDS	University	City	State	Carnegie	DOD	HEGIS	NRSTP	Empl.	Deg.	SED	PQDT	ROR	NSF	GPR	Total
147767	Northwestern U.	Evanston	IL	15	1	1	1	1	1	1	1	1	1	1	10
136215	Nova Southeastern U.	Fort Lauderdale	FL	16	1	1	1	1	1	1	1	1	1	0	9
171571	Oakland U.	Rochester Hills	MI	16	1	1	1	1	1	1	1	1	1	0	9
204796	Ohio State U.	Columbus	OH	15	1	1	1	1	1	1	1	1	1	1	10
204857	Ohio U.	Athens	OH	15	1	1	1	1	1	1	1	1	1	0	9
207388	Oklahoma State U.	Stillwater	OK	15	1	1	1	1	1	1	1	1	1	0	9
232982	Old Dominion U.	Norfolk	VA	15	1	1	1	1	1	1	1	1	1	1	10
209542	Oregon State U.	Corvallis	OR	15	1	1	1	1	1	1	1	1	1	1	10
194310	Pace U.	New York	NY	16	0	1	1	1	1	1	0	1	1	0	7
214777	Pennsylvania State U.	University Park	PA	15	1	1	1	1	1	1	1	1	1	1	10
121150	Pepperdine U.	Malibu	CA	16	1	1	1	1	0	1	0	1	1	0	7
194541	Polytechnic Inst. of New York U.	Brooklyn	NY	16	1	1	1	1	1	1	1	0	1	0	8
209807	Portland State U.	Portland	OR	16	1	1	1	1	1	1	1	1	1	0	9
186131	Princeton U.	Princeton	NJ	15	1	1	1	1	1	1	1	1	1	1	10
243780	Purdue U.	West Lafayette	IN	15	1	1	1	1	1	1	1	1	1	1	10
194824	Rensselaer Polytechnic Inst.	Troy	NY	15	1	1	1	1	1	1	1	1	1	0	9
227757	Rice U.	Houston	TX	15	1	1	1	1	1	1	1	1	1	1	10
195049	Rockefeller U.	New York	NY	16	1	1	1	1	1	1	1	1	1	1	10
186380	Rutgers U.	New Brunswick	NJ	15	1	1	1	1	1	1	1	1	1	1	10
186399	Rutgers U.	Newark	NJ	16	1	1	1	1	1	1	1	0	1	0	8
179159	Saint Louis U.	Saint Louis	MO	15	1	1	1	1	1	1	1	1	1	1	10
122409	San Diego State U.	San Diego	CA	16	1	1	1	1	1	1	1	1	1	1	10
186584	Seton Hall U.	South Orange	NJ	16	1	1	1	1	1	1	1	1	1	0	9
218733	South Carolina State U.	Orangeburg	SC	16	0	1	1	1	0	1	0	1	1	0	6
219356	South Dakota State U.	Brookings	SD	16	1	1	1	1	1	1	1	1	1	0	9
149222	Southern Illinois U.-Carbondale	Carbondale	IL	15	1	1	1	1	1	1	1	1	1	0	9
228246	Southern Methodist U.	Dallas	TX	15	1	1	1	1	1	1	1	1	1	0	9
195809	St. John's U.	Queens	NY	16	1	1	1	1	1	1	1	1	1	0	9
243744	Stanford U.	Stanford	CA	15	1	1	1	1	1	1	1	1	1	1	10
186867	Stevens Inst. of Tech.	Hoboken	NJ	16	1	1	1	1	1	1	1	1	1	1	10
196097	Stony Brook U.	Stony Brook	NY	15	1	1	1	1	1	1	1	1	1	0	9
196060	SUNY at Albany	Albany	NY	15	1	1	1	1	1	1	1	1	1	1	10
196103	SUNY Coll. of Env. Sci. & Forestry	Syracuse	NY	16	1	1	1	1	1	1	1	1	1	0	9
196413	Syracuse U.	Syracuse	NY	15	1	1	1	1	1	1	1	1	1	1	10
196468	Teachers Coll. at Columbia U.	New York	NY	15	0	1	1	1	1	1	1	0	1	0	7
216339	Temple U.	Philadelphia	PA	15	1	1	1	1	1	1	1	1	1	1	10
221838	Tennessee State U.	Nashville	TN	16	1	1	1	1	1	1	1	1	1	0	9
228723	Texas A&M U.-College Station	College Station	TX	15	1	1	1	1	1	1	1	1	1	1	10
224554	Texas A&M U.-Commerce	Commerce	TX	16	0	1	1	1	1	1	1	1	1	0	8
228705	Texas A&M U.-Kingsville	Kingsville	TX	16	0	1	1	1	1	1	0	1	1	0	7
228875	Texas Christian U.	Fort Worth	TX	16	1	1	1	1	1	1	1	1	1	0	9
229063	Texas Southern U.	Houston	TX	16	0	1	1	1	1	1	0	1	1	0	7
229115	Texas Tech U.	Lubbock	TX	15	1	1	1	1	1	1	1	1	1	0	9
229179	Texas Woman's U.	Denton	TX	16	0	1	1	1	1	1	1	1	1	0	8

Table B.4: R1/R2 university sample and presence in each data source (continued)

					Present in source										
								AMWS							
IPEDS	University	City	State	Carnegie	DOD	HEGIS	NRSTP	Empl.	Deg.	SED	PQDT	ROR	NSF	GPR	Total
131283	The Catholic U. of America	Washington	DC	15	1	1	1	1	1	1	1	1	1	1	10
193654	The New School	New York	NY	16	0	1	1	1	1	1	1	1	1	0	8
100751	The U. of Alabama	Tuscaloosa	AL	15	1	1	1	1	1	1	1	1	1	1	10
180489	The U. of Montana	Missoula	MT	16	1	1	1	1	1	1	1	1	1	0	9
221759	The U. of Tennessee-Knoxville	Knoxville	TN	15	1	1	1	1	1	1	1	1	1	1	10
228769	The U. of Texas at Arlington	Arlington	TX	15	1	1	1	1	1	1	1	1	1	0	9
228778	The U. of Texas at Austin	Austin	TX	15	1	1	1	1	1	1	1	1	1	1	10
228787	The U. of Texas at Dallas	Richardson	TX	16	1	1	1	1	1	1	1	1	1	1	10
228796	The U. of Texas at El Paso	El Paso	TX	16	1	1	1	1	1	1	1	1	1	1	10
168148	Tufts U.	Medford	MA	15	1	1	1	1	1	1	1	1	1	0	9
160755	Tulane U. of Louisiana	New Orleans	LA	15	1	1	1	1	1	1	1	1	1	1	10
124885	U.S. International U.	San Diego	CA	16	1	1	1	1	1	1	1	0	1	0	8
206279	Union Inst. & U.	Cincinnati	OH	16	0	1	0	1	1	0	1	1	0	0	5
196088	U. at Buffalo	Buffalo	NY	15	1	1	1	1	1	1	1	1	1	1	10
200800	U. of Akron	Akron	OH	16	1	1	1	1	1	1	1	1	1	1	10
100663	U. of Alabama at Birmingham	Birmingham	AL	15	1	1	1	1	1	1	1	1	1	1	10
100706	U. of Alabama in Huntsville	Huntsville	AL	16	1	1	1	1	1	1	1	1	1	0	9
102614	U. of Alaska Fairbanks	Fairbanks	AK	16	1	1	1	1	1	1	1	1	1	1	10
104179	U. of Arizona	Tucson	AZ	15	1	1	1	1	1	1	1	1	1	1	10
106397	U. of Arkansas	Fayetteville	AR	15	1	1	1	1	1	1	1	1	1	1	10
106245	U. of Arkansas at Little Rock	Little Rock	AR	16	1	1	1	1	1	1	0	1	1	0	8
128744	U. of Bridgeport	Bridgeport	CT	16	1	1	1	1	1	1	0	1	1	0	8
110635	U. of California-Berkeley	Berkeley	CA	15	1	1	1	1	1	1	1	1	1	1	10
110644	U. of California-Davis	Davis	CA	15	1	1	1	1	1	1	1	1	1	1	10
110653	U. of California-Irvine	Irvine	CA	15	1	1	1	1	1	1	1	1	1	1	10
110662	U. of California-Los Angeles	Los Angeles	CA	15	1	1	1	1	1	1	1	1	1	1	10
110671	U. of California-Riverside	Riverside	CA	15	1	1	1	1	1	1	1	1	1	1	10
110680	U. of California-San Diego	La Jolla	CA	15	1	1	1	1	1	1	1	1	1	1	10
110699	U. of California-San Francisco	San Francisco	CA	16	1	1	1	1	1	1	1	1	1	1	10
110705	U. of California-Santa Barbara	Santa Barbara	CA	15	1	1	1	1	1	1	1	1	1	1	10
110714	U. of California-Santa Cruz	Santa Cruz	CA	15	1	1	1	1	1	1	1	1	1	1	10
132903	U. of Central Florida	Orlando	FL	16	1	1	1	1	1	1	1	1	1	1	10
144050	U. of Chicago	Chicago	IL	15	1	1	1	1	1	1	1	1	1	1	10
201885	U. of Cincinnati	Cincinnati	OH	15	1	1	1	1	1	1	1	1	1	1	10
126614	U. of Colorado Boulder	Boulder	CO	15	1	1	1	1	1	1	1	1	1	1	10
126562	U. of Colorado Denver	Denver	CO	16	1	1	0	1	1	1	1	1	1	1	9
129020	U. of Connecticut	Storrs	CT	15	1	1	1	1	1	1	1	1	1	1	10
202480	U. of Dayton	Dayton	OH	16	1	1	1	1	1	1	1	1	1	1	10
130943	U. of Delaware	Newark	DE	15	1	1	1	1	1	1	1	1	1	1	10
127060	U. of Denver	Denver	CO	15	1	1	1	1	1	1	1	1	1	1	10
134130	U. of Florida	Gainesville	FL	15	1	1	1	1	1	1	1	1	1	1	10
139959	U. of Georgia	Athens	GA	15	1	1	1	1	1	1	1	1	1	1	10
129525	U. of Hartford	West Hartford	CT	16	0	1	1	1	1	1	0	1	1	0	7
141574	U. of Hawaii at Manoa	Honolulu	HI	15	1	1	1	1	1	1	1	1	1	1	10

Table B.4: R1/R2 university sample and presence in each data source (continued)

					Present in source										
								AMWS							
IPEDS	University	City	State	Carnegie	DOD	HEGIS	NRSTP	Empl.	Deg.	SED	PQDT	ROR	NSF	GPR	Total
225511	U. of Houston	Houston	TX	15	1	1	1	1	1	1	1	1	1	0	9
142285	U. of Idaho	Moscow	ID	15	1	1	1	1	1	1	1	1	1	1	10
145600	U. of Illinois Chicago	Chicago	IL	15	1	1	1	1	1	1	1	1	1	1	10
145637	U. of Illinois Urbana-Champaign	Champaign	IL	15	1	1	1	1	1	1	1	1	1	1	10
153658	U. of Iowa	Iowa City	IA	15	1	1	1	1	1	1	1	1	1	1	10
155317	U. of Kansas	Lawrence	KS	15	1	1	1	1	1	1	1	1	1	1	10
157085	U. of Kentucky	Lexington	KY	15	1	1	1	1	1	1	1	1	1	1	10
117140	U. of La Verne	La Verne	CA	16	0	1	1	1	0	1	0	1	1	0	6
160658	U. of Louisiana	Lafayette	LA	16	1	1	1	1	1	1	1	1	1	0	9
157289	U. of Louisville	Louisville	KY	15	1	1	1	1	1	1	1	1	1	1	10
161253	U. of Maine	Orono	ME	15	1	1	1	1	1	1	1	1	1	1	10
163259	U. of Maryland, Baltimore	Baltimore	MD	16	1	1	1	1	1	1	1	1	1	0	9
163268	U. of Maryland-Baltimore County	Baltimore	MD	15	0	1	0	1	1	1	1	1	1	0	7
163286	U. of Maryland-College Park	College Park	MD	15	1	1	1	1	1	1	1	1	1	1	10
166629	U. of Massachusetts-Amherst	Amherst	MA	15	1	1	1	1	1	1	1	1	1	1	10
166638	U. of Massachusetts-Boston	Boston	MA	16	1	1	1	1	1	1	0	1	1	0	8
166513	U. of Massachusetts-Lowell	Lowell	MA	16	1	1	1	1	1	1	1	1	1	1	10
220862	U. of Memphis	Memphis	TN	15	1	1	1	1	1	1	1	1	1	0	9
135726	U. of Miami	Coral Gables	FL	15	1	1	1	1	1	1	1	1	1	1	10
170976	U. of Michigan-Ann Arbor	Ann Arbor	MI	15	1	1	1	1	1	1	1	1	1	1	10
174066	U. of Minnesota-Twin Cities	Minneapolis	MN	15	1	1	1	1	1	1	1	1	1	1	10
176017	U. of Mississippi	University	MS	15	1	1	1	1	1	1	1	1	1	1	10
178396	U. of Missouri-Columbia	Columbia	MO	15	1	1	1	1	1	1	1	1	1	1	10
178402	U. of Missouri-Kansas City	Kansas City	MO	16	1	1	1	1	1	1	1	1	1	0	9
178420	U. of Missouri-St. Louis	Saint Louis	MO	16	0	1	1	1	1	1	1	1	1	0	8
181464	U. of Nebraska	Lincoln	NE	15	1	1	1	1	1	1	1	1	1	1	10
182281	U. of Nevada-Las Vegas	Las Vegas	NV	16	1	1	1	1	1	1	0	1	1	0	8
182290	U. of Nevada-Reno	Reno	NV	15	1	1	1	1	1	1	1	1	1	0	9
183044	U. of New Hampshire	Durham	NH	15	1	1	1	1	1	1	1	1	1	1	10
187985	U. of New Mexico	Albuquerque	NM	15	1	1	1	1	1	1	1	1	1	1	10
159939	U. of New Orleans	New Orleans	LA	16	1	1	1	1	1	1	1	1	1	0	9
199120	U. of North Carolina at Chapel Hill	Chapel Hill	NC	15	1	1	1	1	1	1	1	1	1	1	10
199148	U. of North Carolina at Greensboro	Greensboro	NC	16	0	1	1	1	1	1	1	1	1	0	8
200280	U. of North Dakota	Grand Forks	ND	16	1	1	1	1	1	1	1	1	1	1	10
227216	U. of North Texas	Denton	TX	15	1	1	1	1	1	1	1	1	1	0	9
127741	U. of Northern Colorado	Greeley	CO	16	0	1	1	1	1	1	1	1	1	0	8
152080	U. of Notre Dame	Notre Dame	IN	15	1	1	1	1	1	1	1	1	1	1	10
207500	U. of Oklahoma	Norman	OK	15	1	1	1	1	1	1	1	1	1	1	10
209551	U. of Oregon	Eugene	OR	15	1	1	1	1	1	1	1	1	1	1	10
215062	U. of Pennsylvania	Philadelphia	PA	15	1	1	1	1	1	1	1	1	1	1	10
215293	U. of Pittsburgh	Pittsburgh	PA	15	1	1	1	1	1	1	1	1	1	1	10
243221	U. of Puerto Rico-Rio Piedras	San Juan	PR	16	1	1	1	1	0	1	0	0	1	0	6
217484	U. of Rhode Island	Kingston	RI	15	1	1	1	1	1	1	1	1	1	1	10
195030	U. of Rochester	Rochester	NY	15	1	1	1	1	1	1	1	1	1	1	10

Table B.4: R1/R2 university sample and presence in each data source (continued)

					Present in source										
								AMWS							
IPEDS	University	City	State	Carnegie	DOD	HEGIS	NRSTP	Empl.	Deg.	SED	PQDT	ROR	NSF	GPR	Total
122436	U. of San Diego	San Diego	CA	16	1	1	1	1	1	1	0	1	1	0	8
122612	U. of San Francisco	San Francisco	CA	16	1	1	1	1	0	1	0	1	1	0	7
102094	U. of South Alabama	Mobile	AL	16	1	1	1	1	1	1	1	1	1	0	9
218663	U. of South Carolina	Columbia	SC	15	1	1	1	1	1	1	1	1	1	0	9
219471	U. of South Dakota	Vermillion	SD	16	1	1	1	1	1	1	1	1	1	0	9
137351	U. of South Florida	Tampa	FL	15	1	1	1	1	1	1	1	1	1	0	9
123961	U. of Southern California	Los Angeles	CA	15	1	1	1	1	1	1	1	1	1	1	10
176372	U. of Southern Mississippi	Hattiesburg	MS	15	1	1	1	1	1	1	1	1	1	1	10
174914	U. of St. Thomas	Saint Paul	MN	16	0	1	1	1	1	1	0	1	1	0	7
120883	U. of the Pacific	Stockton	CA	16	1	1	1	1	1	1	1	1	1	0	9
206084	U. of Toledo	Toledo	OH	15	1	1	1	1	1	1	1	1	1	0	9
207971	U. of Tulsa	Tulsa	OK	16	1	1	1	1	1	1	1	1	1	0	9
230764	U. of Utah	Salt Lake City	UT	15	1	1	1	1	1	1	1	1	1	1	10
231174	U. of Vermont	Burlington	VT	15	1	1	1	1	1	1	1	1	1	0	9
234076	U. of Virginia	Charlottesville	VA	15	1	1	1	1	1	1	1	1	1	1	10
236948	U. of Washington	Seattle	WA	15	1	1	1	1	1	1	1	1	1	1	10
240444	U. of Wisconsin-Madison	Madison	WI	15	1	1	1	1	1	1	1	1	1	1	10
240453	U. of Wisconsin-Milwaukee	Milwaukee	WI	15	1	1	1	1	1	1	1	1	1	1	10
240727	U. of Wyoming	Laramie	WY	15	1	1	1	1	1	1	1	1	1	1	10
230728	Utah State U.	Logan	UT	15	1	1	1	1	1	1	1	1	1	0	9
221999	Vanderbilt U.	Nashville	TN	15	1	1	1	1	1	1	1	1	1	1	10
234030	Virginia Commonwealth U.	Richmond	VA	15	1	1	1	1	1	1	1	1	1	1	10
233921	Virginia Tech	Blacksburg	VA	15	1	1	1	1	1	1	1	1	1	0	9
199847	Wake Forest U.	Winston-Salem	NC	16	1	1	1	1	1	1	1	1	1	0	9
236939	Washington State U.	Pullman	WA	15	1	1	1	1	1	1	1	1	1	0	9
179867	Washington U. in St. Louis	Saint Louis	MO	15	1	1	1	1	1	1	1	1	1	1	10
172644	Wayne State U.	Detroit	MI	15	1	1	1	1	1	1	1	1	1	1	10
238032	West Virginia U.	Morgantown	WV	15	1	1	1	1	1	1	1	1	1	1	10
172699	Western Michigan U.	Kalamazoo	MI	15	1	1	1	1	1	1	1	1	1	0	9
156125	Wichita State U.	Wichita	KS	16	1	1	1	1	1	1	1	1	1	0	9
216852	Widener U.	Chester	PA	16	0	1	1	1	1	1	0	1	1	0	7
231624	William & Mary	Williamsburg	VA	16	1	1	1	1	1	1	1	1	1	0	9
131113	Wilmington U.	New Castle	DE	16	0	1	0	1	0	1	0	1	0	0	4
168421	Worcester Polytechnic Inst.	Worcester	MA	16	1	1	1	1	1	1	1	1	1	0	9
206604	Wright State U.	Dayton	OH	16	1	1	1	1	1	1	0	1	1	0	8
130794	Yale U.	New Haven	CT	15	1	1	1	1	1	1	1	1	1	1	10
197708	Yeshiva U.	New York	NY	15	1	1	1	1	1	1	1	1	1	1	10
				Average	0.89	1.00	0.97	1.00	0.97	1.00	0.89	0.97	0.98	0.52	9.18

B.4.2 Linking subjects/fields across all data sources

Many of our datasets also report research subjects or research fields, and much of our analysis takes place at the university-field level. For example, NRSTP reports scientists' degree fields and research specialties (with a shared encoding), AMWS scientists have primary subjects, SED and PQDT report graduates' degree fields and subjects, OpenAlex publications have associated primary fields, and NSF grants are made by subject-oriented divisions and programs.

We crosswalk fields and subjects in these data sources to the canonical set of SED major fields shown in Table B.5, specifically focusing on STEM fields only (namely: the life sciences, physical sciences, mathematical and computer sciences, and engineering). The SED data are already provided under this classification. For our other datasets, we create manual crosswalks from their native subjects and fields to this canonical set. In many cases, this is straightforward (e.g., NRSTP and OpenAlex fields map approximately 1-to-1 to SED major fields). For the PQDT data, we manually crosswalk primary degree subjects to major fields (see Shvadron et al. 2025a). In the case of the NSF data, NSF divisions and program names are usually clearly revealing of the major field they pertain to, and we make links accordingly; the results are broadly validating, as we find a substantial share of the NSF portfolio in core scientific fields, and a small share of it in peripheral fields like health sciences (which NIH funds more heavily) and industrial engineering (not a traditional target for NSF funding). The AMWS data again force an exception to our primary manual linking method, with over 80,000 unique subject strings (areas of expertise) that we need to classify. To link these subjects to our target major fields, we first classify AMWS subjects to roughly 200 broad topics and subtopics, using a hierarchical AMWS index provided in modern AMWS volumes. We then manually crosswalk these topic-subtopics to SED major fields.

Table B.5: Canonical set of major fields

Life/Physical/Mathematical Sciences	Engineering Sciences
Agricultural sciences	Aerospace engineering
Biological sciences	Biomedical engineering
Health sciences	Chemical engineering
Chemistry	Civil engineering
Geosciences	Electrical engineering
Physics & astronomy	Industrial engineering
Mathematics & statistics	Materials engineering
Computer science	Mechanical engineering
	Other engineering

B.4.3 Linking individuals across data sources

Finally, we also develop an individual linked sample across data sources, which enables us to compare the evolution of individual scientist careers as a function of DoD exposure (as observed in the 1970 NRSTP). The rich individual-level detail across our datasets (e.g., name and PhD institution/field/year) and specific sample (U.S. PhD scientists) makes it relatively straightforward to make unambiguous links, particularly once all datasets have been crosswalked to our canonical set of university and field codes, which can form a basis for linking.

Given that our NRSTP DoD funding indicator is essential to this analysis, this linking effort begins with the 1970 NRSTP sample, filtered to PhD-holders. We then link this sample to AMWS on last name, first name, middle initial, and PhD institution, field, and year. To accommodate modest discrepancies we have found reported across these datasets, we initially permit a link to be made if two records share the same last name, first name, PhD institution, and PhD graduation years ± 2 of each other. This is an intentionally broadened catchment, but many of the resulting links are unambiguous anyway. We then disambiguate any ambiguous links on the basis of whether two linked records share (i) a PhD graduation year exactly, (ii) a non-missing middle initial, and (iii) a PhD field, sequentially dropping observations via these filters until we arrive at an unambiguous link, and dropping individuals whom we are unable to disambiguate by this procedure. The sequence of filters is deliberate, placing what we believe to be the highest fidelity disambiguation rule first and lowest reliability rule last (degree subjects are most likely to be slightly misremembered by individuals, or inadvertently misclassified in our own standardization due to ambiguity in the sources themselves; e.g., biochemistry could be mapped to biology or chemistry). The NRSTP-AMWS link makes it possible to merge in the AMWS employment data, and in particular to construct an individual x year panel with annual employment, which is central to our analysis.

We make two additional individual-level links. First, we link individuals to principal investigators on NSF grants through a similar procedure, initially linking on last name, employer university, and year. We drop observations with (i) non-matching, non-missing first initials, (ii) non-matching, non-missing middle initials, (iii) dissimilar first names (defined as <50% overlap in 2-character grams), which suggest two linked observations may represent different people. We retain remaining links, which will have a shared last name, university, and year and have a similar or exactly-matching first name—and which we think are good links with high probability.

Second, we link individuals to patents, using information on year and employer to disambiguate links. We first perform a series of successive links where we merge scientists in our AMWS sample with patent inventors on first and last names, and then on first initials and last names, to retrieve candidate patents for each scientist. We then retrieve the individual's AMWS employer(s) in the year the patent was filed, and identify cases where the employer matches the patent assignee listed on the published patent. Rather than doing so manually or programmatically, we develop an LLM-assisted linking pipeline that accounts for the myriad variants of employer and assignee spellings in these records, similar to that used for AMWS employer classification and linking: we send each candidate to both Claude Sonnet 4.6 and GPT 5.4, asking it to score out of 10 whether the employer and assignee are the same. Manual review reveals that this procedure is extremely effective at identifying true links, even where a human or hard-coded linking procedure may struggle, as it benefits from contextual knowledge. Overall, we find that when one of the rating models gives a match a score of $\geq$4, the link is essentially always correctly identifying a true patent of the scientist. These LLM-assisted links include cases where the entities are distinct but related, and where the scientist and inventor are clearly the same person (e.g., an employee of "Harvard Medical School" with a linked patent assigned to "Brigham and Women's Hospital").

While our use of assignee information makes for very precise links, it also presents a significant limitation in that it will only link patents which were assigned on issue to individuals' employers. This may tend to bias the linked sample towards firm patents (over university patents), as prior to the Bayh-Dole era (1980+) many universities did not take title to patents. To circumvent this challenge, we use data from the Government Patent Register (Appendix B.3.2): because most patented inventions resulting from university research were produced with government funding, we can use the GPR to identify the institution where the invention was produced. We thus undertake a second assessment of AMWS employers and GPR institutions, following a similar LLM ensemble procedure, and likewise filter results to those where at least one model scored the link a 4 (out of 10) or higher, which manual review of the results again reinforced.

In total, our effort to link our AMWS sample (2005-2021) to patents between 1960-2000 yields roughly 120,000 person-patent pairs, for 20,000 unique scientists and 105,000 unique patents; 99% of these are picked up by our main linking method, and 1% through the GPR.[19] Note that AMWS is much broader than NRSTP, but because our analytical sample will be restricted to NRSTP scientists (i.e., scientists who were active in 1970 and responded to the survey, yielding key DoD funding measures) who were also in AMWS, in practice we will have roughly 30,000 person-patent pairs in our analytical sample. Of the (coincidentally also) 30,000 people who will be in this linked NRSTP-AMWS sample, roughly 4,200 patented in our study period.

[19]The low additionality of the GPR-based screen reflects that the vast majority of patents associated to scientists in this sample were produced in the private sector or in the Bayh-Dole era.

C Supplementary Results

C.1 Additional features of the 1970s research funding environment

C.1.1 Distribution of exposure to DoD funding cuts

Distribution of pre-1970 DoD support. To better understand variation in the DoD contract data, here we present a few windows into the distribution of DoD research support—particularly focusing on the pre-1970 era, and comparing it to the post-1970 era.

Table C.1 lists the top 20 universities by the per capita value of associated contracts in 1967-1969, normalizing by the 1970 NRSTP respondent population. Most of this list is intuitive and familiar: MIT tops the list; Stanford, Georgia Tech, and other elite technical institutes rank highly; and the list includes New Mexico Institute of Mining and Technology (located near Los Alamos National Laboratory and next to the White Sands Missile Range), the University of Alabama in Huntsville (near Redstone Arsenal, the centerpoint of U.S. missile programs), the University of Dayton (which is linked to Wright-Patterson AFB, a major Air Force research base), the University of California San Diego (through which the military conducted significant oceanographic research), the University of Alaska Fairbanks (through which the military conducted significant Arctic research), and Washington DC-area universities. The table also lists the service branches' share of awards, where the patterns are also consistent with our historical understanding.

Table C.1: Top 20 universities by DoD funding per capita in 1967-1969

University	Total contract value awarded per 1970 NRSTP respondent (MMs)	Share from: Army	Navy	Air Force
Massachusetts Institute of Technology	1.48	7%	12%	81%
University at Buffalo	1.04	15%	74%	11%
University of Dayton	0.85	0%	0%	100%
Nova Southeastern University	0.59	0%	100%	0%
American University	0.53	99%	1%	0%
University of Alaska Fairbanks	0.51	9%	86%	5%
George Washington University	0.51	65%	34%	1%
New Mexico Institute of Mining and Technology	0.42	5%	90%	5%
Stanford University	0.42	18%	57%	24%
University of California-San Diego	0.40	6%	81%	12%
Polytechnic Institute of New York University	0.38	16%	27%	57%
Columbia University in the City of New York	0.37	9%	69%	22%
University of Denver	0.36	6%	4%	90%
Stevens Institute of Technology	0.33	37%	57%	6%
Cornell University	0.29	41%	11%	48%
Syracuse University	0.26	11%	38%	51%
Illinois Institute of Technology	0.24	41%	6%	52%
University of Alabama in Huntsville	0.23	63%	0%	37%
Georgia Institute of Technology-Main Campus	0.22	28%	27%	44%
University of Michigan-Ann Arbor	0.21	51%	12%	37%
The Catholic University of America	0.20	4%	94%	2%

Notes: Table lists the top 20 universities by their total DoD research contract value (6.1/6.2 contracts, in 2025 USD) in 1967-1969 per NRSTP respondent, and the Army, Navy, and Air Force share of each.

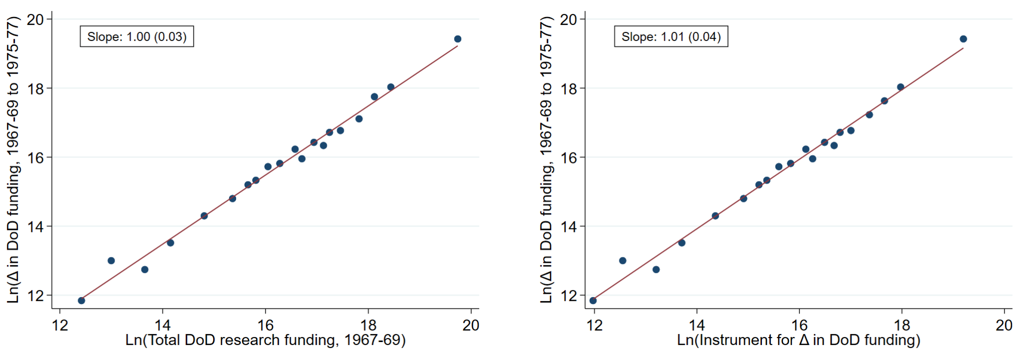
In Figure C.1(A) we correlate universities' log decline in military research contracts from 1967-69 to 1975-77 (calculated only for universities with a decline—which is the majority—and computed from the inverse decline, such that larger numbers indicate larger declines) with the log contracts in 1967-69 (the base value). These two objects correlate nearly 1-for-1, suggesting that the research funding cuts that took place in the 1970s were fairly evenly distributed across universities (proportional to base values)—reinforcing that this period represents a systemic shock.

Panel (B) further supports this interpretation. For every university, we create a shift-share instrument for university declines in research contracts, calculating each university's share of 1967-69 funding and multiplying it by the decline in total funding from 1967-69 to 1975-77. As Panel (B) shows (and Panel (A) implies), this instrument also strongly predicts funding declines. Shift-share instruments constructed from more disaggregated measures, like field service codes in the contract data (i.e., detailed procurement codes), produce similar patterns.

Figure C.1: Universities' decline in DoD funding proportional to base level

Panel (A): Changes vs. base levels

Panel (B): Changes vs. instrument



Notes: Panel (A) provides binned scatterplot correlating universities' log declines in funding between 1967-1969 and 1975-1977 to log funding in 1967-1969 (restricting to universities with funding declines, with larger values indicating larger declines). Panel (B) provides binned scatterplot correlating universities' log declines in funding between 1967-1969 and 1975-1977 to a log shift-share predictor of funding changes, constructed as described in text. The evidence suggests the 1970s funding cuts were evenly distributed, as larger, more heavily supported universities saw larger declines (and the slope is a precisely estimated 1).

C.1.2 Evaluation of NRSTP-based exposure measures

With this evidence on the distribution of DoD research funding in hand, we can also more deeply explore our NRSTP-based exposure measures. Table C.2, for example, lists the top 10 universities in our data by the share of NRSTP respondents reporting DoD support. All but one were also present in the list of top 20 universities by per capita DoD contracts in Table C.1 above. This table provides prima facie evidence that on an apples to apples basis (university-level, per capita), our NRSTP-derived measures represent patterns in contract data—building confidence that NRSTP-derived exposure measures will also be informative at levels that we do not observe in the contract data directly (e.g., at the investigator level or university-field level).

Table C.2: Top 10 universities by share of scientists in 1970 with DoD support

University	NRSTP personnel in 1970 survey	Pct. of NRSTP with DoD support
Nova Southeastern University	12	33.3%
University of Dayton	105	28.6%
Massachusetts Institute of Technology	1045	27.2%
University of Rochester	574	19.2%
Polytechnic Institute of New York University	131	19.1%
University of California-San Diego	520	18.5%
Stanford University	878	17.1%
University of Alabama in Huntsville	42	16.7%
Georgia Institute of Technology-Main Campus	240	15.8%
The Catholic University of America	141	15.6%

Notes: Table lists the top 10 universities by their share of NRSTP scientists with DoD support in 1970. Nine of ten universities in this list were among the 20 largest contractors per capita (Table C.1).

In the body of the paper, and now in this appendix, we have listed the top universities and university-fields with DoD support, based on the NRSTP measures. In Table C.3 we provide the complement: a list of fields along with their NRSTP respondents in 1970 and the share of those respondents reporting support from six federal sources (DoD, AEC, HHS (i.e., NIH), NASA, NSF, and USDA). Here (and in the paper) we group engineering major fields into a single "Engineering" category, which is the lowest level of aggregation available in every data source, though many sources (including NRSTP) can be disaggregated into specific engineering disciplines—where it is apparent that some disciplines (like electronic engineering) are more heavily DoD supported, and others (like biomedical engineering) more supported by other funders.

One pattern apparent in this table is that the research funding landscape was fragmented, with multiple federal agencies supporting research in different disciplines. Though DoD was the largest sponsor of research in most non-biomedical or agricultural fields, DOE was a significant sponsor of physics research, and NASA of engineering and geosciences. To better understand the risk of potential confounding effects from each, in Table C.4 we correlate universities' post-1970 declines in military research funding with the share of NRSTP respondents at those universities with support from each of these funders. We do so first for per capita decreases in funding (in Columns 1 and 2), and then for decreases in funding relative to a university's 1969 total research expenditures (in

Columns 3 and 4). In both cases, we find that only the share of NRSTP respondents with DoD support statistically predicts these funding declines, and that this pattern is similar irrespective of whether we account for rates of support from other agencies.

Table C.3: SED major fields ranked by share of scientists in 1970 with DoD support

Field	NRSTP personnel in 1970 survey	Pct. of respondents with support from: DoD	AEC	HHS	NASA	NSF	USDA
Engineering	2856	17.6%	7.5%	7.5%	13.6%	1.5%	5.9%
Physics & astronomy	10452	17.4%	26.0%	2.5%	12.5%	4.1%	0.2%
Computer science	1686	17.1%	9.5%	10.9%	7.9%	3.0%	1.7%
Geosciences	4627	9.7%	3.6%	2.4%	7.9%	5.0%	2.1%
Chemistry	9939	7.3%	7.8%	20.3%	3.7%	2.3%	3.9%
Mathematics & statistics	7263	6.9%	1.4%	4.6%	2.3%	3.9%	0.9%
Biological sciences	18892	1.8%	3.2%	46.1%	1.2%	1.3%	15.4%
Agricultural sciences	3091	0.9%	2.0%	3.8%	0.6%	0.5%	56.6%

Notes: Table lists the SED major fields in our sample and the share of NRSTP university scientists in 1970 with support from each of six major federal research funding agencies. List is ranked by fields' rate of DoD support. We group engineering disciplines together, as engineering broadly is the common category we can observe across all data sources; specific engineering disciplines such as aeronautical engineering and electronic engineering had substantially higher rates of DoD support than this average. The ranking in this table is consistent with contextual understanding of military research priorities at the time.

Table C.4: Relationship of universities' post-1970 changes in DoD research funding and 1970 NRSTP-based exposure measures

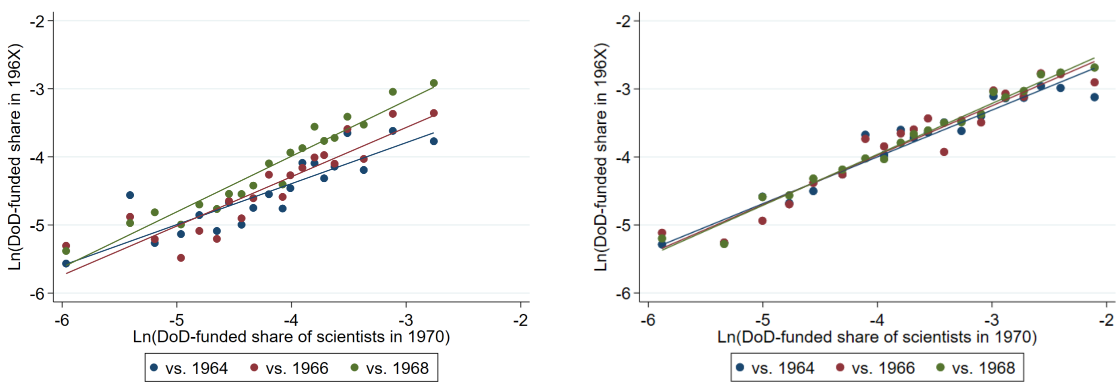
	Δ per capita (1)	(2)	Δ/Cost (3)	(4)
Share of scientists w/ DOD funding	-1.112**	-1.061**	-1.684***	-1.647***
	(0.433)	(0.458)	(0.414)	(0.464)
Share of scientists w/ DOE funding		-0.005		0.296
		(0.103)		(0.240)
Share of scientists w/ HHS funding		-0.020		0.007
		(0.045)		(0.106)
Share of scientists w/ NASA funding		-0.187		-0.317
		(0.134)		(0.235)
Share of scientists w/ NSF funding		0.607		-0.214
		(0.512)		(1.279)
Share of scientists w/ USDA funding		0.057*		0.099
		(0.034)		(0.107)
N	228	228	135	135
R^2	0.23	0.24	0.23	0.24

Notes: Table estimates correlation between a university's change in defense research funding between 1967-1969 and 1975-1977 (2025 USD, in MMs) to the NRSTP-based exposure measures we use in our analysis. Columns (1) and (2) relate the change in research funding per 1970 NRSTP respondent to the share of NRSTP respondents reporting support from DoD and other federal agencies. Columns (3) and (4) relate the change in funding from 1967-69 to 1975-77 normalized by research expenditure to the same predictors. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Robust standard errors in parentheses.

Reliability of exposure measure Throughout this paper we measure exposure to the 1970s DoD research funding cuts based on funding patterns observed in the 1970 NRSTP survey wave, which was run at the start of 1970. As this is only one year of data, we also explore its representativeness. To do so, we construct analogous measures (the share of NRSTP scientists reporting DoD support) using data from prior NRSTP waves where the question was asked—namely, 1964, 1966, and 1968—at both the university and university-field levels. Figure C.2 provides binned scatterplots of (log) exposure in 1964, 1966, and 1968 vs. 1970. The evidence visually illustrates a close correlation between these measures, with slopes near 1, suggesting the analysis in this paper is not contingent on the specific year for which exposure is measured.

Figure C.2: Correlation of NRSTP exposure measures over time (1964-1970)

Panel (A): University-level measure Panel (B): University-field measure



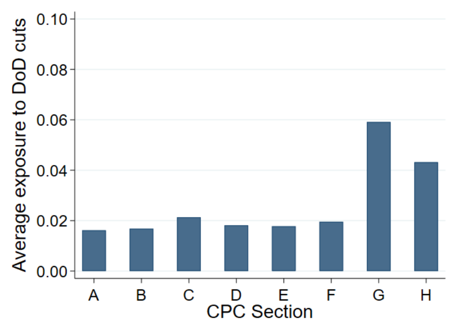
Notes: Figure presents binned scatterplots of 1964, 1966, and 1968 (in blue, red, and green, respectively) NRSTP-based DoD exposure measures against the 1970 measure used throughout this paper, calculated at the university level (Panel A) and university-field level (Panel B).

CPC-level exposure to DoD research. Though most of our analysis examines the effects of DoD research funding on science, a subset of our analysis examines potential impacts on science-based technological innovation. As we describe in Appendix B.3, to do so we create CPC-level measures of exposure to defense science. We refer readers to that appendix section for details; here, we provide evidence on the distribution of this exposure measure.

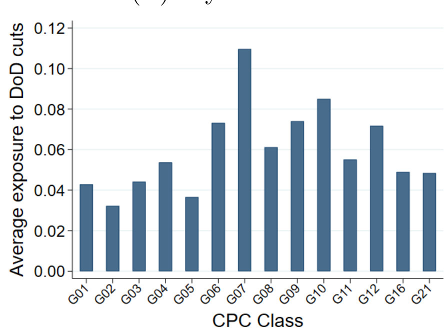
Figure C.3(A) shows average exposure to DoD science among 4-digit CPCs, by CPC section (each bar represents an average among lower-level CPC codes within the identified section). This indicates that Sections G and H ("Physics" and "Electricity", in practice covering computing, sensors, control systems, electronics, and communications, among other things) have substantially higher average exposure than other fields. Panels (B) and (C) further disaggregate to averages within 3-digit CPCs in these sections. Example G classes with high exposure include G06 (computing), G09 (driven by cryptography), and G10 (driven by speech recognition). The H class with the highest average exposure is H04, which represents communications technologies.

Figure C.3: Distribution of exposure to DoD science across technology areas

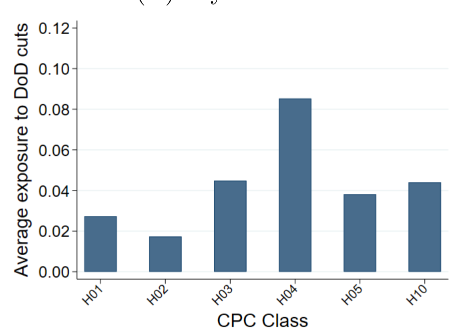
Panel (A): Mean exposure, by CPC section



Panel (B): By Section G classes



Panel (C): By Section H classes



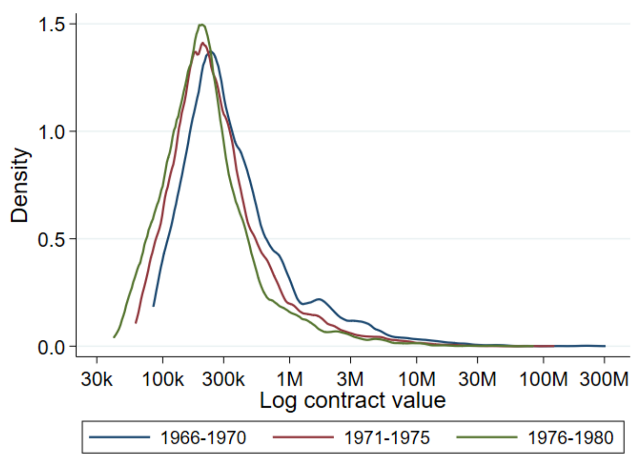
Notes: Figure shows variation in technology areas' exposure to DoD-funded science. Underlying sample consists of 4-character CPC subclasses; each chart shows averages across them at higher levels of aggregation. CPC Section A covers human necessities; B, physical operation and transportation; C, chemistry and metallurgy; D, textiles and paper; E, fixed constructions; F, mechanical engineering, lighting, heating, and blasting; G, measurement, optics, and computing; and H, electrical and electronic systems.

C.1.3 Changes in composition of DoD research funding: Contract sizes

One of the distinctive features of defense research funding in the 1950s and 1960s was its standing up of large projects and research infrastructure, at a scale that other funders (particularly, the NSF) could not match then and typically does not match today. For example, particle accelerators, observatories, major university laboratories, instrumentation centers, computing facilities, and national "centers of excellence" were all beneficiaries of this era; though some of these were transitioned to NSF support in the post-Mansfield era, to our understanding this type of activity was not sustained by NSF other funders at the same breadth and scale.

In this context, post-1970 changes may have not only represented a contraction in overall research support in key DoD-related fields, but also change in the nature of that support, away from large grants and contracts to smaller project-based awards. To explore this possibility, in Figure C.4 we plot the distribution of DoD university research contracts by size, in log scale, for three periods: 1966-1970 (blue), 1971-1975 (red), and 1976-1980 (green). We find that this distribution shifted substantially to the left over this era, with mass excised primarily from the high end (∼\$500K+ and \$1MM+) of the distribution. For parsimony we omit density plots for later periods (1981-1985 or 1986-1990), but they remain similar to the 1976-1980 distribution.

Figure C.4: Declining scale of defense university research contracts



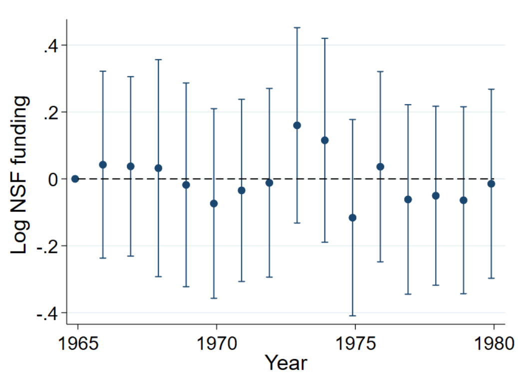
Notes: Figure illustrates the changing distribution of the size of DoD basic and applied research contracts with universities (budget categories 6.1-6.2), in log scale. We show kernel density plots for three periods: 1966-1970, 1971-1975, and 1976-1980. As the mean shifted down, the largest change in mass occurred at the large (\$1+ MM) range.

C.1.4 Were DoD research funding cuts offset by the NSF?

One question the historical narrative raises (e.g., Section 2 or Appendix A) is to what degree declines in DoD research funding were counteracted by increased NSF funding for the same research, which is what Congress intended to happen. Historical accounts suggest that this offset was modest at best, and intrinsically unlikely due to the dual facts that (i) some of the increased NSF appropriations were earmarked for other purposes, and (ii) NSF had different priorities and review procedures than DoD, and other than a few specific program transfers, there was no structural mechanism created through which NSF would specifically fund what DoD left behind. To formally evaluate whether such an offset emerged, we turn to our NSF grant data, which cover all grants made between 1964 and 1983 (digitized from NSF's annual grants and awards publication). We aggregate grants to the university-field level, using PIs' institutions to identify universities and the NSF division and program that issued each grant to associate it to a scientific field. Our analysis focuses on the 1965 to 1980 period, starting the sample in 1965 to match prior analysis and ending at the end of the 1970s—the era over which these adjustments would have taken place.

In Figure C.5 we estimate the same workhorse two-way fixed effects specification we estimate in much of the paper (Equation 1), evaluating changes in log total NSF funding at the university-field level over time in university-fields with above or below median exposure to DoD research funding. The figure shows no evidence of an offsetting increase in NSF research funds during the 1970s at departments which depended more heavily on DoD support, even as that support began to decline: estimated differences across the sample are statistically insignificant and clustered around zero, without any indication of an underlying trend change.

Figure C.5: No countervailing increase in NSF grant funding



Notes: Figure shows estimated differences over time in NSF grant funding to university-fields with above-median (vs. below-median) exposure to DoD funding cuts. Underlying regression estimates differences in log NSF funding and controls for university-field and field-year fixed effects. NSF grants are associated to universities and years based on the principal investigator's institution and the NSF division and program issuing the grant. All estimates are relative to 1965 (the omitted category). Error bars represent 95% confidence intervals, computed from standard errors clustered at the university level.

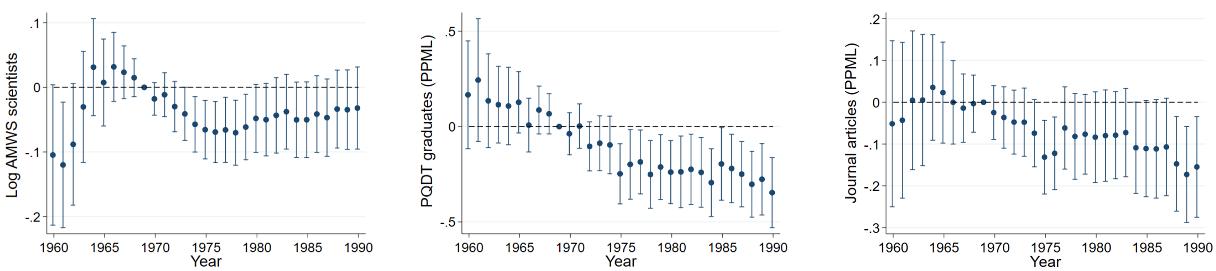
C.2 Results reproduced with field-year fixed effects

In the analysis of university-field scientist employment and PhD production (Section 4.1), our primary specification controls for university-field and university-year fixed effects. This choice accounts for time-varying differences that we might see at the university level, restricting comparisons to being across departments within the same university, over time.

We could instead account for field-year fixed effects, which would condition comparisons to being across same-field departments at different universities. This choice presents tradeoffs, but we view as less desirable than university-year fixed effects, given the range of evolving university-level factors that could coincide with defense-supported departments and confound causal interpretations. Nevertheless, it is useful to evaluate results both ways. We do so below, where Figure C.6 and Table C.5 reproduce Figure 3 and Table 3 of the paper, replacing university-year FEs with field-year FEs. The results are broadly similar to those in the body of the paper, with attenuated declines in scientist counts but similar patterns for PhD graduate counts.

Figure C.6: Scientists, PhD grads, and pubs at more vs. less exposed university fields, 1960-1990

Panel (A): AMWS scientists | Panel (B): PQDT graduates | Panel (C): Journal publications



Notes: Figure shows estimated differences over time in early-career AMWS scientists, PQDT PhD graduates, and journal articles at/from university-fields with versus without exposure to DoD funding cuts (Panels A to C, respectively). Underlying regression estimates differences in log scientists by OLS and PhD graduates and publication counts by Poisson pseudo-maximum likelihood (PPML). All regressions control for university-field and field-year fixed effects. Journal articles are fractionally associated to each listed author and their affiliated institution. All estimates are relative to 1969 (the omitted category). Error bars represent 95% confidence intervals, computed from standard errors clustered at the university level.

Table C.5: University-field scientist headcount and PhD production over time, 1965-1990

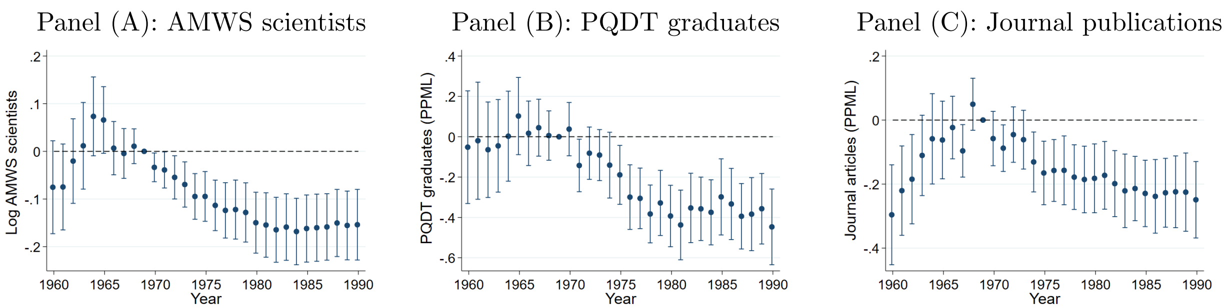
	AMWS scientists					PhD graduates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	All	All	$\leq$5y in	$\leq$10y in	SED PhDs	PQDT PhDs	Def. base	Def. base
Any DoD exposure * 1(1971-1975)	-0.079***	-0.051**	-0.050**	-0.030	-0.060**	-0.116**	-0.137**	-0.599***	-0.571**
	(0.020)	(0.022)	(0.020)	(0.032)	(0.028)	(0.058)	(0.053)	(0.175)	(0.242)
Any DoD exposure * 1(1976-1980)	-0.121***	-0.099***	-0.072***	-0.061	-0.052	-0.235***	-0.252***	-0.882***	-0.818***
	(0.026)	(0.028)	(0.025)	(0.041)	(0.042)	(0.081)	(0.074)	(0.185)	(0.227)
Any DoD exposure * 1(1981-1985)	-0.114***	-0.113***	-0.056*	-0.058	-0.048	-0.262***	-0.274***	-0.907***	-0.827***
	(0.031)	(0.033)	(0.030)	(0.044)	(0.045)	(0.085)	(0.081)	(0.204)	(0.239)
Any DoD exposure * 1(1986-1990)	-0.106***	-0.128***	-0.047	-0.117***	-0.067	-0.310***	-0.318***	-0.745***	-0.615**
	(0.034)	(0.035)	(0.032)	(0.043)	(0.046)	(0.087)	(0.083)	(0.199)	(0.247)
N	36514	36438	36514	25841	31805	29283	32096	21090	18934
R^2	0.95	0.97	0.95	0.79	0.86				
Y mean	2.219	2.223	2.219	1.089	1.503	9.725	9.073	0.406	0.294
Method	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Inst x Field FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y								
Inst x Year FEs		Y							
Field x Year FEs			Y	Y	Y	Y	Y	Y	Y

Notes: Table estimates differences over time in the number of PhD scientists employed at and PhDs graduating from university-fields with versus without exposure to DoD funding cuts. Scientists are measured using biographical listings in American Men and Women of Science (AMWS) from 2005 onward, from which we can extract listed scientists' previous employers and years of employment, and using these, count up scientists at the university-field-year level. We separately evaluate post-1970 changes in total AMWS scientists (Columns 1 to 3) and early-career scientists (Columns 4 and 5), which we alternatively define as researchers less than five or ten years into their careers. PhD graduates are independently measured in the SED and from PQDT (Columns 6 and 7). The final columns report changes in the number of PhD graduates produced who later enter the defense industrial base, using a more liberal (Column 8) and conservative (Column 9) definition of its boundaries (see text for details). Columns (1) to (5) estimate log outcomes by OLS and Columns (6) to (9) count outcomes by Poisson pseudo-maximum likelihood, reflecting the nature of the variation in each outcome. Columns (1) to (3) control for university-field fixed effects (FEs) and (1) year FEs, (2) university-year FEs, and (3) field-year FEs. Columns (4) to (9) control for university-field and field-year fixed effects. All columns include controls for time-varying differences by units' size (measured by a university-field's 1970 NRSTP respondents) and are estimated relative to 1965-1970 (the omitted category). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by university in parentheses.

C.3 Results reproduced with a 1968 exposure measure

As emphasized in Appendix C.1, our analysis in the body of the paper measures universities', fields', and individuals' exposure to the 1970s DoD research funding cuts using the 1970 NRSTP survey results. Because there remains a possibility that the NRSTP returns may vary year to year and/or that the 1970 data may not be representative of the exposure we are interested in, in this appendix we explore whether our results may be sensitive to this choice, reproducing key analyses using the 1968 NRSTP data. We specifically do so for our analysis that examines impacts on university-fields' scientist employment, PhD production, and publication activity, forgoing similar analysis on DoD-funded individuals in the 1968 NRSTP data, as these comprise a different cohort and may not be comparable. Figure C.7 and Table C.6 reproduce Figure 3 and Table 3 of the paper; in all cases, the results are similar to those in the paper.

Figure C.7: Scientists, PhD grads, and pubs at more vs. less exposed university fields, 1960-1990



Notes: Figure shows estimated differences over time in early-career AMWS scientists, PQDT PhD graduates, and journal articles at/from university-fields with versus without exposure to DoD funding cuts (Panels A to C, respectively), using an exposure measure created from the 1968 (rather than 1970) NRSTP data. Underlying regression estimates differences in log scientists by OLS and PhD graduates and publication counts by Poisson pseudo-maximum likelihood (PPML). All regressions control for university-field and university-year fixed effects. Journal articles are fractionally associated to each listed author and their affiliated institution. All estimates are relative to 1969 (the omitted category). Error bars represent 95% confidence intervals, computed from standard errors clustered at the university level.

Table C.6: University-field scientist headcount and PhD production over time, 1965-1990

	AMWS scientists					PhD graduates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	All	All	$\leq$5y in	$\leq$10y in	SED PhDs	PQDT PhDs	Def. base	Def. base
Any DoD exposure * 1(1971-1975)	-0.094***	-0.077***	-0.058***	-0.197***	-0.141***	-0.090*	-0.155***	-0.279	-0.452
	(0.021)	(0.022)	(0.021)	(0.044)	(0.036)	(0.054)	(0.048)	(0.230)	(0.292)
Any DoD exposure * 1(1976-1980)	-0.133***	-0.134***	-0.073***	-0.290***	-0.317***	-0.281***	-0.368***	-0.652**	-0.876***
	(0.028)	(0.029)	(0.027)	(0.052)	(0.051)	(0.066)	(0.062)	(0.255)	(0.314)
Any DoD exposure * 1(1981-1985)	-0.138***	-0.168***	-0.066**	-0.233***	-0.362***	-0.339***	-0.390***	-0.425	-0.584*
	(0.032)	(0.034)	(0.031)	(0.048)	(0.055)	(0.075)	(0.071)	(0.262)	(0.343)
Any DoD exposure * 1(1986-1990)	-0.123***	-0.162***	-0.048	-0.278***	-0.272***	-0.312***	-0.411***	-0.630***	-0.661**
	(0.036)	(0.036)	(0.034)	(0.053)	(0.056)	(0.083)	(0.084)	(0.213)	(0.277)
N	36051	35942	36051	25091	31248	28684	30165	14056	11329
R^2	0.95	0.97	0.95	0.83	0.88				
Y mean	2.245	2.248	2.245	1.113	1.525	9.943	9.657	0.608	0.490
Method	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Inst x Field FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y								
Inst x Year FEs		Y		Y	Y	Y	Y	Y	Y
Field x Year FEs			Y						

Notes: Table estimates differences over time in the number of PhD scientists employed at and PhDs graduating from university-fields with versus without exposure to DoD funding cuts, using an exposure measure created from the 1968 (rather than 1970) NRSTP data. Scientists are measured using biographical listings in American Men and Women of Science (AMWS) from 2005 onward, from which we can extract listed scientists' previous employers and years of employment, and using these, count up scientists at the university-field-year level. We separately evaluate post-1970 changes in total AMWS scientists (Columns 1 to 3) and early-career scientists (Columns 4 and 5), which we alternatively define as researchers less than five or ten years into their careers. PhD graduates are independently measured in the SED and from PQDT (Columns 6 and 7). The final columns report changes in the number of PhD graduates produced who later enter the defense industrial base, using a more liberal (Column 8) and conservative (Column 9) definition of its boundaries (see text for details). Columns (1) to (5) estimate log outcomes by OLS and Columns (6) to (9) count outcomes by Poisson pseudo-maximum likelihood, reflecting the nature of the variation in each outcome. Columns (1) to (3) control for university-field fixed effects (FEs) and (1) year FEs, (2) university-year FEs, and (3) field-year FEs. Columns (4) to (9) control for university-field and university-year fixed effects. All columns include controls for time-varying differences by units' size (measured by a university-field's 1970 NRSTP respondents) and are estimated relative to 1965-1970 (the omitted category). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by university in parentheses.

C.4 Intensive margin analysis: Dose response

As we emphasize in Section 4.1, our analysis of changes in university researcher counts, PhD production, and research output in the paper compares outcomes at university-fields ("departments", as shorthand) with versus without exposure to defense research funding.

In this appendix we extend this analysis by separately estimating differences for units with any versus high exposure to DoD funding cuts, where the latter is measured as being in the top 20% of university-fields by share of affiliated scientists reporting DoD support in the 1970 NRSTP. We do so by adding parameters to Equation (1) that estimate the incremental effect of being in this top quintile. This dose-response analysis serves as both a robustness check on the main results—as we expect more heavily exposed departments to experience at least weakly larger effects—and an extension to them, documenting heterogeneous effects across the sample.

Table C.7 shows evidence of a dose response across nearly all outcomes, either weakly (consistently negative, but not statistically significant at traditional levels) or strongly (statistically significant) across nearly all columns. The one exception to this pattern is the final two columns, measuring production of PhD graduates who later enter the defense industrial base (under more liberal and conservative definitions of the DIB), where we find muted differential effects for the most heavily-exposed departments (Column 8) or even somewhat slightly attenuated effects (Column 9). Given low graduate counts in these columns, we edge towards caution in drawing strong inferences—but the evidence suggests the defense-oriented career paths of PhD graduates in heavily defense-oriented departments may have been partially insulated from the effect of these research funding cuts, perhaps by department culture or professional networks.

Table C.7: University-field scientist headcount and PhD production over time, 1965-1990

	AMWS scientists					PhD graduates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	All	All	$\leq$5y in	$\leq$10y in	SED PhDs	PQDT PhDs	Def. base	Def. base
Any DoD exposure * 1(1971-1975)	-0.042**	-0.034	-0.025	-0.042	-0.088**	0.024	-0.051	-0.530**	-0.729**
	(0.021)	(0.023)	(0.020)	(0.042)	(0.036)	(0.052)	(0.053)	(0.215)	(0.339)
Any DoD exposure * 1(1976-1980)	-0.084***	-0.088***	-0.057**	-0.063	-0.164***	-0.088	-0.229***	-0.808***	-1.083***
	(0.029)	(0.031)	(0.028)	(0.056)	(0.055)	(0.070)	(0.068)	(0.208)	(0.300)
Any DoD exposure * 1(1981-1985)	-0.067*	-0.096***	-0.035	-0.110*	-0.197***	-0.113	-0.196***	-0.932***	-1.045***
	(0.034)	(0.035)	(0.032)	(0.061)	(0.062)	(0.083)	(0.074)	(0.255)	(0.319)
Any DoD exposure * 1(1986-1990)	-0.067*	-0.115***	-0.031	-0.206***	-0.211***	-0.147	-0.250***	-0.681***	-0.791**
	(0.037)	(0.039)	(0.033)	(0.060)	(0.061)	(0.090)	(0.078)	(0.244)	(0.330)
Top DoD exposure * 1(1971-1975)	-0.070***	-0.037*	-0.052**	-0.134***	-0.058*	-0.049*	-0.048	0.121	0.247*
	(0.021)	(0.021)	(0.022)	(0.039)	(0.033)	(0.028)	(0.030)	(0.106)	(0.144)
Top DoD exposure * 1(1976-1980)	-0.071**	-0.023	-0.031	-0.127***	-0.118**	-0.133***	-0.141***	0.250**	0.356***
	(0.028)	(0.028)	(0.029)	(0.048)	(0.047)	(0.043)	(0.048)	(0.118)	(0.126)
Top DoD exposure * 1(1981-1985)	-0.088***	-0.037	-0.041	-0.057	-0.096*	-0.163***	-0.185***	0.184	0.345**
	(0.031)	(0.029)	(0.032)	(0.055)	(0.055)	(0.045)	(0.049)	(0.123)	(0.136)
Top DoD exposure * 1(1986-1990)	-0.075**	-0.029	-0.033	0.076	-0.012	-0.140***	-0.209***	0.054	0.283*
	(0.035)	(0.032)	(0.034)	(0.054)	(0.054)	(0.054)	(0.052)	(0.141)	(0.154)
N	36514	36438	36514	25245	31547	28793	30289	13945	11253
R^2	0.95	0.97	0.95	0.83	0.88				
Y mean	2.219	2.223	2.219	1.105	1.510	9.883	9.601	0.611	0.491
Method	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Inst x Field FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y								
Inst x Year FEs		Y		Y	Y	Y	Y	Y	Y
Field x Year FEs			Y						

Notes: Table estimates differences over time in the number of PhD scientists employed at and PhDs graduating from university-fields with versus without exposure to DoD funding cuts. Extending Table 3 from the body of the paper, we separately estimate differences in university-fields with higher exposure to DoD funding cuts, measured as being in the top 20% of university-fields by share of affiliated researchers in the 1970 NRSTP reporting DoD support. Scientists are measured using biographical listings in American Men and Women of Science (AMWS) from 2005 onward, from which we can extract listed scientists' previous employers and years of employment, and using these, count up scientists at the university-field-year level. We separately evaluate post-1970 changes in total AMWS scientists (Columns 1 to 3) and early-career scientists (Columns 4 and 5), which we alternatively define as researchers less than five or ten years into their careers. PhD graduates are independently measured in the SED and from PQDT (Columns 6 and 7). The final columns report changes in the number of PhD graduates produced who later enter the defense industrial base, using a more liberal (Column 8) and conservative (Column 9) definition of its boundaries (see text for details). Columns (1) to (5) estimate log outcomes by OLS and Columns (6) to (9) count outcomes by Poisson pseudo-maximum likelihood, reflecting the nature of the variation in each outcome. Columns (1) to (3) control for university-field fixed effects (FEs) and (1) year FEs, (2) university-year FEs, and (3) field-year FEs. Columns (4) to (9) control for university-field and field-year fixed effects. All columns include controls for time-varying differences by units' size (measured by a university-field's 1970 NRSTP respondents) and are estimated relative to 1965-1970 (the omitted category). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by university in parentheses.

C.5 Individual-level analysis on older cohorts

Section 4.2 examines the post-1970 career trajectories of early-career university scientists—defined as scientists who earned a PhD in the 1965-1970 period and worked at a university continuously until 1970—who reported DoD support in the 1970 NRSTP, in effect testing whether DoD-supported scientists' careers changed after 1970 as defense research funding declined.

One threat to identification in this analysis is selection: the possibility that DoD-funded scientists are intrinsically more likely to transition out of the academy and into industry, or move in other directions, due to (for example) the specific focus of their work. The NRSTP provides an opportunity to test this possibility by studying earlier cohorts. In particular, we can examine early career trajectories of slightly older scientists using otherwise similar sampling criteria. In Table C.8 we estimate the differential propensity for (i) university scientists from the 1959-1963 PhD cohort who were DoD-funded in 1964 to leave the university sector by 1969 (Panel A), and (ii) university scientists from the 1965-1969 PhD cohort who were DoD-funded in 1970 to leave the university sector by 1975 (Panel B). The availability of DoD funding measures in the 1964 and 1970 NRSTP data makes this comparison possible, and we focus our analysis on early career job transitions (through 1969 and through 1975) to ensure that the two cohorts are evaluated over same-length periods but the earlier cohort's window ends before 1970. The patterns in Panel (B) echo those visible in Table 4 for the 1965-1969 cohort in the early 1970s. We are unable to reproduce the same patterns for the earlier cohort in Panel (A), suggesting that the changes we find for DoD-funded early-career scientists in the 1970s are not general to DoD-funded early-career scientists at all times but rather specific to the generation which was exposed to the 1970s funding decline.

Table C.9 provides complementary analysis on an overlapping early cohort: here we estimate the differential propensity for university scientists from the 1960-1964 PhD cohort who worked at universities until 1970 and were observed DoD-funded *in 1970* to subsequently leave the university sector. In contrast to the 1965-1970 cohort studied in Table 4, we find no consistent, long-run differences between DoD-funded scientists from this cohort and their otherwise-similar peers, further reinforcing the interpretation that the effects we find in Section 4.2 are specific to scientists at the start of their career in the early 1970s. It is important to recognize that this comparison is not completely apples-to-apples, however, as (i) the career stage evaluated in this table is different (the 1970s represents the early career stage of the 1965-1969 cohort and mid-career stage of the 1960-1964 cohort), and (ii) the conditioning slightly varies (conditioning the sample to scientists working at universities until at least 1970 imposes a more stringent requirement on the 1960-1964 cohort than the 1965-1969 cohort). The comparison is, in our view, nevertheless instructive of the distinctive mobility patterns of the early career Mansfield cohort.

Table C.8: Employment sector over time for PhD graduates from the (i) 1959-1963 and (ii) 1965-1969 cohorts, as a function of whether they were DoD funded in (i) 1964 and (ii) 1970

Panel (A): PhD graduates from 1959-1963 cohort, evaluated through 1969

	(1) University	(2) Industry	(3) Govt.	(4) Multiple	(5) Univ-Ind	(6) Univ-Gov	(7) Any Pats.
DoD-funded in 1964 * Post-1964	-0.015	0.001	0.013*	0.009	-0.002	0.001	0.000
	(0.015)	(0.006)	(0.007)	(0.011)	(0.006)	(0.006)	(0.001)
N	21643	21643	21643	21643	21643	21643	21649
R^2	0.05	0.01	0.01	0.03	0.02	0.01	0.01
Y mean	0.949	0.008	0.007	0.029	0.007	0.011	0.001
Field-Year FEs	Y	Y	Y	Y	Y	Y	Y

Panel (B): PhD graduates from 1965-1969 cohort, evaluated through 1975

	(1) University	(2) Industry	(3) Govt.	(4) Multiple	(5) Univ-Ind	(6) Univ-Gov	(7) Any Pats.
DoD-funded in 1970 * Post-1970	-0.056***	0.029***	0.013*	0.010	0.005	0.005	0.003
	(0.017)	(0.011)	(0.007)	(0.011)	(0.005)	(0.007)	(0.002)
N	36860	36860	36860	36860	36860	36860	36877
R^2	0.07	0.02	0.01	0.04	0.01	0.02	0.01
Y mean	0.950	0.008	0.005	0.029	0.006	0.012	0.001
Field-Year FEs	Y	Y	Y	Y	Y	Y	Y

Notes: Panel (A) estimates propensity for AMWS-listed university scientists from the 1959-1963 PhD cohort to work in assorted sectors in 1964-1969, as a function of whether they had DoD support in 1964. Sample restricted to scientists who received their PhD in 1959-1963 and had been working continuously at a university until at least 1963, following Table 4. Panel (B) repeats this exercise for university scientists from the 1965-1969 PhD cohort and 1970-1975 employment, as a function of whether each scientist had DoD support in 1970. Observations are person-years, in each panel over an 11-year horizon (1959-1969 and 1965-1975), which are chosen to evaluate differences in early career mobility patterns for DoD-funded scientists in the pre-Mansfield era vs. in the Mansfield era, comparing cohorts that might otherwise seem similar. Our sampling ends in 1969/1975 to ensure that analysis of the pre-Mansfield cohort ends before 1970 and analysis of the Mansfield cohort covers an identical time span. As such, this table evaluates short-run early career mobility only. Outcomes indicate employment in the university, industry, or government sectors (Columns 1 to 3) or a mixture of sectors (i.e., individuals with either multiple affiliations in a given year or who are transitioning between sectors, Columns 4 to 6). The final outcome (Column 7) measures patenting, as an indicator for whether the given scientists filed one or more patents in a given year. All columns control for field-year fixed effects; because the sample is conditioned to pre-period university scientists, all post-period outcomes should be interpreted as a transition away from university employment (and similarly for patenting, of which there was almost none in these populations in their respective pre-periods). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by individual in parentheses.

Table C.9: Employment sector over time for PhD graduates from the 1960-1964 cohort, as a function of whether they were DoD funded in 1970

	(1) University	(2) Industry	(3) Government	(4) Multiple	(5) Univ-Ind	(6) Univ-Gov	(7) Any Pats.
DoD-funded in 1970 * 1(1965-1970)	0.000	0.000	0.000	0.000	0.000	0.000	0.007**
	(.)	(.)	(0.000)	(.)	(.)	(.)	(0.003)
DoD-funded in 1970 * 1(1971-1975)	-0.026	-0.001	-0.003***	0.020	0.003	0.001	0.008*
	(0.017)	(0.004)	(0.001)	(0.015)	(0.005)	(0.009)	(0.004)
DoD-funded in 1970 * 1(1976-1980)	-0.031	-0.003	-0.007***	0.035	0.011	-0.002	0.002
	(0.024)	(0.006)	(0.002)	(0.022)	(0.011)	(0.010)	(0.002)
DoD-funded in 1970 * 1(1981-1985)	-0.038	0.016	-0.002	0.030	0.017	0.011	0.004
	(0.027)	(0.013)	(0.003)	(0.023)	(0.013)	(0.013)	(0.004)
DoD-funded in 1970 * 1(1986-1990)	-0.076**	0.030*	0.004	0.050*	0.011	0.010	0.009
	(0.031)	(0.017)	(0.007)	(0.026)	(0.012)	(0.014)	(0.008)
N	80878	80878	80878	80878	80878	80878	80908
R^2	0.05	0.01	0.00	0.04	0.01	0.01	0.01
Y mean	0.932	0.008	0.005	0.049	0.008	0.018	0.003
Field-Year FEs	Y	Y	Y	Y	Y	Y	Y

Notes: Table estimates propensity for AMWS-listed, early career university scientists to work in assorted sectors over time, as a function of whether they had DoD support in 1970. Sample restricted to scientists who received their PhD in 1960-1964 and worked at universities until at least 1970. Outcomes indicate employment in the university, industry, or government sectors (Columns 1 to 3) or a mixture of sectors (i.e., individuals with either multiple affiliations in a given year or who are transitioning between sectors, Columns 4 to 6). The final outcome (Column 7) measures patenting, as an indicator for whether the given scientists filed one or more patents in a given year. All columns control for field-year fixed effects and present estimates relative to 1965-1970 (the omitted category); because the sample is conditioned to pre-1970 university scientists, all post-1970 outcomes should be interpreted as a transition away from university employment (and similarly for patenting, of which there was almost none in this population prior to 1970). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by individual in parentheses.

C.6 Changes in other mission agency support

Although our analysis focuses on post-1970 declines in military research funding specifically, this decline coincided with shifts in research support at other federal mission agencies. In particular, the early 1970s saw a substantial retrenchment at NASA following the end of the Apollo program, as well as some reductions in some AEC-supported research as the Cold War began to ease. These developments affected many of the same scientific communities that had historically depended on military funding—including in physics, earth sciences, and some engineering fields. Their concurrence may therefore complicate attempts to fully attribute the changes in university research activity we find specifically to changes in DoD research policy alone.[20]

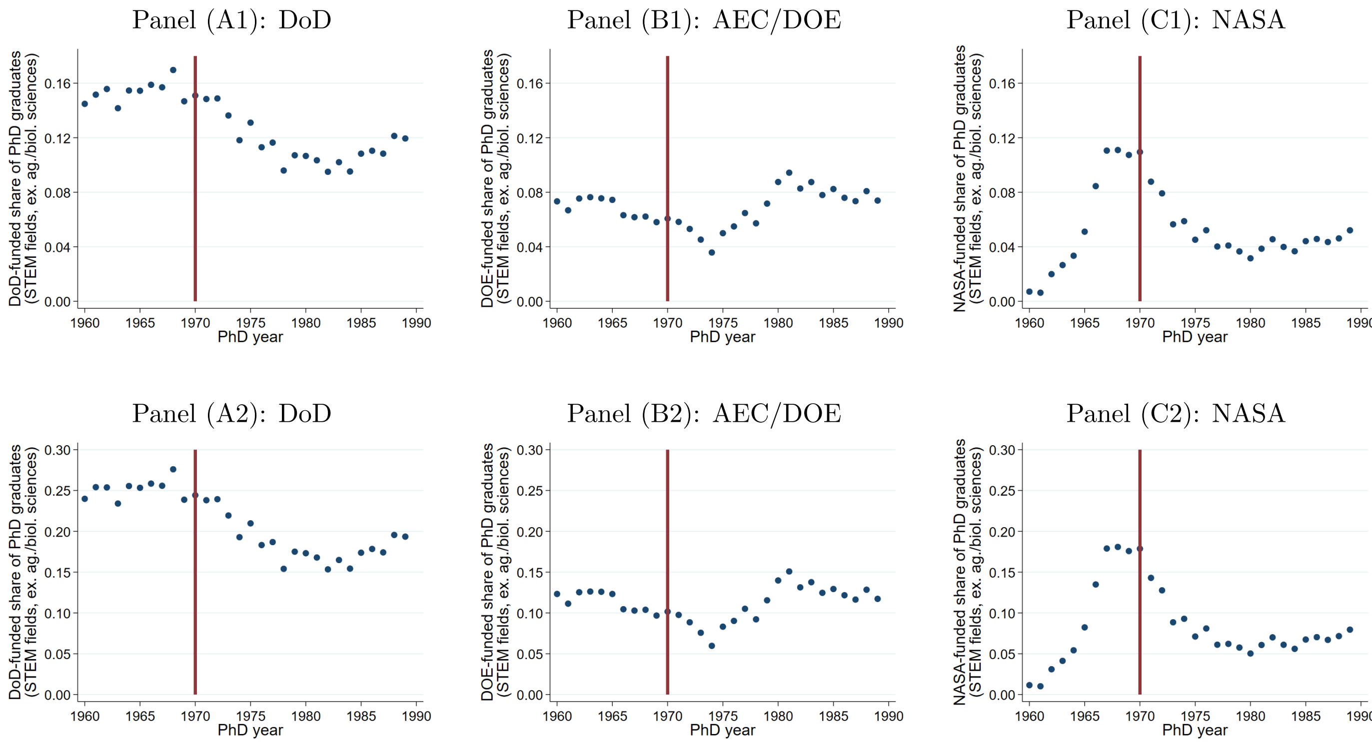
Insofar as the NASA contraction coincides with declines in military research support, we see this less as a threat to identification (of the effects of public research funding) and more as a challenge for attribution (to military research funding specifically, versus public research funding more generally). Indeed, all three sources could be grouped together as mission agencies with a national security orientation, given the Cold War geopolitics which shaped them. Reflecting this view, in Figures C.9-C.10 and Tables C.10-C.12 we reproduce Figure 3-5 and Tables 3-5 of the paper, replacing the DoD exposure measure with a DoD/AEC/NASA exposure measure, computed from the share of a university-field's scientists in 1970 supported by any of these agencies.

In all of these cases, the results are similar to those in the paper in both significance and magnitude, showing sustained, significant reductions in academic hiring, PhD training, publications, and patents.[21] In additional checks, we have included analogous measures of HHS (i.e., NIH) and NSF support, which do not change our focal result. From this evidence we thus conclude that the 1970s was an era of austerity on multiple fronts, and even as the Defense Department's research funding was the largest of these three and the focus of our analysis, the phenomenon of declining mission research support in this period could be interpreted more broadly.

[20] Figure C.8 provides one window into these broader patterns using our data on PhD students' sources of support, showing the share of U.S. STEM PhD graduates acknowledging support from DoD, AEC (later DOE), and NASA in their dissertations between 1960 and 1990. We provide both the raw shares in the data and adjusted shares that account for underreporting using inverse propensity weights; both series show similar patterns, even if at different levels (see Shvadron et al. 2025a for sources, methods, and discussion): DoD and NASA each show large, sustained declines, and AEC/DOE a brief dip before a recovery in the mid/late-1970s.

[21] If anything, a few patterns may present themselves more clearly. For example, a rippling effect on employment can be seen in Table C.10, where entry-level employment declines immediately after 1970 (Column 2), early/mid career employment a few years later (Column 3), and late career employment even later (Column 4)—a pattern which reflects that (untenured) junior faculty are easier to reduce than (tenured) senior faculty, and lower entry-level hiring eventually results in a smaller senior faculty population in later years.

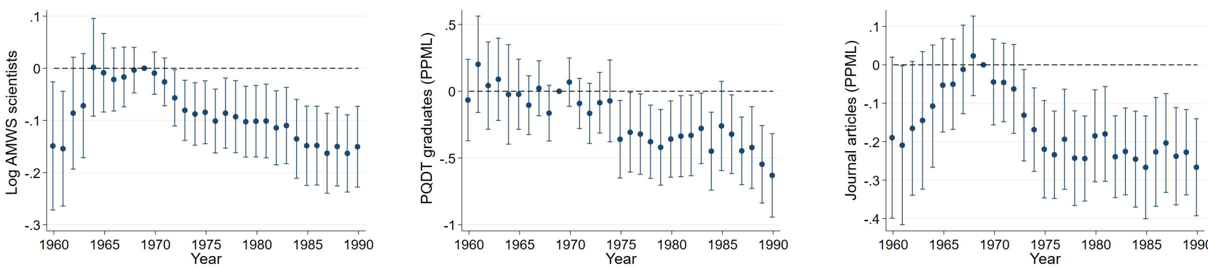
Figure C.8: Patterns in agency share of STEM PhD graduates supported



Notes: Figure shows the share of US STEM PhDs between 1960 and 1990 who acknowledge support from each of the named agencies in their thesis. Top row reports shares as observed in the raw data, calculated over the set of students with any thesis acknowledgments (data from Shvadron et al. 2025a). Bottom row reports shares of all graduates, using inverse propensity weights to adjust for underreporting. IPWs calculated as the inverse of the product of the (predicted) probabilities that (i) a graduate has dissertation full text available from ProQuest, and (ii) a graduate accurately reports funding sources, based on a ground truth sample (NSF Graduate Research Fellowship award winners). The likelihood of each of these conditions is independently estimated via probit regressions on field and decade fixed effects, and propensities calculated from the results. All figures restrict sample to the physical, mathematical, and engineering sciences.

Figure C.9: Scientists, PhD grads, and pubs at more vs. less exposed university fields, 1960-1990, replacing 1970 DoD exposure with 1970 DoD/AEC/NASA exposure

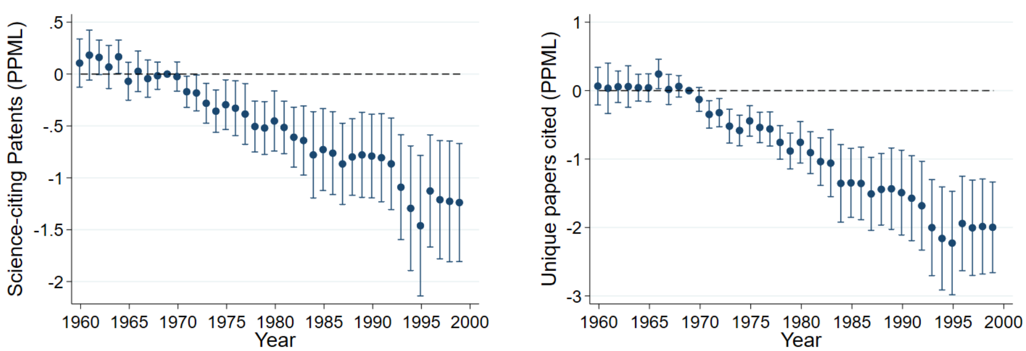
Panel (A): AMWS scientists   Panel (B): PQDT graduates   Panel (C): Journal publications



Notes: Figure shows estimated differences over time in early-career AMWS scientists, PQDT PhD graduates, and journal articles at/from university-fields with versus without exposure to DoD/AEC/NASA funding cuts (Panels A to C, respectively), measured as the share of university-field scientists in 1970 supported by any (or all) of these agencies. Underlying regression estimates differences in log scientists by OLS and PhD graduates and publication counts by Poisson pseudo-maximum likelihood (PPML). All regressions control for university-field and university-year fixed effects. Journal articles are fractionally associated to each listed author and their affiliated institution. All estimates are relative to 1969 (the omitted category). Error bars represent 95% confidence intervals, computed from standard errors clustered at the university level.

Figure C.10: Patenting in technology areas with differential exposure to DoD-funded science, replacing 1970 DoD exposure with 1970 DoD/AEC/NASA exposure

Panel (A): Science-citing patents   Panel (B): Breadth of science cited



Notes: Figure shows estimated differences over time in US patenting in technology areas (CPC subclasses, henceforth CPC) with higher (vs. lower) exposure to DoD/AEC/NASA funding cuts, measured as the share of university-field scientists in 1970 supported by any (or all) of these agencies. CPC-level exposure is calculated by (i) beginning with a dataset of patents filed by US inventors and merging in their in-text citations to scientific publications, (ii) calculating the distribution of scientific fields of these cited publications, (iii) calculating the share of researchers in each of these fields that was DoD/AEC/NASA-supported in 1970, and (iv) crossing the two to get a weighted average exposure measure. Subclasses where most scientific citations are to papers in subjects with heavy mission agency support will thus be measured as more exposed. We restrict the sample to patents filed by US inventors and associate patents to their primary inventive CPC. We then divide CPCs into terciles of exposure and measure assorted outcomes at the CPC x year level. Panel (A) shows estimated differences in more vs. less exposed CPCs' number of science-citing patents, and Panel (B) shows differences in the breadth of science they cite (number of unique papers cited each year). Underlying regression estimated by Poisson pseudo-maximum likelihood (PPML) and controls for CPC and year fixed effects. All estimates are relative to 1969 (the omitted category). Error bars represent 95% confidence intervals, computed from standard errors clustered at the CPC level.

Table C.10: University-field scientist headcount and PhD production over time, 1965-1990, replacing 1970 DoD exposure with 1970 DoD/AEC/NASA exposure

	AMWS scientists					PhD graduates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	All	All	≤5y in	≤10y in	SED PhDs	PQDT PhDs	Def. base	Def. base
Any DoD/AEC/NASA exposure * 1(1971-1975)	-0.076***	-0.059**	-0.051**	-0.086**	-0.138***	0.012	-0.124	-0.261	-0.199
	(0.022)	(0.025)	(0.023)	(0.041)	(0.038)	(0.074)	(0.084)	(0.404)	(0.514)
Any DoD/AEC/NASA exposure * 1(1976-1980)	-0.106***	-0.088***	-0.062**	-0.126**	-0.226***	-0.147	-0.324***	-0.601*	-0.568
	(0.029)	(0.032)	(0.029)	(0.056)	(0.052)	(0.109)	(0.112)	(0.361)	(0.491)
Any DoD/AEC/NASA exposure * 1(1981-1985)	-0.105***	-0.113***	-0.047	-0.169***	-0.268***	-0.185	-0.300**	-0.767*	-0.688
	(0.034)	(0.035)	(0.034)	(0.060)	(0.059)	(0.118)	(0.117)	(0.407)	(0.477)
Any DoD/AEC/NASA exposure * 1(1986-1990)	-0.115***	-0.146***	-0.053	-0.209***	-0.256***	-0.336***	-0.453***	-0.812**	-0.389
	(0.037)	(0.037)	(0.036)	(0.062)	(0.060)	(0.116)	(0.115)	(0.354)	(0.460)
N	36514	36438	36514	25245	31547	28793	30289	13945	11253
R^2	0.95	0.97	0.95	0.83	0.88				
Y mean	2.219	2.223	2.219	1.105	1.510	9.883	9.601	0.611	0.491
Method	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Inst x Field FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y								
Inst x Year FEs		Y		Y	Y	Y	Y	Y	Y
Field x Year FEs			Y						

Notes: Table estimates differences over time in the number of PhD scientists employed at and PhDs graduating from university-fields with versus without exposure to DoD/AEC/NASA funding cuts, measured as the share of university-field scientists in 1970 supported by any (or all) of these agencies. Scientists are measured using biographical listings in American Men and Women of Science (AMWS) from 2005 onward, from which we can extract listed scientists' previous employers and years of employment, and using these, count up scientists at the university-field-year level. We separately evaluate post-1970 changes in total AMWS scientists (Columns 1 to 3) and early-career scientists (Columns 4 and 5), which we alternatively define as researchers less than five or ten years into their careers. PhD graduates are independently measured in the SED and from PQDT (Columns 6 and 7). The final columns report changes in the number of PhD graduates produced who later enter the defense industrial base, using a more liberal (Column 8) and conservative (Column 9) definition of its boundaries (see text for details). Columns (1) to (5) estimate log outcomes by OLS and Columns (6) to (9) count outcomes by Poisson pseudo-maximum likelihood, reflecting the nature of the variation in each outcome. Columns (1) to (3) control for university-field fixed effects (FEs) and (1) year FEs, (2) university-year FEs, and (3) field-year FEs. Columns (4) to (9) control for university-field and university-year fixed effects. All columns include controls for time-varying differences by units' size (measured by a university-field's 1970 NRSTP respondents) and are estimated relative to 1965-1970 (the omitted category). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by university in parentheses.

Table C.11: Early career researchers (PhD in 1965-1969): Employment sector over time, replacing 1970 DoD exposure with 1970 DoD/AEC/NASA exposure

	(1) University	(2) Industry	(3) Government	(4) Multiple	(5) Univ-Ind	(6) Univ-Gov	(7) Any Pats.
DoD/AEC/NASA-funded in 1970 * 1(1971-1975)	-0.073***	0.020***	0.010**	0.020**	0.001	0.009	0.001
	(0.013)	(0.007)	(0.005)	(0.009)	(0.004)	(0.006)	(0.001)
DoD/AEC/NASA-funded in 1970 * 1(1976-1980)	-0.142***	0.026**	0.010	0.064***	0.017**	0.021**	0.005*
	(0.019)	(0.010)	(0.008)	(0.013)	(0.007)	(0.009)	(0.003)
DoD/AEC/NASA-funded in 1970 * 1(1981-1985)	-0.151***	0.030**	0.006	0.077***	0.021**	0.019**	0.006**
	(0.021)	(0.012)	(0.008)	(0.016)	(0.009)	(0.010)	(0.002)
DoD/AEC/NASA-funded in 1970 * 1(1986-1990)	-0.133***	0.031**	0.007	0.066***	0.019**	0.020**	0.011***
	(0.022)	(0.013)	(0.008)	(0.017)	(0.009)	(0.010)	(0.004)
N	105371	105371	105371	105371	105371	105371	105502
R^2	0.09	0.02	0.01	0.04	0.01	0.02	0.01
Y mean	0.856	0.028	0.018	0.077	0.018	0.030	0.005
Field-Year FEs	Y	Y	Y	Y	Y	Y	Y

Notes: Table estimates propensity for AMWS-listed, early career university scientists to work in assorted sectors over time, as a function of whether they had DoD/AEC/NASA support in 1970. Sample restricted to scientists who received their PhD in 1965-1969 and worked continuously at a university up to 1970. Outcomes indicate employment in the university, industry, or government sectors (Columns 1 to 3) or a mixture of sectors (i.e., individuals with either multiple affiliations in a given year or who are transitioning between sectors, Columns 4 to 6). The final outcome (Column 7) measures patenting, as an indicator for whether the given scientists filed one or more patents in a given year. All columns control for field-year fixed effects and present estimates relative to 1965-1970 (the omitted category); because the sample is conditioned to pre-1970 university scientists, all post-1970 outcomes should be interpreted as a transition away from university employment (and similarly for patenting, of which there was almost none in this population prior to 1970). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by individual in parentheses.

Table C.12: US patenting in technology areas with differential exposure, 1965-1990, replacing 1970 DoD exposure with 1970 DoD/AEC/NASA exposure

	(1) Patents	(2) DoD pats.	(3) PCS pats.	(4) Uniq. cites	(5) DoD-PCS pats.
Above-median exposure * 1(1971-1975)	-0.018	0.056	-0.240***	-0.482***	0.374*
	(0.029)	(0.067)	(0.088)	(0.078)	(0.206)
Above-median exposure * 1(1976-1980)	-0.022	0.029	-0.420***	-0.748***	0.521**
	(0.047)	(0.103)	(0.134)	(0.114)	(0.215)
Above-median exposure * 1(1981-1985)	0.006	0.128	-0.642***	-1.208***	-0.080
	(0.063)	(0.103)	(0.184)	(0.236)	(0.231)
Above-median exposure * 1(1986-1990)	-0.058	-0.053	-0.777***	-1.481***	-0.320
	(0.082)	(0.144)	(0.218)	(0.295)	(0.229)
Above-median exposure * 1(1991-1995)	-0.060	-0.036	-1.159***	-2.065***	-0.432
	(0.130)	(0.156)	(0.305)	(0.374)	(0.332)
Above-median exposure * 1(1996-2000)	0.148	-0.036	-1.188***	-1.995***	-0.815***
	(0.184)	(0.196)	(0.302)	(0.354)	(0.286)
N	22968	18036	21096	21312	10548
Y mean	81.893	2.487	10.560	79.589	0.766
Method	PPML	PPML	PPML	PPML	PPML
CPC FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y

Notes: Table shows estimated differences over time in US patenting in technology areas (CPC subclasses, henceforth CPC) with higher (vs. lower) exposure to DoD/AEC/NASA funding cuts, measured as the share of university-field scientists in 1970 supported by any (or all) of these agencies. CPC-level exposure is calculated by (i) beginning with a dataset of patents filed by US inventors and merging in their in-text citations to scientific publications, (ii) calculating the distribution of scientific fields of these cited publications, (iii) calculating the share of researchers in each of these fields that was DoD/AEC/NASA-supported in 1970, and (iv) crossing the two to get a weighted average exposure measure. Subclasses where most scientific citations are to papers in subjects with heavy mission agency support will thus be measured as more exposed. We restrict the sample to patents filed by US inventors and associate patents to their primary inventive CPC. We then divide CPCs into above and below median exposure and measure assorted outcomes at the CPC x year level. Column (1) evaluates total patents; Column (2), defense patents (measured as DoD-funded patents; Gross and Sampat 2025a); Column (3), science-citing patents; Column (4), the breadth of science cited (number of unique papers cited each year); and Column (5), science-citing defense patents. All columns control for CPC and year fixed effects. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors clustered by CPC in parentheses.

Appendix References

Airoldi, Anna and Petra Moser. 2024. *Inequality in Science: Who Becomes a Star?* NBER working paper no. 33063.

Arora, Ashish, Sharon Belenzon, Larisa C Cioaca, Lia Sheer, and Hansen Zhang. 2023. *The effect of public science on corporate R&D*. NBER working paper no. 31899.

Arora, Abhishek and Melissa Dell. 2023. "LinkTransformer: A Unified Package for Record Linkage with Transformer Language Models."

Aspray, William. 1989. *Oral History: Edward Feigenbaum*. Available at https://hdl.handle.net/11299/107282.

Bergeaud, Antonin and Cyril Verluise. 2024. "A new dataset to study a century of innovation in Europe and in the US." *Research Policy* **53**(1):104903.

Berkes, Enrico. 2018. *Comprehensive Universe of U.S. Patents (CUSP): Data and facts*. Working paper.

Boffey, Philip M. 1970a. "DuBridge and His Critics." *Science* **169**(3943):356-357.

Boffey, Philip M. 1970b. "Mansfield Amendment Curb on Basic Research May Spread." *Science* **167**(3924):1473.

Bryan, Kevin A, Yasin Ozcan, and Bhaven Sampat. 2020. "In-text patent citations: A user's guide." *Research Policy* **49**(4):103946.

Deitchman, Seymour J. 1976. *The Best-Laid Schemes: A Tale of Social Research and Bureaucracy*. Quantico: Marine Corps University PRess.

Finney, John W. 1969. *$5 Billion Slash in Defense Urged*. New York Times, April 21, 1969, available at https://timesmachine.nytimes.com/timesmachine/1969/04/21/90093940.html.

Gross, Daniel P. and Bhaven N. Sampat. 2023. "America, jump-started: World War II R&D and the takeoff of the US innovation system." *American Economic Review* **113**(12):3323-3356.

Gross, Daniel P and Bhaven N Sampat. 2025. "The Government Patent Register: A new resource for measuring U.S. government-funded patenting." *Research Policy* **54**(1):105142.

Kay, Alan. 2006. *Oral History: Butler Lampson*. Available at https://www.computerhistory.org/collections/catalog/102658024/.

Kim, Scott and Petra Moser. 2025. "Women in Science: Lessons from the Baby Boom." *Econometrica* **93**(5):1521-1560.

Laitinen, Herbert A. 1970. "Reverberations from the Mansfield Amendment." *Analytical Chemistry* **42**(7):689-689.

Lubczyk, Moritz and Petra Moser. 2025a. *The Ms. Allocation of Talent*. Working paper.

Lubczyk, Moritz and Petra Moser. 2025b. *Rosie the Researcher: How Female WWII Hires Changed Science in US Firms*. Working paper.

Lubkin, Gloria B. 1971. "Mansfield aide discusses amendment impact." *Physics Today* **24**(9):61-62.

Lunch, William L. and Peter W. Sperlich. 1979. "American Public Opinion and the War in Vietnam." *The Western Political Quarterly* **32**(1):21-44.

Marx, Matt and Aaron Fuegi. 2020. "Reliance on Science: Worldwide Front-page Patent Citations to Scientific Articles." *Strategic Management Journal* **41**(9):1572-1594.

Marx, Matt and Aaron Fuegi. 2022. "Reliance on science by inventors: Hybrid extraction of in-text patent-to-article citations." *Journal of Economics & Management Strategy* **31**(2):369-392.

Mears, Walter R. 1969. *Mansfield Attacks Pentagon Non-War Research Funding*. Austin American-Statesman, November 10, 1969, available at https://www.newspapers.com/image/355891461.

Miller, Arthur H. 1974. "Political Issues and Trust in Government: 1964–1970." *The American Political Science Review* **68**(3):951-972.

Moser, Petra, Sahar Parsa, and Shmuel San. 2025. *Immigration and Innovation: Lessons from the Quota Acts*. Working paper.

Nichols, Rodney W. 1971. "Mission-Oriented R&D: Senator Mansfield's questions sharpen congressional uncertainties about federal R&D patterns." *Science* **172**(3978):29-37.

Petralia, Sergio, Pierre-Alexandre Balland, and David Rigby. 2016. *HistPat dataset*. Accessed in 2019.

Pew Research Center. 2015. "Trust in Government: 1958–2015." Pew Research Center – U.S. Politics & Policy, May 30, 2020.

Priem, Jason, Heather Piwowar, and Richard Orr. 2022. "OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts." *arXiv preprint arXiv:2205.01833* .

RMAP. 1970. "Mission Agency Support of Basic Research." Report to the Committee on Science, Research, and Development of the Committee on Science and Astronautics of the U.S. House of Representatives by the Research Management Advisory Panel, February 25, 1970, available at https://www.govinfo.gov/content/pkg/CPRT-91HPRT40025/pdf/CPRT-91HPRT40025.pdf.

Shvadron, Dror, Hansen Zhang, Lee Fleming, and Daniel P Gross. 2025a. *Measuring the Production of Scientific Human Capital: New Data, Methods, and Evidence on the U.S. Scientific Training Ecosystem*. NBER working paper no. 33944.

Shvadron, Dror, Hansen Zhang, Lee Fleming, and Daniel P Gross. 2025b. "A Quarter of US-Trained Scientists Eventually Leave. Is the US Giving Away Its Edge?" *arXiv preprint arXiv:2512.11146* .

The Akron Beacon Journal. 1970. *There Were 3 Days of Violent Agitation*. The Akron Beacon Journal, May 24, 1970, available at https://www.newspapers.com/image/148364822.

Washington Correspondent. 1970. "Continuing Debate about Backdoor Science." *Nature* **227**:1291.