

The Social Returns to Public R&D^{*}

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May 30, 2025

Abstract

Recent empirical evidence by Fieldhouse and Mertens (2024) points to a strong causal link between federal nondefense R&D funding and private-sector productivity growth, and large implied social returns to public R&D investment. We show that these high social return estimates broadly align with existing evidence on the social returns to private or total R&D spending. If the R&D increases authorized under the CHIPS and Science Act were fully appropriated, our modeling indicates a boost in U.S. productivity within a few years, reaching gains of 0.2–0.4% after seven years or more. At their peak, the direct productivity effects of the implied expansion in nondefense R&D alone would raise output by over \$40 billion in a single year—exceeding total outlays from the CHIPS Act R&D provisions over a decade. The potential productivity impact of fiscal consolidations changing R&D spending is not clear ex ante. We show that in recent fiscal consolidations, cuts to federal R&D funding were largely borne by defense R&D, whereas funding for nondefense R&D was largely spared or was increased. Our evidence suggests that future deficit reduction efforts that instead emphasize cuts to nondefense R&D funding could have a larger adverse impact on productivity and economic growth than previous fiscal consolidations.

JEL classification: E62, O38, O47.

Keywords: Public R&D, Productivity, Growth, Innovation, Fiscal Consolidations.

^{*}This paper was prepared for the National Bureau of Economic Research (NBER) Entrepreneurship and Innovation Policy and the Economy Conference, 2025. We are grateful to the editors, Ben Jones and Josh Lerner, for helpful comments and discussion. We thank Matt Hourihan for providing data. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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Understanding productivity growth is undoubtedly the Holy Grail for the economics of growth and innovation. Productivity growth generally refers to more economic output being produced without using more inputs to production, like workers or machinery, reflecting increased technological know-how instead. Broadly speaking, productivity growth is what fuels real economic growth per capita in the long run and raises living standards. As such, a better understanding how policy levers can influence or foster productivity growth is key for public policy and welfare.

Recent empirical evidence finds a strong causal link between federal R&D funding and private-sector productivity growth, which imply high social rates of return to public R&D investments. By social returns, we mean the aggregate economic benefits of R&D, including all spillover effects benefiting other firms, industries, or sectors, above and beyond the private returns captured by the performers of said R&D activity. It has long been understood that such social returns to R&D are likely substantially higher than the private returns to R&D (Griliches 1979; Jones and Williams 1998). Empirical evidence from Bloom et al. (2013) and Jones and Summers (2022) similarly suggests that social returns to private R&D and total R&D spending, respectively, are much higher than most estimates of private returns to R&D (Hall et al. 2010).

While there is a rich literature documenting significant spillovers from specific federal R&D programs, such as those proxied by patents or citations, finding convincing causal evidence on the aggregate productivity effects of public R&D is much more challenging.¹ However, Fieldhouse and Mertens (2024) use recent econometric techniques to identify the causal effects of federal R&D spending shocks on U.S. productivity growth and measures of innovation. Critically, their time series regressions capture all domestic innovation spillovers across different sectors and industries, thus providing direct estimates of social returns to public R&D. Fieldhouse and Mertens (2024) estimate highly significant gross social returns ranging between 140% to 210% for nondefense public R&D spending—even higher than the social returns to private R&D or total R&D estimated by Bloom et al. (2013) and Jones and Summers (2022), respectively. We first overview this recent evidence linking federal R&D spending with U.S. productivity growth. We then show that these high estimates of the social returns to public R&D align with existing evidence on the spillovers from public R&D and estimates of the social returns to private R&D or total R&D spending.

If the social returns to public R&D are so high, why is the federal government not investing substantially more in these areas? Measured as a share of gross domestic product (GDP), federal R&D spending currently stands at 0.75%, down considerably from Cold-War-era highs (over 1.8%) in the mid-1960s. Broadly speaking, the development and deployment of the nuclear triad in the early 1960s, the successes of the Apollo program and waning interest in the space race after the mid-1960s, and the collapse of the Soviet Union and ensuing “peace dividend” in the 1990s all contributed to the decline in federal R&D spending for the Department of Defense (DoD) and National Aeronautics and Space Administration (NASA)—which accounted for most Cold War-era R&D spending (Fieldhouse and Mertens 2023). Congressional appropriations for health science and basic research funded by the National Institutes of Health (NIH) and National Science Foundation (NSF) gradually trended upwards, but were never compelled with the same urgency

¹The Congressional Budget Office recently notes that “Economics research has not resolved several key questions about the effects of such federal [R&D] spending on macroeconomic output...” (Campbell and Shirley 2018).

(or funded at the same scale) as for DoD or NASA during the Cold War. And as Fieldhouse and Mertens (2023) document, R&D funding is usually on the chopping block whenever Congress pivots to fiscal consolidation, which is perhaps unsurprising: the benefits of R&D take many years to materialize but are often opaque, and research grants can be cut faster—and likely with less constituent backlash—than current services or popular social insurance programs.

The present outlook for U.S. federal R&D funding is a microcosm of these broad historical trends. On the upside, the biggest question is whether Congress appropriates a substantial increase in semiconductor R&D funding recently authorized by the CHIPS and Science Act (CHIPS Act for short), which was motivated by national security concerns and geopolitical competition with China verging on a “new Cold War” (Brands and Gaddis 2021). And the biggest downside risk is likely the degree to which the next fiscal consolidation falls on federal R&D investments.

Analyzing the upsides to this outlook, we apply Fieldhouse and Mertens’s (2024) estimates of the social returns to public R&D to quantify the potential effects of the CHIPS Act R&D provisions, should they be fully funded, on U.S. productivity. Our modeling indicates that the CHIPS Act R&D provisions would boost U.S. productivity within a few years, reaching gains of 0.2–0.4% after seven years or more. At their peak, the productivity effects from increased public R&D would raise output by over \$40 billion in a single year—exceeding the total outlays from the CHIPS Act R&D provisions over a decade, if all authorized R&D funds were actually appropriated.

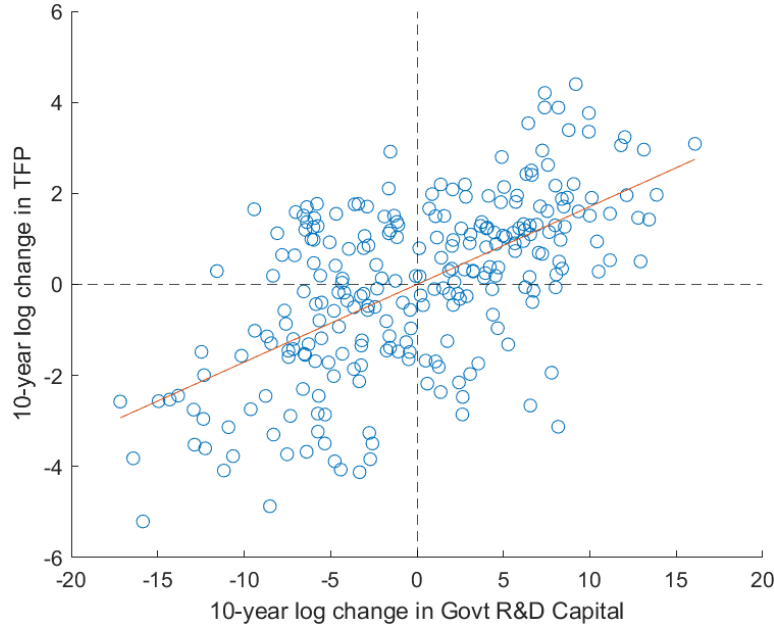
The potential productivity impact of fiscal consolidations changing R&D spending is not clear *ex ante*. We analyze how federal R&D spending has fared during past fiscal consolidations and implications for future deficit reduction efforts. We show that federal R&D spending has been significantly cut in all recent fiscal consolidations; the three most recent consolidations can account for 60% of the total decline in federal R&D spending as a share of GDP, and more than 25% of the spending cuts in these packages came from R&D budgets. In these consolidations, however, Congress has typically increased nondefense R&D even while cutting defense R&D and spending more broadly. Future fiscal consolidations again increasing nondefense R&D would complement deficit reduction efforts by stimulating productivity, whereas instead cutting nondefense R&D spending would likely cause larger drags to productivity growth than from past consolidations.

1 Link Between Public R&D Capital and Private-Sector Productivity

Does publicly funded R&D benefit economic growth, and if so, by how much? In a recent paper, Fieldhouse and Mertens (2024) present new evidence of a strong causal link between public R&D capital and private-sector productivity growth, which we survey here; the estimates suggest large social returns to public R&D spending, substantially higher than estimated returns to R&D funded by the private sector, and substantial underfunding of federal R&D historically.

Before diving into the relationship between these variables, a few preliminaries are in order. Public R&D spending refers to basic research, applied research, and experimental development work *funded* by the government, regardless of who actually *performs* this R&D work—much of which is done by private firms and universities, in addition to the national laboratories and government agencies themselves. Public R&D capital, in turn, measures all current and past public R&D spending, accounting for depreciation of past investments. Unlike the depreciation of phys-

Figure 1: Government R&D Capital and Productivity Growth



Notes: Productivity is Fernald’s (2012) measure of utilization-adjusted business-sector TFP. The public R&D capital and TFP series have both been conditioned on a set of lagged controls, see footnote 2 for details. *Sources:* BEA, Fernald (2012), and Fieldhouse and Mertens (2024).

ical capital assets, like the value of equipment and machinery being eroded from use, measuring depreciation of “intangible” knowledge capital is inherently difficult. That said, it is generally accepted that older ideas and innovative work become less valuable over time, relative to newer work. Fieldhouse and Mertens (2024) follow the Bureau of Economic Analysis (BEA) in capitalizing past R&D spending in a similar manner as physical capital but using different depreciation rates.

Abstracting from the full details of the regression specifications, the key relationship being studied by Fieldhouse and Mertens (2024) can be easily visualized. Figure 1 plots changes in the (log) real public R&D capital stock measured over 10-year horizons (x-axis) against log-point changes in utilization-adjusted total factor productivity (TFP) over the same 10-year horizons (y-axis). This measure of productivity essentially reflects all private-sector output net of the contributions from all private-sector inputs, adjusted for any underutilization of inputs across the business cycle, e.g., hours worked falling in recessions. Rather than plotting raw data for growth in public R&D capital and TFP, both series have first been conditioned on a set of lagged controls to remove predictable variation in these variables.² The scatter plot in Figure 1 shows a positive relationship: Faster (slower) accumulation of public R&D capital is associated with faster (slower) productivity growth. The slope of the regression line suggests an elasticity of 0.17, meaning that a 1% increase in public R&D capital is associated with a 0.17% increase in TFP.

However, identifying the elasticity capturing the causal relationship of public R&D capital on productivity or economic growth is more challenging than evaluating the best linear fit in Figure 1.

²The controls replicated in this analysis include multiple lags of utilization-adjusted TFP, public R&D capital, private-sector R&D capital, past federal R&D appropriations, the Ramey and Zubairy (2018) measure of defense spending news shocks, and real stock market returns for relevant sectors.

One concern is that policymakers’ decisions to increase or decrease public R&D spending may be correlated with forces exerting independent influences on productivity growth, such as recessions or news about promising technologies. Because of complementarities or economic feedback effects, changes in public R&D spending may also influence other factors of production with independent effects on productivity, such as private-sector R&D spending or public infrastructure investments, like highways and bridges; we refer to the latter effects as indirect productivity spillovers from public R&D spending. Lastly, any spillovers from public R&D spending to productivity growth likely occur with long, unknown lags, not necessarily those captured in 10-year windows.

Fieldhouse and Mertens (2024) use modern econometric techniques to address these concerns and estimate the causal relationship between public R&D capital and productivity. A companion paper combs through the post-war legislative history of the major R&D funding agencies—NASA, NIH, NSF, DoD, and the Department of Energy (DoE)—to identify shocks to their R&D budgets that are, after conditioning on appropriate lagged controls, relatively unanticipated and unrelated to the business cycle (Fieldhouse and Mertens 2023). Fieldhouse and Mertens (2024) use these exogenous R&D appropriations shocks as instrumental variables in appropriately specified regressions that also include lagged economic controls to remove predictable variation in TFP and public R&D spending driven by other influences (the same controls used in Figure 1). They also study the scope for indirect spillovers from public R&D spending and, based on this analysis, remove the influence of public infrastructure spending from productivity growth to isolate the direct effects from public R&D spending on an adjusted TFP measure. Broadly speaking, they use the R&D appropriations shocks to identify the causal relationship between the public R&D capital and adjusted TFP, summarizing the relationship across many horizons, not just 10-year windows.³

Through this framework, Fieldhouse and Mertens (2024) estimate that the production function elasticity of public R&D capital is 0.11, somewhat below the slope of 0.17 plotted in Figure 1, but nonetheless large enough to imply very high social returns to public R&D spending. Their estimated elasticities suggest that a dollar of public R&D capital generates a gross return of between 150% to 200% of economic output via higher productivity. They also directly estimate the returns to public R&D capital, which finds comparable and precisely estimated gross returns ranging between 140% to 210%, depending on the specification. But Fieldhouse and Mertens (2024) only find these large, highly statistically significant effects on productivity from shocks to nondefense R&D appropriations, i.e., those for NASA, NIH, NSF, and DoE’s civilian physics and energy R&D work.⁴ They do not find any evidence of shocks to defense R&D appropriations generating measurable productivity spillovers, at least within the 15-year horizons of study.

2 Are the Effects Really that Large? Comparisons with Existing Evidence

Can the returns to publicly funded R&D really be as large as the evidence of Fieldhouse and Mertens (2024) suggests? A higher social return to nondefense public R&D spending than privately

³More specifically, they use the system projections on instrumental variables (SP-IV) methodology of Lewis and Mertens (2023) for the structural estimation of production function elasticities of public R&D capital and rates of return; this essentially amounts to using the R&D appropriations shocks as instrumental variables for both public R&D capital and TFP, and regressing the impulse response of TFP on that of the public R&D capital stock.

⁴DoE’s other R&D functions related to nuclear weapons and national security are classified as defense R&D.

funded R&D could partly reflect the public sector investing relatively more in fundamental research and less on development. It has long been understood that the private sector tends to underinvest in basic research because knowledge spillovers cannot be fully internalized (Nelson 1959) and these spillovers are greater for research than for development (Akcigit et al. 2021). High social returns to publicly funded R&D are also supported by the empirical innovation literature, which tends to find large spillover effects—typically proxied by patents or citations—from various federal R&D programs, as surveyed in Section 2.1. Empirical estimates of social returns to private or total R&D spending similarly lend support to Fieldhouse and Mertens’s (2024) higher estimates of the returns to public R&D spending, as we detail in Section 2.2.

2.1 Spillovers from Public R&D Spending

Numerous studies have documented various patent or industry-specific spillovers from the R&D activities of the federal agencies that Fieldhouse and Mertens (2024) study collectively at the aggregate level; these broader spillovers all point toward high social returns to public R&D spending.

On the health research side, Azoulay et al. (2019) find evidence of significant spillovers from NIH research grant funding to private-sector patents in the pharmaceutical and biotech industries. Similarly, Li et al. (2017) find that within 15 years of a NIH grant approval, only about 7% of federal grants yield a direct acknowledgment link to a patent, whereas about 33% yield an indirect citation link to a patent—reflecting broader spillovers to different firms or industries than the recipient. And looking to an earlier era, Gross and Sampat (2025) find that targeted federal investments in health research during World War II had significant, persistent spillover effects for U.S. biomedical research and innovation through the 1950s and 1960s.

Turning to energy, Myers and Lanahan (2022) study DoE’s Small Business Innovation Research (SBIR) program and find that firms receiving SBIR grants only capture 25% to 50% of the value, proxied by patents, generated from their R&D work, again consistent with large spillover effects from publicly funded research. In a similar vein, Howell (2017) finds evidence that receipt of an SBIR award roughly doubles the likelihood that a firm raises venture capital and significantly increases patenting activity, relative to firms that were just shy of being awarded a grant.

Not all related studies find evidence of big spillovers from public R&D spending, but the unit of analysis and agency in question clearly matters. Kantor and Whalley (2024) test for spillovers from NASA contract R&D performed by firms during the Moon mission. They find significant, persistent effects on manufacturing value added and employment for firms in counties and industries exposed to the NASA shock, but no evidence of persistent local productivity spillovers. Their framework would not, however, capture any technological spillovers from NASA R&D work performed by universities or intramural R&D performed by NASA, nor would it capture broader national spillover effects. Conversely, Gross and Sampat (2023) study the longer-run effects of large increases in federal R&D spending by the Office of Scientific Research and Development during WWII; they find that this wartime R&D funding seeded enduring technology clusters across the country and heavily influenced the post-war direction of U.S. scientific research and innovation.

The distinction between defense and nondefense R&D spending also appears crucial in the related literature, entirely consistent with the results of Fieldhouse and Mertens (2024). Moretti

et al. (2025) study the effects of defense R&D spending across OECD countries and in a panel of French firms. They find significant complementarities between publicly funded defense R&D and privately funded R&D, similar to Fieldhouse and Mertens’s (2024) finding that U.S. defense R&D spending “crowds in” private-sector R&D spending. Moretti et al. (2025) also find statistically significant but economically small spillovers from defense R&D spending to productivity growth.

Zooming out from funding agency to performer, Babina et al. (2023) estimate spillovers from federally funded R&D performed at 22 universities over 2001-2017, exploiting sharp cuts to appropriations as event studies; they find that funding cuts to a researcher’s particular area of study reduces the volume of research publications (especially highly cited ones) and high-tech entrepreneurship coming out of university labs, while increasing the number of (less cited) patents, as private funding inflows introduce different incentives. While their results do not focus on R&D funded by particular agencies, they effectively cover the same agencies studied by Fieldhouse and Mertens (2024), as the NIH (64%), NSF (14%), DoD (10%), DoE (4%), and NASA (4%) funded roughly 95% of all federal R&D performed at universities over their sample. Their results are again consistent with broader knowledge spillovers from publicly funded than privately funded R&D.

Similarly studying spillovers from R&D funded by many federal agencies, Dyèvre (2024) finds that firm-level patent spillovers from public R&D are two- to three-times larger than those from privately funded R&D, again consistent with higher social returns to the former than latter.⁵ Dyèvre (2024) estimates that falling federal R&D spending can account for 33% of the decline in TFP growth over 1950-2017—reaching similar conclusions as Fieldhouse and Mertens (2024) about the influence of declining public R&D spending on slowing U.S. productivity growth, despite taking an entirely different methodological approach based on patents linked to firm-level Compustat data. That said, Dyèvre’s (2024) estimates capture a narrower degree of spillovers than full social rates of return captured in Fieldhouse and Mertens’s (2024) aggregate time-series regression framework.

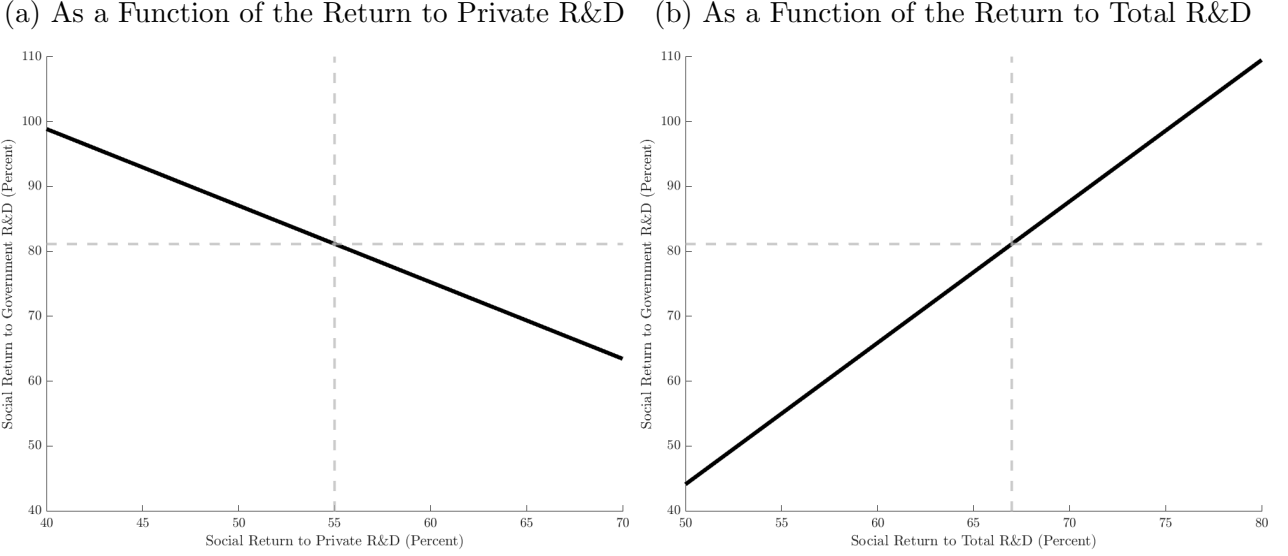
Broadly speaking, the innovation literature surveyed in this section finds substantial evidence of patent and citation spillovers from publicly funded R&D, which suggests that the social returns to public R&D are much higher than the private returns to the performers. Moreover, some papers, notably Dyèvre (2024), find evidence of greater patent spillovers to publicly funded R&D than to privately funded R&D, suggesting higher social returns to the former than the latter. While supporting the same general conclusions, the evidence on public R&D surveyed here does not map cleanly into the aggregate social returns to public R&D estimated by Fieldhouse and Mertens (2024); the smaller literature on social returns to private R&D spending does, however, and lends a different kind of support to Fieldhouse and Mertens’s (2024) estimates, as we next analyze below.

2.2 Squaring Estimates of Social Returns to Public vs. Private R&D

Jones and Summers (2022) calculate a gross social return to total U.S. R&D spending of 67%, Bloom et al. (2013) estimate social returns to private R&D spending of 55%, and Fieldhouse and Mertens (2024) estimate social returns ranging between 140% to 210% for nondefense public R&D

⁵To mitigate potential concerns about reverse causality from any cyclical government spending shocks, Dyèvre (2024) removes all firms in more exposed industries, notably including those covering defense contractors and aerospace engineering; the remaining firms in his dataset would largely be linked to changes in federal nondefense R&D contracts, but this is not evidence specifically from nondefense R&D (or total federal R&D or that matter).

Figure 2: Social Returns to Government R&D Under Varying Assumptions



Notes: The dashed vertical gray lines depict the Bloom et al. (2013) estimate of the social returns to private R&D spending (panel a) and the Jones and Summers (2022) estimate of the social returns to total R&D spending (panel b); the dashed horizontal gray lines plot the social returns to public R&D implied by these estimates using equation (1).

spending but only find inconclusive evidence for defense R&D. How well we can square these various social return estimates with one another, either taken at face value or with a grain of salt?

Jones and Summers (2022) calculate social returns to total R&D spending based on insights from endogenous growth theory, notably that in the long run, growth in real GDP per capita is equal to TFP growth, which is believed to be driven solely by innovative investment, i.e., R&D. They essentially weigh the opportunity cost of investing a marginally higher share of current output into R&D today with the benefit of higher future growth resulting from increased R&D in present discounted value; based on average U.S. productivity growth rates and R&D investment shares of GDP in the national income and product accounts (NIPAs), they calculate a gross internal rate of return of 67%, i.e., the rate of return equating costs and benefits to total R&D investment.

Building from their framework, first assume that the gross social return to total R&D spending, r , is a linear function of the gross social returns to private R&D spending, r^p , and government R&D spending, r^g , each weighted by their average shares of total R&D expenditure in the NIPAs:

$$(1) \quad r = \alpha r^p + (1 - \alpha) r^g.$$

Over 1947Q1-2024Q4, private R&D spending as a share of total R&D (α) has averaged 54.1%, while the government R&D share ($1 - \alpha$) has averaged 45.9%.⁶ As such, the Jones and Summers (2022) estimate of the social returns to total R&D ($r = 67\%$) and Bloom et al. (2013) estimate for private R&D ($r^p = 55\%$) would imply a social return to government R&D of $r^g = 81\%$, substantially higher than the estimated social returns to private R&D.

⁶For a closer mapping to the Jones and Summers (2022) framework, we focus solely on R&D expenditures in the NIPAs, ignoring software and other intellectual property investments.

What if the Jones and Summers (2022) or Bloom et al. (2013) estimates are off, either overestimating or underestimating the social returns to total or private R&D spending, respectively? The left panel of Figure 2 plots the social returns to government R&D spending implied by equation (1) as a decreasing function of the social returns to private R&D spending, conditional on the Jones and Summers (2022) estimate of a 67% social return to total R&D spending. The right panel plots the implied social returns to government R&D as an increasing function of the social returns to total R&D, conditional on the Bloom et al. (2013) estimate of a 55% social return to private R&D. Both panels broadly paint the same picture: The implied gross social rates of return to government R&D spending remain quite high (e.g., within a range of 70% to 90%) even if the estimates of Jones and Summers (2022) or Bloom et al. (2013) are modestly biased in either direction.

This stylized modeling approach can also shed some light on the rough ballpark of social returns to federal defense R&D spending, for which there is less direct evidence to date. Fieldhouse and Mertens (2024) estimate elasticities and returns to public R&D capital using several cuts of their R&D appropriations instruments and varying assumptions about the productivity contribution from public infrastructure. These estimates are generally quite precise for nondefense R&D spending, and their preferred specification—using exogenous nondefense R&D appropriations as an instrumental variable for total public R&D capital—yields a 171% gross return that is statistically significant at the 99% confidence level. On the other hand, their elasticity estimates for defense R&D capital are mostly negative and are all imprecisely estimated, leading the authors to conclude that “we cannot draw any sharp conclusions regarding the size—or even the sign—of any direct spillovers of defense R&D.”

In this vein, further assume that the contribution from government R&D expenditures in (1) can be disaggregated into contributions from government nondefense R&D, r^n , and federal defense R&D, r^d , again weighted by NIPA expenditure shares:

$$(2) \quad r = \alpha r^p + \beta r^n + (1 - \alpha - \beta) r^d$$

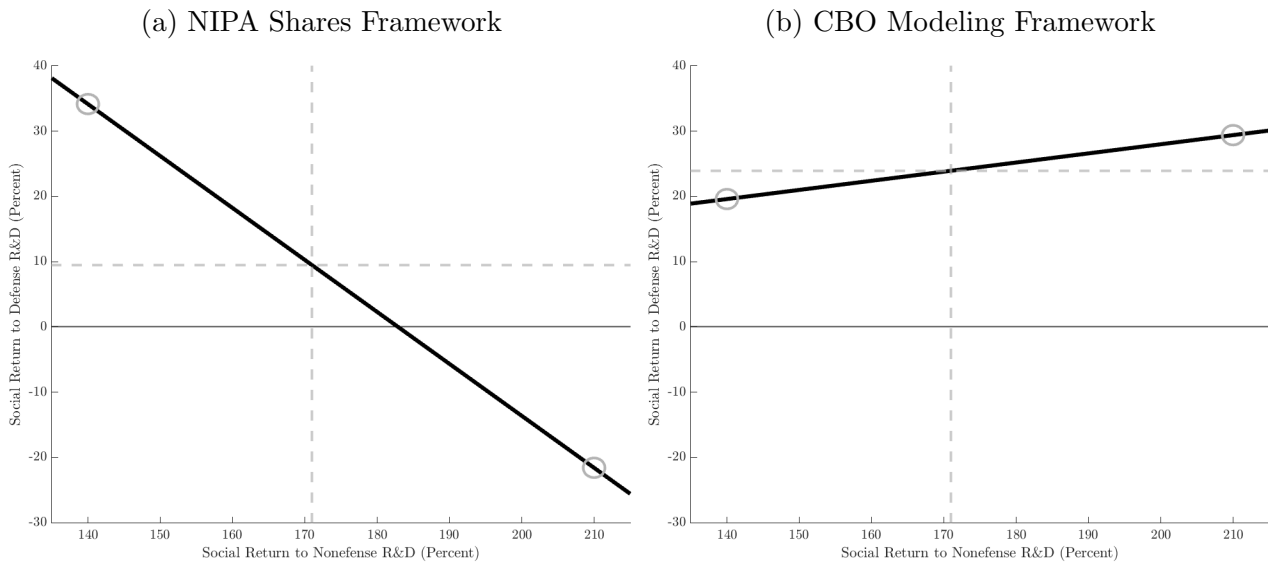
The shares of government nondefense R&D (β) and federal defense R&D ($1 - \alpha - \beta$) relative to total R&D spending have averaged 20.3% and 25.6%, respectively, over 1947Q1-2024Q4.⁷

The left panel of Figure 3 plots the social returns to defense R&D implied by equation (2) as a function of the returns to nondefense public R&D, conditional on the Bloom et al. (2013) and Jones and Summers (2022) estimates of the social returns to private R&D and total R&D, respectively. The dashed gray lines correspond to Fieldhouse and Mertens’s (2024) preferred estimate of a 171% gross return to nondefense R&D, which would imply a social return to defense R&D of just under 10%; the gray circles correspond with the low- and high-end of their estimates for nondefense R&D, which would correspond with social returns to defense R&D ranging between 34% to -22% if equation (2) is a reasonable approximation for modeling R&D contributions across sectors.

An alternative approach to ballparking the social returns to federal defense R&D builds from work by the Congressional Budget Office (CBO) in modeling the macroeconomic effects of federal

⁷Government nondefense R&D refers to the sum of federal nondefense R&D expenditures and R&D expenditures by state and local governments, which are overwhelmingly for public universities and of a nondefense nature.

Figure 3: Implied Social Returns to Federal Defense R&D as a Function of Returns to Nondefense R&D



Notes: The dashed vertical gray lines depict Fieldhouse and Mertens’s (2024) preferred estimate of the social returns to public nondefense R&D spending (171%) and the dashed horizontal gray lines plot the corresponding social return to federal defense R&D (10%) implied by (panel a) equation (2) and the Bloom et al. (2013) and Jones and Summers (2022) estimates of returns to private and total R&D spending, respectively, or (panel b) CBO’s modeling framework. The gray circles correspond to the lower and upper bound of the range of social returns to nondefense R&D spending estimated by Fieldhouse and Mertens (2024).

R&D spending. CBO currently assumes zero productivity spillovers from development work by the Department of Defense (i.e., weapons development), instead assuming that the only spillovers from defense R&D spending come from the small share spent on basic and applied research—which is assumed to generate the same degree of spillovers as federal nondefense R&D (Campbell and Shirley 2018). Over FY1956-2020, 86% of annual federal defense R&D spending went to development work on average, with just 3% going to basic research and 11% to applied research.⁸

The right panel of Figure 3 plots social returns to defense R&D as a function of the returns to nondefense public R&D instead assuming the same return as for nondefense R&D from only the 14% average share going to research, irrespective of estimated returns to private or total R&D. Applied to Fieldhouse and Mertens’s (2024) range of estimates for the social returns to nondefense R&D, this “CBO modeling framework” would imply social returns to defense R&D ranging between 20% and 29%, reflecting the small share of defense R&D spent on fundamental research. Their preferred estimate of a 171% return to nondefense R&D would imply a 24% social return to defense R&D; mapped into equation (2), these differentiated returns to public R&D coupled with Bloom et al.’s (2013) estimate of the returns to private R&D would imply a 71% social return to total R&D, quite consistent with the findings of Jones and Summers (2022).

Are the implied returns to defense R&D plotted in Figure 3, which are substantially lower than our fairly precise estimates for the returns to nondefense R&D, so low as to raise suspicion?

Lower returns to defense R&D within a comparable time-frame could be expected to arise from the

⁸The breakout between development and applied research obligations is not available from the NSF before FY1956.

classified nature of defense-related work (deliberately slowing the diffusion of knowledge spillovers), a heavier focus on weapons development instead of more fundamental research (generating fewer knowledge spillovers), and certain weapons development work proving inapplicable for civilian use or even defense use (less conducive to spillovers).⁹ But save possible crowd-out effects, it is difficult to see how defense R&D could detract from technological know-how and productivity. Moreover, Fieldhouse and Mertens (2024) find that defense R&D *crowds in* private R&D spending.¹⁰ So while lower returns for defense R&D than for nondefense R&D should be expected, we are skeptical of negative returns, as depicted in Figure 3a for higher returns to nondefense R&D.

Several other caveats are also in order. First, these are all back-of-the-envelope calculations and must be taken with a grain of salt, even when building from more precise estimates in the related literature. Second, the estimates from Jones and Summers (2022), Bloom et al. (2013), and Fieldhouse and Mertens (2024) all follow from different methodologies and are not quite apples-to-apples comparisons; for instance, Jones and Summers (2022) calculate social returns from NIPA R&D expenditure shares whereas Fieldhouse and Mertens (2024) estimate them from R&D capital stocks, which also include a capitalization of software expenditures. Moreover, the assumed linear disaggregation of social returns to all R&D into contributions by major sector may not be realistic, and assuming constant returns to historical average shares in this exercise is surely overly simplistic; the NIPA R&D expenditure shares are not remotely stable, with the private R&D share rising considerably and the public nondefense R&D and federal defense R&D shares trending down. Lastly, aggregate evidence on social returns to public R&D, reflecting average effects over the past 75 years, may not be the most accurate guide moving forward; for instance, Bloom et al. (2020) find that total research productivity—defined as productivity growth per researcher—has fallen in recent decades, though they suggest that the relative decline in public R&D spending on fundamental research may be contributing to this slowdown in aggregate research productivity.

That said, our analysis broadly suggests that Fieldhouse and Mertens’s (2024) estimates of the social returns to nondefense R&D align with the Bloom et al. (2013) and Jones and Summers (2022) estimates of returns to private and total R&D, respectively. Even though we have relatively little direct evidence on the social returns to defense R&D, the related literature and analysis above also broadly offer support for above-average social returns to nondefense R&D and below-average social returns to defense R&D, relative to the estimates for either private R&D or total R&D.

3 Application: CHIPS and Sciences Act

If the social returns to public R&D are so high, why is the government not investing substantially more in these areas? Compelled by new national security concerns, it might soon be doing just that. In August 2022, President Biden signed into law the CHIPS Act (P.L. 117-167), legislation intended to spur domestic manufacturing capacity and innovation in semiconductors. Of the \$60

⁹The Airborne Laser anti-ballistic missile program illustrates the latter points; the project sought to modify Boeing 747s into giant airborne lasers to shoot down ICBMs in flight—a far cry from a dual-use technology—and was mothballed as unworkable in 2012 after 16 years in development and roughly \$5 billion in costs (Collina and Davenport 2012).

¹⁰Barring measurement error, Fernald’s (2012) TFP series fully accounts for the influence of private R&D, so this indirect crowd-in effect is not biasing Fieldhouse and Mertens’s (2024) estimated returns to public R&D.

billion actually appropriated by Congress in the bill, nearly two-thirds went to financial incentives to increase semiconductor manufacturing capacity. The CHIPS Act also intended to substantially increase semiconductor R&D through federal investments by the NSF, National Institute of Standards and Technology (NIST), and DoE Office of Science, but Congress *authorized* a substantial increase in R&D funding for these agencies over the next five years without *appropriating* those funds.¹¹ And after the bill was enacted, congressional appropriations quickly started falling short of fully funding the CHIPS Act authorizations for semiconductor R&D (Hourihan et al. 2023).

Everything else being equal, federal R&D spending would, however, rise significantly if Congress were to appropriate the full CHIPS Act authorization for expanded R&D activities of NSF, NIST, and the DoE Office of Science. For our analysis of the macroeconomic effects related to this policy decision, we first model the effect of fully funding the CHIPS Act R&D authorization on real outlays and the public R&D capital stock, relative to a zero-funding counterfactual; we then apply the Fieldhouse and Mertens (2024) production function elasticity estimates to the projected impact on public R&D capital to calculate the implied influence on U.S. productivity.¹²

3.1 Modeling the CHIPS Act Authorization on Public R&D Capital

We model the effect of the CHIPS Act on federal R&D spending in four steps: First, we construct a pre-CHIPS Act “current policy” baseline for the relevant R&D appropriations for NSF, NIST, and the DOE Office of Science using CBO’s *Spending Projections, by Budget Account* from May 2022, the last vintage of these projections published (shortly) before the enactment of the CHIPS Act (CBO 2022).¹³ Second, we take the difference between the CHIPS Act R&D authorization for these three agencies and the pre-CHIPS Act current policy baseline to measure the implied change in R&D budget authority over FY2022-2027.¹⁴ There can be considerable lags between Congress appropriating funds, those funds being obligated by agencies, and those obligations eventually resulting in outlays. As such, we convert the change in budget authority for each year into lagged changes in outlays over five years using CBO’s discretionary spending budget authority-to-outlay “waterfall” model (CBO 2024), and then sum the implied outlays for each year (over FY2022-2031). Finally, we deflate the nominal changes in outlays into real (inflation-adjusted) dollars using CBO’s forecast of the personal consumption expenditures (PCE) price index.¹⁵ Table 1 summarizes these modeling steps and the projected change in real nondefense R&D outlays.

To study the effect of these changes in outlays on productivity, we use them to calculate the cumulative change in public R&D capital. We first convert the annual changes in real nondefense

¹¹Appropriations provide budget authority allowing agencies to enter obligations that will result in outlays from the U.S. Treasury. Authorizations do not provide such funding, but grant new or continued authority for federal programs to operate and often authorize subsequent appropriations; unauthorized appropriations are subject to procedural hurdles.

¹²See Gullo et al. (2025) for an overview of considerations regarding dynamic scoring of federal investments in R&D.

¹³For their forecasts, CBO is required to project future discretionary spending by adjusting the most recently enacted appropriations (ignoring pending legislation) for inflation, using forecasts of the employee cost index for spending on wages and salaries and forecasts of the GDP price index for all other discretionary spending.

¹⁴We thank Matt Hourihan for providing data on the CHIPS Act authorizations for these three agencies. For comparability, our CBO current policy baseline is constructed as the sum of all nondefense discretionary spending categories for the NSF and NIST and just the ‘Science’ spending category for DoE.

¹⁵Of the price indices for which CBO publishes forecasts, the PCE price index best tracks the government R&D price index used to construct real public R&D capital stocks; the correlation between the series is 99.9% over 1949-2024.

TABLE 1: IMPACT OF CHIPS ACT ON R&D BUDGET AUTHORITY AND OUTLAYS

Fiscal Year	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
CHIPS Authorization	17.5	22.4	26.8	28.8	30.5	32.0				
Pre-CHIPS Baseline	17.6	18.2	18.6	19.0	19.4	19.8				
Δ Budget Authority	-0.1	4.2	8.2	9.8	11.1	12.2				
Δ Outlays (nominal)	0.0	2.3	5.7	8.2	9.8	11.2	5.2	1.8	0.7	0.3
Δ Outlays (real)	0.0	1.8	4.4	6.1	7.2	8.1	3.7	1.2	0.4	0.2

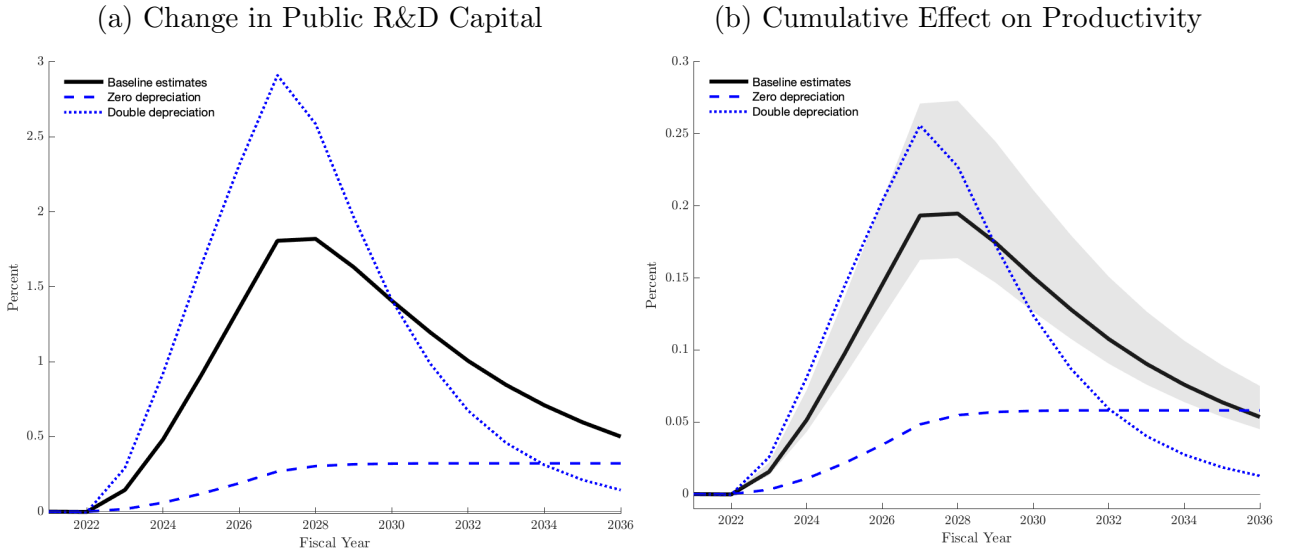
Notes: Billions of nominal dollars for the first four lines and billions of real (\$2012) dollars in the final line. The change in budget authority between the CHIPS Act authorization and pre-CHIPS Act appropriations for FY2022-27 are mapped into changes in outlays using CBO’s “waterfall” model (CBO 2024). The change in real outlays is deflated using CBO’s forecast for the PCE price index. *Sources:* Matt Hourihan, CBO.

R&D outlays into changes in the real public R&D capital stock using the perpetual inventory method, which models the current capital stock as the flow of new investment (outlays) plus past investments net of depreciation; this step hinges on the assumed depreciation rate, δ . Following the BEA and Fieldhouse and Mertens (2024), we apply a 16% depreciation rate to R&D spending for our preferred specification. To assess the sensitivity of our analysis to the assumed depreciation rate, we also replicate the exercise and report results assuming zero depreciation ($\delta = 0\%$) or twice as much depreciation ($\delta = 32\%$). After modeling the potential impact of the CHIPS Act on the public R&D capital stock in dollar terms for each depreciation rate, we calculate the cumulative percentage change for each year relative to the respective public R&D capital stock in FY2021, as a pre-CHIPS Act policy baseline.

The left panel of Figure 4 plots the projected effect of full CHIPS Act funding on the cumulative growth of the real public R&D capital stock from this modeling exercise; the solid black line plots our preferred specification assuming a 16% depreciation rate, the dashed blue line shows the 0% depreciation version, and the dotted blue line the 32% depreciation rate version. There are two forces here pushing in opposite directions: A higher depreciation rate means the CHIPS Act would result in a smaller and more transient dollar impact on the public R&D capital stock, as new outlays depreciate faster. But a higher depreciation rate also means a smaller public R&D capital stock to begin with, increasing the percentage increase associated with additional CHIPS Act R&D funding, everything else being equal. As seen in Figure 4, in the preferred specification the public R&D capital stock would gradually rise by up to nearly 2% in FY2028 and then gradually fall as the increase in outlays fades and recent outlays depreciate more.¹⁶ With a higher depreciation rate, we initially see faster and greater growth in the public R&D capital stock because of the smaller baseline, followed by a faster decline and less persistent effect because the additional R&D outlays are depreciating faster; with zero depreciation, there is a much more gradual rise because of a larger baseline public R&D capital stock, but an entirely persistent effect because none of the

¹⁶Beyond the assumed depreciation rate, the persistence also depends on a budgetary assumption: We only model a temporary increase in R&D appropriations based on the “current law” CHIPS Act authorization through FY2027 and zero increase thereafter. If Congress fully funded the CHIPS Act authorization and then maintained these higher R&D appropriations thereafter, the effect on the public R&D capital stock would be more persistent, regardless of the assumed depreciation rate. But historical evidence suggests that positive shocks to public R&D spending tend to be reversed within a decade (Fieldhouse and Mertens 2024).

Figure 4: Projected Direct Impact of CHIPS Act R&D Funding on Public R&D Capital and TFP



Notes: The baseline projections (black lines) reflect a 16% depreciation rate for public R&D capital; the dashed and dotted blue lines assume 0% or 32% depreciation rates, respectively. In the right panel, the cumulative effects on productivity are based on Fieldhouse and Mertens’s (2024) estimates of the production function elasticity of public R&D capital for these three depreciation rates, all assuming an intermediate elasticity of public infrastructure capital. Shaded gray bands are 95% weak-instrument-robust confidence sets for the baseline TFP projections. Productivity is Fernald’s (2012) measure of utilization-adjusted business-sector TFP. *Sources:* Matt Hourihan, CBO, and Fieldhouse and Mertens (2024).

new CHIPS Act R&D outlays are ever lost to depreciation.

Finally, to quantify the potential effects of full CHIPS Act R&D funding on U.S. productivity, we apply Fieldhouse and Mertens’s (2024) estimates of the elasticity of public R&D capital to the implied cumulative growth in public R&D capital plotted in Figure 4a. For our preferred specification, we apply their benchmark estimate, which also assumed a 16% depreciation rate, to the projected growth of public R&D capital from the CHIPS Act assuming the same depreciation rate.¹⁷ We also report projected CHIPS Act productivity responses using Fieldhouse and Mertens’s (2024) alternative estimates corresponding to 0% depreciation and 32% depreciation, which are applied to the cumulative growth of public R&D capital assuming the same depreciation rates.

3.2 Potential Lagged Productivity Effects of the CHIPS Act Authorization

The right panel of Figure 4 plots the projected effect of full CHIPS Act funding on cumulative TFP growth from this modeling exercise. The solid black line plots our preferred specification assuming a 16% depreciation rate, and the gray bands plot the corresponding 95% weak-instrument-robust confidence sets. Figure 4 also plots the alternative projected effects on U.S. productivity instead assuming 0% depreciation (dashed blue) or 32% depreciation (dotted blue). Based on our preferred modeling using a 16% depreciation rate, the peak increase in the public R&D capital stock in FY2028 would translate to a peak increase in U.S. productivity of 0.19% the same year, relative

¹⁷Their preferred estimate is based on instrumenting the public R&D capital stock with the exogenous nondefense R&D appropriations shocks; if funded, the CHIPS Act R&D authorization would similarly be a shock to nondefense R&D appropriations, and likely classified as motivated by national security and exogenous with respect to cyclical conditions.

to the no-CHIPS Act counterfactual.¹⁸ This preferred specification also shows a somewhat transitory response of U.S. productivity from the full CHIPS Act authorization; the positive influence gradually recedes at longer horizons, but productivity would still be roughly 0.05% higher 15 years after the bill was signed into law. Assuming away depreciation, the effect is entirely persistent, with full CHIPS Act R&D funding yielding a comparable 0.06% increase in productivity after 15 years but much smaller effects at shorter horizons because of the slower relative accumulation of public R&D capital, which outweighs the higher estimated elasticity without depreciation. With a 32% depreciation rate, we see a higher peak effect on productivity of 0.26% in FY2027, with the faster growth in public R&D capital outweighing the lower estimated elasticity in this case, followed by a more rapid decline and much less persistent effect due to greater depreciation.

While the projected increases in productivity plotted in Figure 4 may appear small, the associated increase in economic output in dollar terms is substantial and even exceeds the budgetary cost of the CHIPS Act R&D provisions. Based on our preferred specification (assuming $\delta=16\%$), an additional 0.19% in cumulative TFP growth—scaled to the \$26 trillion U.S. economy just before the bill was enacted—would amount to roughly an additional \$50 billion in real annual output by FY2028 driven solely by increased technological know-how and knowledge spillovers. Alternatively, a back-of-the-envelope calculation from rearranging the production function elasticity of public R&D capital suggests that a peak increase in real public R&D capital of \$22 billion in FY2028 could increase real output by a comparable \$41 billion that year.¹⁹ Either way, the impact on real output from higher U.S. productivity *in a single year* would exceed the total \$33 billion increase in real outlays *over a decade* if the CHIPS Act R&D provisions were funded.

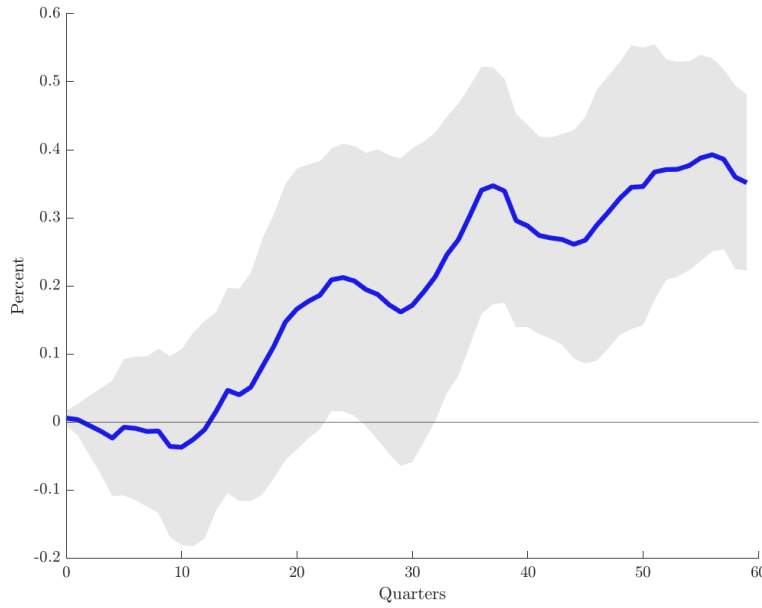
Two important caveats are in order for the modeling approach above. First, the Cobb-Douglas assumption of a contemporaneous relationship between productivity growth and growth of factor inputs, such as public R&D capital—a common assumption in the literature—is not necessarily realistic. That said, Appendix Figure E.1 of Fieldhouse and Mertens (2024) shows that the Cobb-Douglas functional form seems reasonable in this context, with the fitted values of adjusted TFP (i.e., applying their elasticity estimates to the response of public R&D capital) closely tracking the underlying impulse response of adjusted TFP to the nondefense R&D appropriations shocks, which made no assumption about the lag structure between appropriations, outlays, and productivity.

The second caveat is that this approach only models the direct effects of public R&D capital on growth through a growth accounting lens, ignoring indirect channels. In the traditional Cobb-Douglas framework, that essentially means ignoring any growth effects from public R&D also increasing quality-adjusted labor inputs or crowding in private-sector R&D capital or non-R&D

¹⁸The nondefense R&D appropriations shocks also cause significant increases in public infrastructure capital, which is understood to independently influence TFP growth. To isolate direct effects of public R&D on productivity, i.e., without capturing TFP effects from public infrastructure, Fieldhouse and Mertens (2024) first remove the likely contribution of public infrastructure from TFP, taking an intermediate value and upper and lower bounds for the elasticity of public infrastructure capital from the literature (CBO 2016; Ramey 2021). Fieldhouse and Mertens (2024) separately apply these elasticities to the actual growth in public infrastructure capital, subtract that contribution from TFP, and use the adjusted measures of TFP for their structural estimates. The projected TFP effects from full CHIPS Act R&D funding reported here (based on the intermediate public infrastructure elasticity) are robust to alternative assumptions; the peak TFP effect only ranges from 0.18% to 0.20% across the upper to lower bounds for the public infrastructure elasticity.

¹⁹Rearranging the public R&D capital elasticity, $\phi \equiv \frac{\Delta Y}{\Delta K} \frac{K}{Y}$, yields $\Delta Y = \phi \times \Delta K \times \frac{Y}{K}$. Using the ratio $Y/K=17.35$ in FY2021 as a pre-CHIPS Act baseline and $\Delta K = \$22$ billion, the estimate $\hat{\phi} = 0.107$ would imply $\Delta Y = \$41$ billion.

Figure 5: Projected Full Impact of CHIPS Act R&D Funding on Productivity

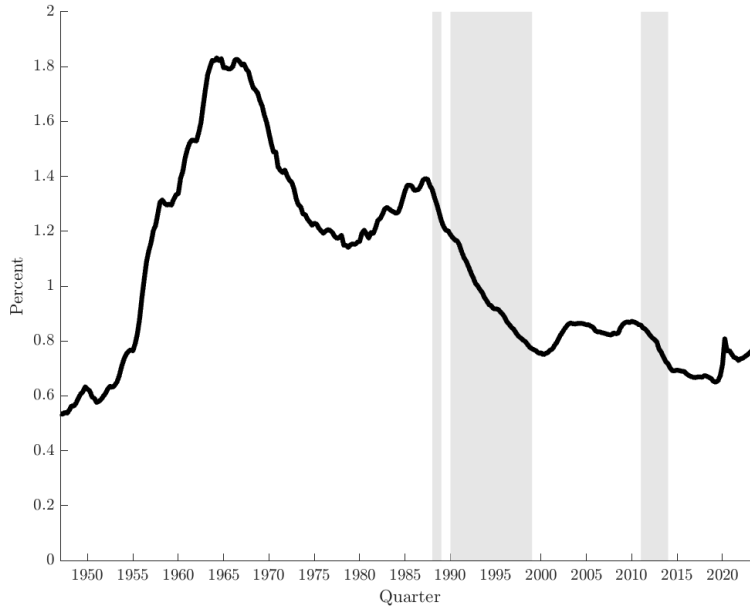


Notes: The response of productivity (blue lines) assumes a 16% depreciation rate for public R&D capital. Shaded bands are 95% heteroskedasticity and autocorrelation robust confidence intervals. Productivity is Fernald’s (2012) measure of utilization-adjusted business-sector TFP. *Source:* Fieldhouse and Mertens (2024).

capital. In Fieldhouse and Mertens’s (2024) augmented Cobb-Douglas framework, it also means ignoring any growth effects from crowding in public infrastructure capital. But Fieldhouse and Mertens (2024) find that the nondefense R&D appropriations shocks also cause increases in public infrastructure capital, private-sector R&D capital, and other private-sector capital. Put differently, the estimates above reflect a lower bound on the *total* potential growth effects from the CHIPS Act, as other factors of production and sources of TFP growth may rise via indirect channels.

To address these two points seriously, we also take a more reduced-form approach to estimating the total potential effect of fully funding the CHIPS Act R&D provisions on U.S. productivity i) capturing all indirect effects of increased public R&D spending ii) without imposing any assumptions about the lag structure between public R&D spending and productivity. To do so, we build from the reduced-form regressions in Fieldhouse and Mertens (2024) estimating the response of private-sector TFP (without any adjustment for the influence of public infrastructure) to the exogenous nondefense R&D appropriations shocks. The TFP response in Figure 6 of their paper is scaled to a 1% peak increase in public R&D capital, which occurs roughly eight years after the “news shock” from legislation changing appropriations. Figure 5 plots the total effect of a nondefense R&D appropriations shock on TFP (blue line) from Fieldhouse and Mertens (2024), rescaled to match the peak projected effect of the CHIPS Act on the public R&D capital seen in Figure 4a, along with 95% confidence intervals (gray bands). Figure 5 suggests that fully funding the CHIPS Act would significantly increase productivity by between 0.2% to 0.4% at horizons above 8 years, and suggests a more gradual but more persistent increase in productivity than that plotted in Figure 4. But unlike the results in Figure 4, the productivity response in Figure 5 reflects broader economic growth effects from additional public infrastructure spending, among other channels.

Figure 6: Federal R&D Spending as a Share of GDP



Notes: Gray bars denote U.S. fiscal consolidations with spending cuts as identified by Adler et al. (2024). *Sources:* BEA, Adler et al. (2024).

4 Application: How Federal R&D Spending Fares in Fiscal Consolidations

While increasing federal R&D funding through the CHIPS Act would boost productivity and growth, a pivot to fiscal consolidation might instead have the opposite effect—if spending cuts reduce productivity-enhancing investments such as nondefense R&D. In this section, we analyze how federal R&D spending has fared in recent fiscal consolidations, relative to other expenditures. We find that recent U.S. fiscal consolidations have all significantly cut federal R&D spending, roughly as much if not more than total expenditures; however, nondefense R&D spending has actually been increased or roughly held steady during these episodes, while cuts have overwhelmingly fallen on defense R&D. Our analysis above suggests that this pattern of shielding nondefense R&D spending from widespread cuts has likely kept recent fiscal consolidations from inducing medium-term drags on productivity growth.

4.1 Measuring Federal R&D Spending in Fiscal Consolidations

We base our analysis on the U.S. fiscal consolidations identified by Adler et al. (2024) in their “action-based” fiscal consolidation database for OECD countries over 1978–2020.²⁰ Adler et al. (2024) identify 1988, 1990–1998, and 2011–2013 as the only recent U.S. fiscal consolidations in which spending is cut, our focus here. Figure 6 plots federal R&D spending as a share of GDP, with gray bars for each of these fiscal consolidation years. Unsurprisingly, federal R&D spending sees a sharp retrenchment throughout each of these fiscal consolidations; as a share of GDP, federal

²⁰The authors use primary sources and historical records to try to identify policymakers intent, in the narrative analysis spirit of Romer and Romer (2010) and Ramey (2011), among others.

R&D spending cumulatively fell by 0.66 percentage points during these three fiscal consolidation episodes—equating to 60% of the total cumulative decline since the mid-1960s.

But just how much of the onus of these fiscal consolidations falls on federal R&D spending? Adler et al.’s (2024) database reports annual fiscal consolidations for each country as a share of GDP, along with the related contributions from spending cuts versus tax hikes. Table 2 reports these total fiscal consolidation packages and spending cuts for all U.S. spending consolidation years, along with the decline in federal R&D spending as a share of GDP during the same year; the final two columns of Table 2 report the annual share of the total fiscal consolidation and spending cuts, respectively, effectively borne by the decline in R&D spending that year. Table 2 shows that, on average, cuts to federal R&D spending have accounted for 18% of the total fiscal consolidation packages and 26% of the spending cuts during these years, and anywhere between 4% and 73% of the annual fiscal consolidation packages are borne by cutting federal R&D spending.

TABLE 2: FEDERAL R&D SPENDING AS A SHARE OF FISCAL CONSOLIDATIONS

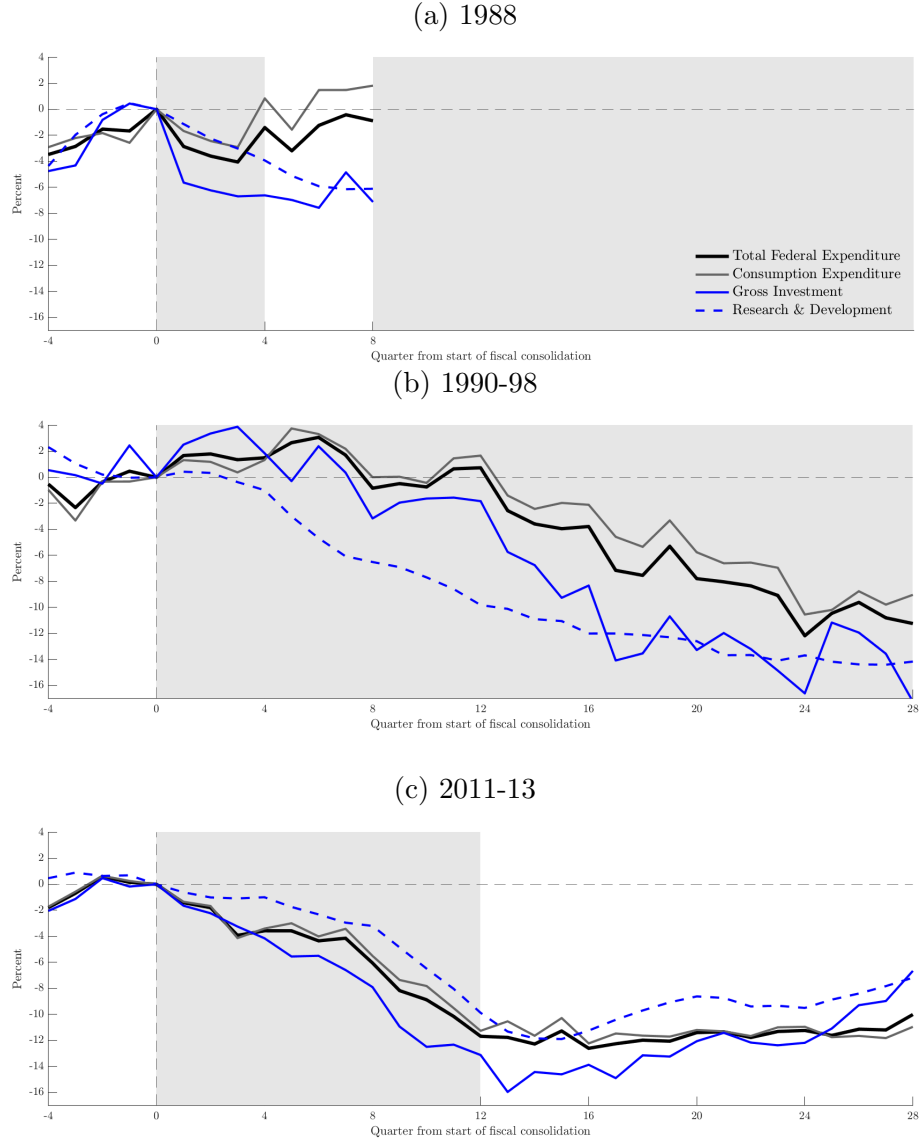
Year	Δ Deficit (% GDP)	Δ Spending (% GDP)	Δ R&D (% GDP)	R&D (% Total)	R&D (% Spending)
1988	-0.85	-0.46	-0.10	11.4%	21.1%
1990	-0.33	-0.07	-0.04	11.2%	52.9%
1991	-0.58	-0.29	-0.08	12.9%	25.9%
1992	-0.52	-0.28	-0.08	15.2%	28.2%
1993	-0.32	-0.23	-0.05	16.4%	22.2%
1994	-0.90	-0.50	-0.04	4.6%	8.2%
1995	-0.53	-0.33	-0.02	3.8%	6.1%
1996	-0.29	-0.22	-0.05	16.9%	22.8%
1997	-0.30	-0.24	-0.04	12.7%	15.8%
1998	-0.15	-0.15	-0.03	22.7%	22.7%
2011	-0.04	-0.04	-0.03	73.0%	73.0%
2012	-0.14	-0.14	-0.04	25.4%	25.4%
2013	-0.56	-0.38	-0.07	13.1%	19.0%
Avg.	-0.42	-0.26	-0.05	18.4%	26.4%

Notes: The change in the budget deficit and change in spending during identified U.S. fiscal consolidations are from Adler et al. (2024). The change in federal R&D as a share of GDP for each year is from the NIPAs and is measured fourth quarter-to-fourth quarter. *Sources:* Adler et al. (2024), BEA.

As an alternative way of visualizing what has happened to federal R&D spending during these recent fiscal consolidations, we next examine the cumulative changes in real federal R&D expenditures versus those of other major categories of federal consumption expenditure and gross investment. As a baseline, we index cumulative changes in these real federal expenditures relative to the last quarter preceding each consolidation period identified by Adler et al. (2024).

Figure 7 plots these expenditure changes for the consolidations of 1988 (top panel), 1990-98 (middle), and 2011-13 (bottom). In each panel, we track the cumulative percentage change in real i) total federal consumption expenditure and gross investment (black line), its two sub-components, ii) federal consumption expenditure (gray line) and iii) gross investment (solid blue), and iv) the

Figure 7: Federal R&D Spending and Other Expenditures in Fiscal Consolidations



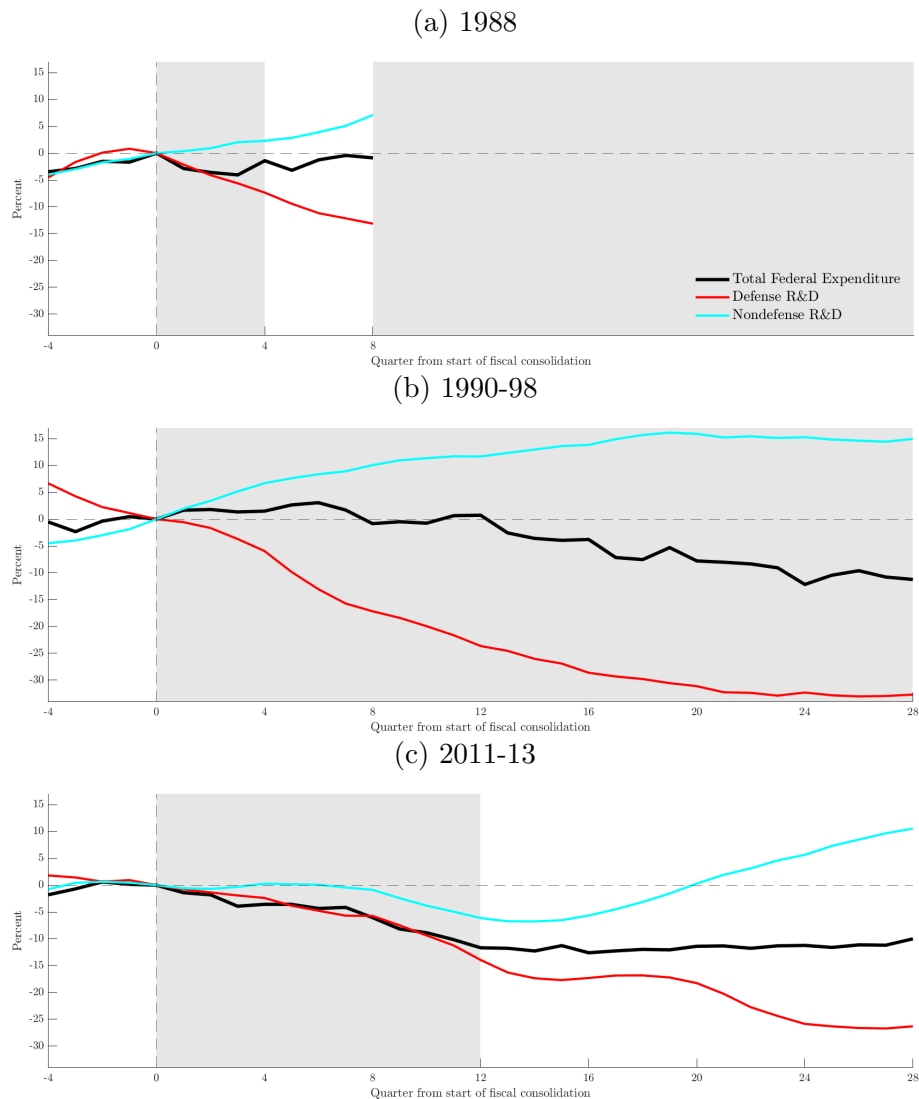
Notes: Gray bars denote U.S. fiscal consolidations with spending cuts as identified by Adler et al. (2024). We index all cumulative changes in real expenditures relative to levels in 1987Q4 for the 1988 consolidation (panel a), 1989Q4 for the 1990-90 consolidation (panel b), and 2010Q4 for the 2011-13 consolidations (panel c). *Sources:* BEA, Adler et al. (2024).

‘Research & development’ portion of gross investment (dashed blue).²¹ The shaded bars in Figure 7 again denote the fiscal consolidation years identified by Adler et al. (2024). For the shorter 1988 and 2011-13 consolidations, we also plot continued trends post-consolidation, unless interrupted by another fiscal consolidation, as in Figure 7a.

Several key trends emerge from Figure 7. More of the onus of spending cuts tends to fall on public investment, including R&D, than consumption expenditures during these fiscal consolidations.

²¹Broadly speaking, federal consumption expenditure reflects the value of government services based on the costs providing them (e.g., federal employees and operating costs), while gross investment refers to capital investments in infrastructure and other structures (e.g., highways, buildings), durable equipment (e.g., naval ships and aircraft), and intellectual property products (i.e., R&D and software).

Figure 8: Federal Defense vs. Nondefense R&D Spending in Fiscal Consolidations



Notes: See notes to Table 7. Sources: BEA, Adler et al. (2024).

Federal R&D spending saw deeper cuts relative to total expenditures during the 1988 and 1990-98 consolidations, roughly in line with the decline in total gross investment. Federal R&D spending only saw a smaller relative decline than gross investment during 2011-13 fiscal consolidation, but nonetheless saw a fairly substantial 12% cumulative drop in real terms, roughly in line with the decline in total federal expenditure. We also see some evidence of outlay lags and persistence in R&D spending cuts. Federal R&D spending continued to fall for another three quarters after the 1988 and 2011-13 fiscal consolidations. After the 2011-13 consolidation, the cleanest example from these case studies, the cuts to real R&D spending proved quite persistent, with less than half of the cumulative decline being reversed within four years of the spending cuts ending.

Pertinent to the implications of fiscal consolidations for medium-term productivity growth, the trajectories of federal defense versus nondefense R&D spending are, however, quite different in all three consolidations. Figure 8 replicates Figure 7, but instead depicts the cumulative changes in defense R&D (red) and nondefense R&D (teal), again plotted against the change in total federal

expenditure (black). In all three fiscal consolidations, we see a pronounced reduction in real defense R&D of an equal or much greater degree than the reduction in total federal expenditure, and these cuts are quite persistent. In stark contrast, nondefense R&D spending actually rose considerably in spite of the 1988 and 1990-98 fiscal consolidations, and saw only a delayed, modest reduction during the 2011-13 consolidation, followed by a quick rebound. Increasing nondefense R&D spending in the midst of a fiscal consolidation, as Congress has historically prioritized, would boost medium-term productivity growth, and in doing so, would actually complement short-run deficit reduction efforts via increased economic growth and revenue feedback effects at longer horizons.

Whether such sharp reductions in defense R&D are desirable from a national security perspective is an entirely different matter, and there may be negative influences on U.S. productivity from such cuts at even longer horizons, which remains an open empirical question. Falling defense R&D and rising nondefense R&D spending during the 1988 and 1990-98 fiscal consolidations also coincided with a broader Cold War “peace dividend” reprioritizing federal spending away from the military, but also specifically with the George H.W. Bush administration’s Space Exploration Initiative and increased NASA funding, the Human Genome Project, and then a bipartisan effort to double the NIH’s budget later in the 1990s (Fieldhouse and Mertens 2023). Regardless, the related literature and our analysis above suggest that fiscal consolidations that increase (or merely spare) nondefense R&D spending from otherwise widespread cuts to government spending will boost (or merely prevent related drags to) productivity growth, at least in the medium term.

5 Concluding Thoughts

Recent empirical macroeconomic studies and a large literature on innovation all point toward very high social returns to public R&D, well above those estimated for private R&D spending or total R&D spending. However, future research will need to address a myriad of lingering first-order questions to better guide science, technology, and innovation policy.

Is public R&D special simply because it funds relatively more fundamental research and relatively less development work than private R&D, thus doing more to ameliorate market failures and generate knowledge spillovers? Or do other factors also matter, such as the scale and time horizon of public R&D investments or the selection of technological frontiers being funded? And to what extent are Fieldhouse and Mertens’s (2024) imprecisely estimated, inconclusive results on the returns to defense R&D being driven by the composition of that R&D work being overwhelmingly tilted toward weapons development instead of fundamental research? Or does this instead reflect the classified nature of defense R&D work and longer related lags between defense R&D spending and productivity spillovers? Or is there simply inadequate identifying variation in the post-war time series to date? To the extent identification is feasible, causal evidence specifically on the relative returns to basic research, applied research, and development spending would help to better inform these lingering questions about the mechanisms through which public R&D investments—or certain types of public R&D spending—generate high social returns.²²

²²In this vein, Akcigit et al. (2021) develop a calibrated general equilibrium endogenous growth model with both basic and applied research; they find that basic research produces large spillovers that are not privately internalized, suggesting that policy should do more to promote investment in basic research, but they do not estimate returns by R&D type.

Campbell and Shirley (2018) note that empirical evidence was lacking on the nature of complementarities between federal R&D spending and private R&D spending, which remains broadly true today. While Fieldhouse and Mertens (2024) document broad complementarities between public R&D capital and private-sector R&D capital, particularly for defense R&D spending, more granular evidence on these relationships across industries and federal funding agencies would surely be useful for informing federal R&D policy analysis and budgetary priorities.

Lastly, it should also be noted that the social returns to public R&D estimated by Fieldhouse and Mertens (2024) and surveyed in this paper only reflect *domestic* returns, as measured from U.S. productivity growth, and are likely a lower bound for the *global* social returns to public R&D, as knowledge spillovers are not constrained by national boundaries. Moretti et al. (2025) find evidence of defense R&D generating spillovers between countries, with increased public R&D spending in one country increasing private-sector R&D spending in other OECD countries, consistent with broader knowledge and productivity spillovers across borders. However, the aggregate degree to which domestic public R&D spending crowds in certain foreign R&D spending because of complementarities or crowds out other foreign R&D spending through free riding remains an open question. Another important line for future research would be estimating how U.S. public R&D spending influences public versus private R&D spending abroad and quantifying the degree of international patent and productivity spillovers, if any.

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