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Estimating the Economic Effects of Federally Funded R&D

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Abstract

In recent years, there has been Congressional interest in changing various policies related to research and development (R&D). Recent legislation has included provisions that would modify federal funding for R&D investments and tax provisions affecting the after-tax price of R&D. The Congressional Budget Office (CBO) has developed analytical frameworks for estimating how changes in R&D investments affect the economy and the federal budget. This paper describes the agency's current analytical framework for modeling the economic effects of changes in federal funding for R&D, focusing on two distinct approaches that CBO has developed: an R&D capital stock approach and an R&D components approach.

JEL Classification: E62, H54, O38

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1. Introduction

The federal government subsidizes research and development (R&D) directly and indirectly through a variety of channels. Most directly, the federal government provides funds for R&D investment; in fiscal year 2024, for example, it spent $179 billion on R&D (NCSES 2026a, Table 4). The federal government also supports R&D indirectly through other mechanisms, such as tax provisions and the patent system. In recent years, there has been Congressional interest in changing various policies related to R&D, including modifying federally funded R&D investments and tax provisions that affect the after-tax price of R&D (see, for example, the CHIPS and Science Act, Public Law 117-167, and the 2025 reconciliation act, P.L. 119-21).

In the course of the agency's work for Congress, the Congressional Budget Office (CBO) has developed analytical frameworks for estimating how federal investment—in physical capital, education, and R&D—affects private-sector productivity (CBO 2016, 2021). In 2018, CBO published a short piece identifying areas in which additional research would enhance the agency's capacity to apply those frameworks specifically to federally funded R&D. In 2025, CBO received a Congressional request to assess how changes to federal funding for nondefense R&D would affect the economy and the federal budget; the agency published a preliminary version of its analysis in July 2025 (CBO 2025). When CBO provides Congress with that type of analysis, the agency makes assessments on the basis of its understanding of federal programs and revenue sources, the relevant research literature, its analysis of data, and consultation with outside experts. This paper provides more detail about the basis of assessment for an updated version of the analytical framework underpinning CBO's July 2025 analysis, with the goal of eliciting feedback on the agency's current analytic framework as well suggestions for alternative frameworks that the agency could consider in the future when analyzing questions about the effects of federal investment.

This paper describes two distinct analytical frameworks that we used to estimate the economic effects of changes in federal funding for R&D: first, an R&D capital stock framework; and second, an R&D components framework. The R&D capital stock approach builds on the standard framework that CBO uses to model the economic effects of changes in other types of federal investment, including in physical infrastructure such as highways (CBO 2021). That approach is consistent with the standard way in which R&D investments appear in the Bureau of Economic Analysis's (BEA's) national income and product accounts (NIPA) data and can draw on the evidence in recent papers in the macroeconomic literature, such as Fieldhouse and Mertens (2026), that take a conceptually similar approach to estimating the economic effects of changes in R&D capital stock. Under the R&D capital stock framework, changes in R&D investment generate changes in the R&D capital stock, and the economic effects of those changes can be traced in a "top-down" approach that does not require observing detailed information about, for example, what those R&D funds are spent on. Rather, changes in the

R&D capital stock are connected to changes in economywide macroeconomic aggregates such as total factor productivity (TFP) and gross domestic product (GDP).

Our second approach, the R&D components approach, starts with the observation that federal funding for R&D can be allocated to either labor or capital. On the basis of data from National Science Foundation (NSF) surveys and other sources, we estimate the share of federal funding for R&D that supports labor and how that share is allocated across different types of labor, such as postdoctoral researchers and staff researchers. The labor share of federal funding for R&D supports additional work by existing researchers and other staff (such as administrative support staff working in scientific labs) and the education or training of additional researchers. Under this framework, we model the effects of changes in the number of researchers and in the education of those researchers using a "bottom-up" approach that is consistent with CBO's previous assessments of the economic effects of changes in the number of STEM (science, technology, engineering, and mathematics) workers in the economy (CBO 2024a) and with CBO's previous assessments of the economic effects of changes in the capital stock in general (Lasky 2018).

Our goals in pursuing two distinct analytic approaches in parallel are threefold: first, to consider a broad and diverse range of evidence relevant to this question; second, to ensure consistency across different parts of CBO's work (in this case, changes in STEM immigration and changes in federal funding for R&D); and third, to compare and cross-validate evidence derived from two different analytical approaches that draw on different sets of data and evidence.

Section 2 offers background on how federal funding for nondefense R&D is spent and provides descriptive statistics relevant to the two analytic frameworks. Section 3 describes the R&D capital stock framework, and Section 4 describes the R&D components framework, specifically focusing on the labor component. Section 5 presents estimates from each of those two analytic approaches, applied to a policy experiment that would increase federal funding for nondefense R&D by $30 billion per year for 10 years, from 2027 to 2036. Section 6 concludes by highlighting some key areas of uncertainty in our analysis.

2. Preliminaries: Federal Funding for R&D

This section provides background information about the types of expenditures that federal funding for R&D supports. Subsection 2.1 describes the distribution of federal R&D funding (defense and nondefense) across federal agencies to provide context for the types of research being supported by those funds (for example, health versus space research). Subsection 2.2 then provides descriptive statistics on the types of expenditures federal funding for R&D supports. The NSF's National Center for Science and Engineering Statistics (NCSES) and Bureau of Economic Analysis's R&D Satellite Account data provide key windows into understanding the allocation of federal spending for R&D along those dimensions.

2.1 Federally Funded R&D Across Federal Agencies

The federal government funds defense and nondefense R&D; those outlays totaled roughly $179 billion in 2024, the most recent year for which such data are available (NCSES 2026a, Table 4).[1] For the allocation of federal R&D outlays by agency, see Table 1. In 2024, the Department of Defense had the highest level of federal spending for R&D. The National Institutes of Health (NIH) in the Department of Health and Human Services (NIH accounts for $45 billion of the $49 billion of such spending for HHS) had the highest level of federal spending for nondefense R&D, followed by the National Aeronautics and Space Administration ($11 billion), the Department of Energy ($10 billion for nondefense R&D), and the National Science Foundation ($7 billion). This paper, which builds on CBO's July 2025 analysis, focuses on nondefense R&D.

Table 1.

Federal Outlays for R&D, 2024

Billions of dollars

	Agency	Outlays
Nondefense R&D	Department of Health and Human Services	48.7
	National Aeronautics and Space Administration	11.4
	Department of Energy (nondefense)	10.2
	National Science Foundation	6.9
	Department of Agriculture	3.4
	Department of Commerce	2.3
	Department of Veterans Affairs	1.8
	Department of Transportation	0.9
	Patient-Centered Outcomes Research Trust Fund	0.6
	Environmental Protection Agency	0.5
	Other nondefense agencies	2.2
	Subtotal, nondefense R&D	88.9
Defense R&D	Department of Defense	85.6
	Department of Energy, National Nuclear Security Administration	4.3
	Subtotal, defense R&D	89.9
	Total outlays for R&D	**178.9**

Data source: National Center for Science and Engineering Statistics (2026a, Table 4). See www.cbo.gov/publication/62387#data.

This table shows data for fiscal year 2024, the most recent year for which such data are available.

[1] The phrase *nondefense R&D* generally refers to the federal spending for R&D that is not for defense purposes (that is, not in budget function 050). Because of the way data analyzed in this paper are reported by the National Science Foundation, we use the phrase to refer to all R&D funded by agencies other than the Department of Defense and the National Nuclear Security Administration in the Department of Energy.

2.2 Types of Expenditures That Federal Funding for R&D Supports

Federal funding for R&D pays for work in government labs and facilities—including NIH intramural research and research conducted at federally funded research and development centers such as the Jet Propulsion Laboratory.[2] It also pays for R&D performed at universities, private firms, and other nonfederal organizations that receive federal grants, contracts, or cooperative agreements to conduct the work (NCSES 2026b). Those receiving organizations are sometimes referred to as performers of R&D. See Table 2 for the percentage of total federal obligations for nondefense R&D that was awarded to different types of performers from 2010 to 2023.

Table 2.

Total Federal Obligations for Nondefense R&D, 2010 to 2023

Percent

Higher education institutions	37
Federal agencies	27
Businesses	15
Federally funded research and development centers	11
Nonprofit organizations	9
State and local governments	1

Data source: National Center for Science and Engineering Statistics (2025d). See www.cbo.gov/publication/62387#data.

The share for each type of performer was calculated by dividing the cumulative federal obligations for nondefense R&D made to that type of performer over the 2010–2023 period by the total federal obligations for nondefense R&D over that period. An obligation is a legally binding commitment by the federal government that will result in outlays, immediately or in the future.

Federal funding for R&D generally pays for both labor costs associated with R&D personnel and nonlabor costs, such as equipment, supplies, and new lab buildings. Using tabulations of various NSF NCSES surveys and information from BEA's R&D Satellite Account, we compiled data from 2010 to 2023 on the R&D costs incurred by the set of all R&D performers (federal, state, and local governments; higher education institutions; businesses; and nonprofit organizations). Those R&D cost data reflect expenditures funded by all sources, not just the federal government. Labor costs include the wages and benefits for people directly and indirectly involved in research, as determined by the time they spent in support of R&D work (NCSES 2025a, 2025b, 2025c, 2025e, 2025f, 2025h). At higher education institutions, R&D labor costs include the research-related wages and benefits of faculty, postdoctoral researchers, staff, and students.[3]

[2] Federally funded research and development centers (FFRDCs) are exclusively or substantially funded by the federal government and are administered by firms, universities, or other nonprofit organizations.

[3] We are unable to capture tuition waivers for students within labor costs, since tuition is not accounted for separately in NCSES (2025f).

The NCSES surveys report direct and indirect costs separately for higher education R&D but not for other performers of R&D. Disaggregation of cost-type data into labor and nonlabor costs for higher education performers is available only for direct costs. Indirect costs cover expenses for shared resources, such as administrative costs (including labor) and facilities, such as lab buildings; one recent analysis estimates that indirect costs equal about 42 percent of direct costs for NIH grants, on average, between 2005 and 2024 (Azoulay et al. 2025). For this analysis, we imputed the breakdown of indirect costs into labor and nonlabor costs using indirect cost-rate decompositions from two sources: the Government Accountability Office (1995, Table II.1) and Goldman et al. (2000, Tables 4.1 and 4.2).[4] Those tabulations provide insight into how indirect costs are distributed across facility costs, administrative costs, and library costs; administrative costs account for a little more than half of total indirect costs. In the absence of other available information, we used the share of administrative costs as a proxy for the labor share of indirect costs, implying that labor costs account for just over 50 percent of total indirect costs.

For information about labor and nonlabor cost shares by type of performer over the 2010–2023, see Table A-1.[5] We approximated the shares of federal spending attributable to labor and nonlabor costs by weighting each type of performer's spending shares on labor and nonlabor costs by that performer type's typical share of federal spending on R&D. Overall, that approach suggests that, on average, 54 percent of federal spending for nondefense R&D pays for labor costs and 46 percent pays for nonlabor costs.[6]

3. R&D Capital Stock Framework

Our first approach, the R&D capital stock framework, builds on a framework that CBO developed to estimate how changes in federal investment more generally—including in physical infrastructure such as highways, in R&D, and in human capital—affect the economy (see, for example, CBO 2021). In that framework, changes in federal funding for R&D can be treated like

[4] The Government Accountability Office's tabulations are based on data from 118 major research universities for which the Department of Health and Human Services (HHS) was the "lead" or "cognizant" agency from 1986 to 1995; Goldman et al.'s tabulations are based on data from about 150 institutions for which HHS or the Office of Naval Research in the Department of Defense was the cognizant agency between 1988 and 1999. Although neither source is comprehensive, we expect those samples to offer a reasonable representation of institutions of higher education weighted by receipt of federal funds for R&D; over a time period similar to that of those two studies, the 100 universities receiving the largest amounts of federal funding for R&D accounted for more than 80 percent of such funding received by institutions of higher education. See National Science Foundation (1995, Table 12) and NCSES (2025f).

[5] For a detailed account of data sources and methods used to calculate spending shares, see the appendix.

[6] In the appendix, nonlabor costs are broken out into "R&D plant" and "other" costs to align with how NSF surveys account for R&D costs. R&D plant costs (called capital expenditures in some surveys) are investments in assets with a useful life of more than one or two years (depending on the survey), such as land, physical assets, or equipment (for example, see NCSES 2025b, 2025d). "Other costs" is a residual category, encompassing all nonlabor R&D costs not recorded under R&D plant or capital expenditures.

a “black box” (Rosenberg 1983) that can be related directly to changes in macroeconomic aggregates (such as total factor productivity) without needing to measure or model the allocation of those changes in federal funding for R&D across different factors. In this section, we describe CBO’s basis of assessment for how this framework can be applied to the case of federally funded R&D investments.

3.1 Time Between Funding and Outlays

An appropriation is the budget authority or funding provided in an appropriation or authorization act that allows federal programs and agencies to incur financial obligations and make payments or outlays. The federal government spends appropriated funds over several years. In order to estimate the time lag between funding (appropriations) and outlays, we estimate how much of an annual appropriation (and any remaining amounts from previous years’ appropriations) will be spent in a given year and each subsequent year on the basis of historical spending patterns, as detailed below.[7] Overall, our estimates suggest that about three-quarters of appropriated R&D funds will be spent in the first two years, but that it will take up to seven years, on average, for agencies to spend the full amount of additional funding provided in each year.

The historical spending patterns that provide the basis for this assessment are drawn from the SF-133 *Report on Budget Execution and Budgetary Resources* (Office of Management and Budget, various years). A spending rate is calculated by dividing the amount of spending in a given year by the total appropriation from which that spending originated, averaging that rate over multiple years and removing outliers as necessary. Spending rates may differ across agencies, accounts, and programs.

Over the 2020–2024 period, seven federal R&D accounts individually had outlays larger than one percent of total outlays for nondefense R&D. (For their estimated spending rates, see Figure 1.) The figure illustrates, for a dollar of R&D appropriated in year t=1, how much is estimated to be spent in each subsequent year. There is meaningful heterogeneity across agencies and types of R&D. For example, for NASA spending on Deep Space Exploration Systems, nearly 60 percent is spent in the year funds are appropriated, and nearly all of the spending is completed by three years after the appropriation. In contrast, for NSF Basic Research, less than 20 percent is spent in the year of appropriation, and it takes about seven years for all of the spending to be completed. In our analysis, we rely on a weighted average of the spending rates. (For those weighted averages, see Figure 1, bottom right panel.)

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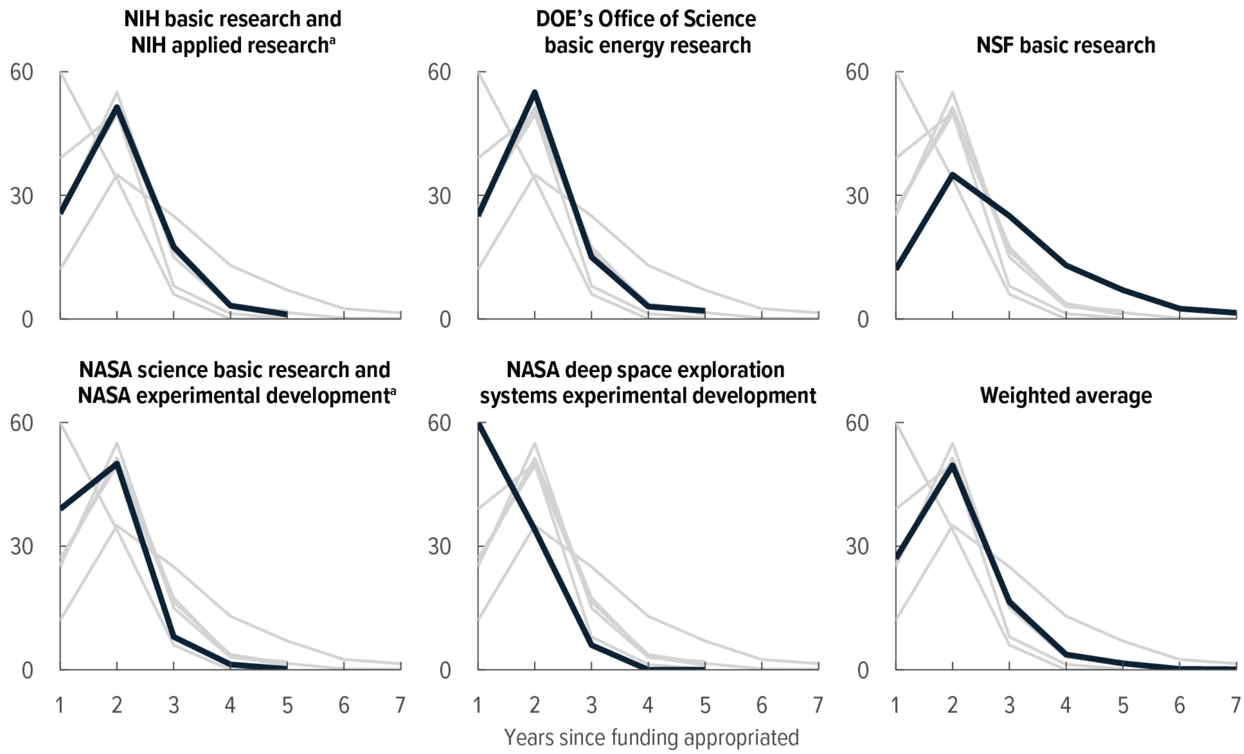
[7] Brunet (2023) shows that accounting for the lags between the time budget appropriations are authorized and funds are spent is critical for accurately measuring and estimating the effect of government spending on economic outcomes.

Figure 1.

Spending Rates for Selected R&D Accounts

Percentage of funding spent



Data source: Congressional Budget Office, using data from the Office of Management and Budget (various years). See www.cbo.gov/publication/62387#data.

The combined outlays for the accounts shown in the figure constituted 74 percent of the total federal outlays for nondefense R&D over the 2020–2024 period. The remaining 26 percent was distributed among a variety of smaller programs, each accounting for less than 1 percent of federal outlays for nondefense R&D over that period, housed at agencies including the Department of Agriculture, the Department of Energy, the National Aeronautics and Space Administration, and the National Science Foundation. In CBO's calculations, a small portion of funding for some accounts remains unspent.

DOE = Department of Energy; NASA = National Aeronautics and Space Administration; NIH = National Institutes of Health;
NSF = National Science Foundation.

a. The series represents two accounts with identical spending rates.

3.2 Response of Nonfederal Spending on R&D

A key input into estimating the effects of changes in federal funding for R&D on the economy is how those changes substitute or complement other organizations' R&D investments.

In the case of physical infrastructure, CBO (2021) estimated that federal investment was a substitute for nonfederal (in that report, nonfederal investment was made up of state and local investment) infrastructure investment. Specifically, CBO estimated that an additional dollar of federal infrastructure investment increases physical infrastructure spending by 85 cents; the remaining 15 cents is offset by a decrease in infrastructure spending by state and local governments. In contrast, in the case of federally funded R&D, we assess that an additional dollar of federal nondefense R&D increases nonfederal R&D by 25 cents.

The research literature on the response of nonfederal spending on R&D to changes in federal funding for R&D presents evidence from a wide range of methodological approaches, most of which are not straightforward to map to the version of that parameter that is most relevant to CBO's analysis. The primary basis for our 25-cent estimate is drawn from Fieldhouse and Mertens (2026). Figure 9(a) in that paper presents evidence about how two sources of nonfederal spending on R&D—private R&D spending and state and local government spending on R&D—respond to the appropriations shocks analyzed in their paper. The impulse response estimates presented in their paper represent the dynamic response of aggregate outcomes to the appropriations shocks in their sample; the shocks they analyze are of different magnitudes and timings than those implied by the policy experiments in our analysis. Hence, rather than relying directly on the impulse response estimates presented in their paper, we use Fieldhouse and Mertens' replication data to estimate impulse response functions of real R&D spending. We then use those estimates to map the R&D appropriations in our policy experiments to the empirical response of changes in various outcomes.[8] Here, we apply that analytical approach to estimate how private spending on and state and local funding for R&D respond to our policy experiments of changes in federal nondefense R&D. Specifically, we sum the by-year coefficients for private and state and local R&D investment in our estimated impulse response functions over the 10-year window to arrive at our 25-cent estimate.[9]

While it is difficult to map many of the other available estimates in the literature to that type of 10-year estimate, it is helpful to discuss our estimate in the context of the broader literature. A frequently cited review of the literature prior to the year 2000 by David, Hall, and Toole concluded that the evidence available at that time was "ambivalent" about whether public R&D investment was a complement or a substitute for private R&D investment. Since the publication of that review, additional research has generally found that public R&D investment complements private R&D investment.

Some of those studies quantify changes in dollars of private spending on R&D in response to changes in dollars of publicly funded R&D. For example, Diamond (1999) analyzes annual aggregates of spending on basic research from four funding sources—the federal government, industry, universities and colleges, and nonprofits—and estimates that a $1 million increase in

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[8] When mapping aggregate outcomes to our shock, we impose a sign restriction requiring the implied impulse response to either maintain the same sign at all horizons or be set to zero because the implied spending shock generated by our policy experiment does not reverse sign.

[9] Because this 25-cent estimate is a multiplicative factor on outlays, the timing of the private R&D response follows the same timing as the outlays for federally funded R&D discussed in Section 3.1.

federal spending results in about a $700,000 increase in total private spending. However, it is difficult to translate that result into a change over 10 years.

Some studies, such as Lichtenberg (1984), estimate changes within firms in government-contracted R&D and private R&D. Such estimates are not straightforward to translate into the type of economywide change that CBO is interested in. Other studies, such as Archibald and Pereira (2003), estimate multivariate time-series models that in principle reflect economywide changes but lack an analog of the appropriations shock variation present in Fieldhouse and Mertens' analysis.

Other studies focus specifically on private biomedical research investment; those studies include Ward and Dranove (1995), Toole (2007), Blume et al. (2015), and Blume-Kohout (2023). Although most of the estimates in those studies are difficult to put in apples-to-apples terms with the Fieldhouse and Mertens estimates, the peak impulse response of nonfederal R&D investment to a federal R&D funding shock in Blume-Kohout (2023) is 0.7 whereas that peak in Fieldhouse and Mertens' study is 0.2.

Additional studies, such as Azoulay et al. (2019), Myers and Lanahan (2022), and Dyevre (2024), estimate the relationship between changes in public R&D investment and changes in private patents, documenting evidence of complementarities that are of the same sign (positive) but which are not straightforward to map into a dollar-for-dollar estimate. A similar issue arises in translating Blume-Kohout's (2012) evidence on changes in public funding for R&D and changes in phase I clinical trial starts.

The implementation of our R&D capital stock approach does not require explicitly estimating the economic effects of changes in nonfederal R&D because those returns are implicitly included in Fieldhouse and Mertens' overall estimates on total factor productivity.[10]

3.3 Time Profile of Productivity Effects

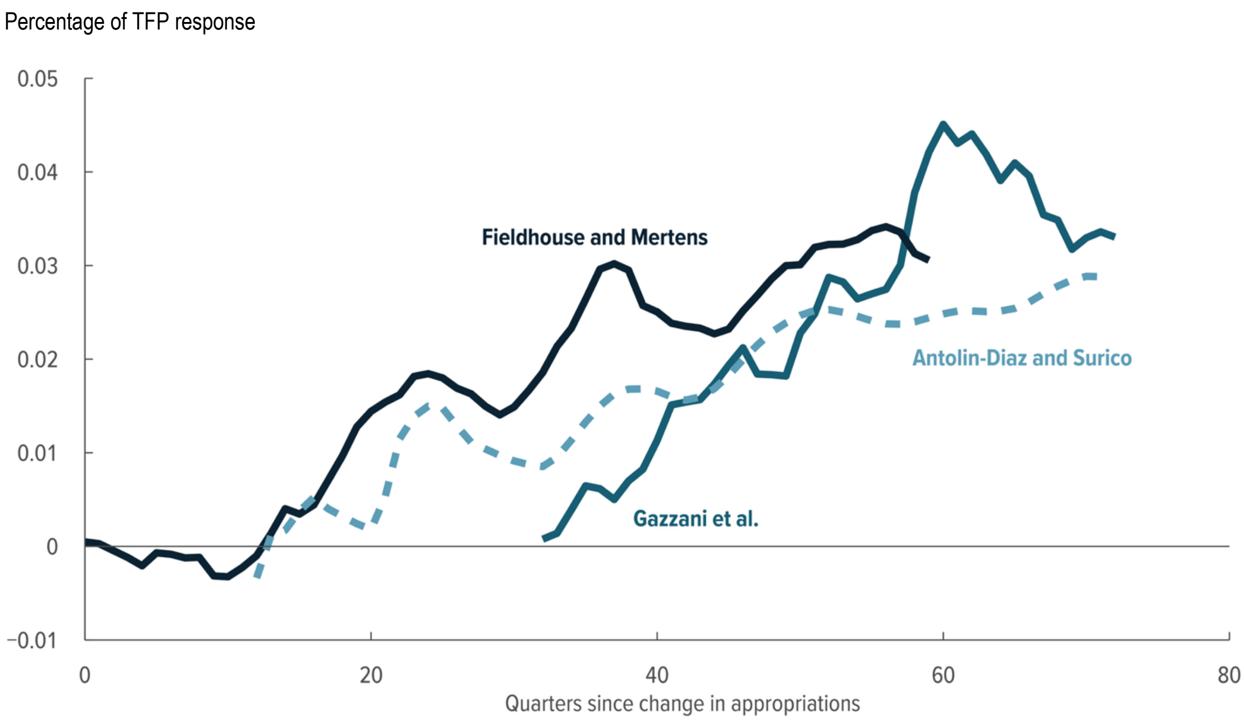
Estimated lags between when R&D funds are spent and when effects on productivity are observed are a key input in our analysis. The available evidence provides a wide range of timings over which changes in productivity are realized. Overall, in our assessment, the effect of federally funded R&D on productivity accelerates over the first 15 years after outlays are made, an effect that then attenuates and declines over the next 15 years. Productivity growth is thus affected for about three decades after outlays are made.

[10] We abstract from the economic effects of changes in nonfederal R&D other than those captured in TFP, such as potential impacts on aggregate demand or in the private returns to those changes which would appear in GDP outside of TFP. Incorporating such additional effects is a goal for future work.

In earlier work, CBO modeled the economic effects of changes in federal funding for R&D along the same time path as changes in federal spending on infrastructure (see, for example, CBO 2016, Figure 1, and CBO 2021). More recently, three more direct sources of evidence have been published in the research literature that shed light on the timing of TFP effects arising from federal R&D spending in particular: Fieldhouse and Mertens (2026), Antolin-Diaz and Surico (2025), and Gazzani et al. (2025). The implementation of our R&D capital stock approach primarily draws on the estimates from Fieldhouse and Mertens (2026); Figure 2 plots the estimates from Fieldhouse and Mertens alongside the estimates from the other two papers to give a sense of the similarities and differences across the three sets of estimates.[11]

Figure 2.

Timing of Productivity Effects



Data source: Congressional Budget Office, using data from the following sources: Antolin-Diaz and Surico (2025, Figure 10, adjusted TFP panel); Fieldhouse and Mertens (2026, Figure 6, business-sector TFP panel); Gazzani et al. (2025, unpublished results). See www.cbo.gov/publication/62387#data.

For each set of results, we summed the observed TFP responses over the period of analysis described in the corresponding paper and then calculated the share of the total response for each quarter. The start of TFP effects in the Antolin-Diaz and Surico series is delayed by three years to reflect the time between appropriations and spending. The Gazzani et al. series is delayed by eight years: three years for the time between appropriations and spending and an additional five years to reflect the time between spending and patent applications suggested by Li et al. (2017, Figure 1).

[11] The notes to Figure 2 detail adjustments we made to the estimates presented in those papers in order to make them more comparable.

Fieldhouse and Mertens (2026) apply local projection methods to estimate the effects of changes in federal funding for nondefense R&D over a 15-year period.[12] In their analysis, positive TFP effects begin to appear in years 4 and 5 after an exogenous shock to appropriations for nondefense R&D. When combined with the estimated time between when an appropriation is made and when outlays occur, that timing implies a fairly immediate effect on productivity from changes in spending.[13] The largest portion of TFP effects occur in later years, towards the end of the period they analyze.

The primary focus of Antolin-Diaz and Surico (2025) is defense spending, which they estimate has GDP effects for most of the 15 years after a change in federal spending on defense that they analyze. More relevant to our work is the analysis in the second half of their paper that focuses on the direct effects of a change in R&D spending itself on TFP over 15 years (see Antolin-Diaz and Surico 2025, Figure 10). We delay the start of the TFP effects for the Antolin-Diaz and Surico series by 3 years, reflecting the time between appropriations and spending to make the projections more comparable with the estimates from Fieldhouse and Mertens. Like Fieldhouse and Mertens, Antolin-Diaz and Surico estimate that the largest portion of the effects occur towards the end of the 15-year window.[14]

Gazzani et al. (2025) rely on patents rather than spending to compare how government-funded and privately funded patents contribute to productivity over a 10-year window following the granting of a patent. In Figure 2, we delay the start of the TFP effects in the Gazzani et al. series by 8 years to account for a 3-year lag from appropriations to spending, consistent with the data we presented in Section 3.1, as well as an additional 5-year lag from spending to patent applications, consistent with the data presented in Li et al. (2017, Figure 1). With that adjustment, the bulk of the TFP effects of government-funded patents occurs around 15 years after the change in funding for R&D.

3.4 Size of Productivity Effect

As with the timing of the estimated TFP response to a change in public R&D appropriations, the estimated size of the TFP response to such a change varies across the three research papers. In

[12] Figure 3, which compares the magnitude of TFP effects from each of the cited papers, includes an extension of the Fieldhouse and Mertens estimates to 20 years; their estimated effects are identical for the first 15 years. By contrast, we do not include a 20-year extension of Fieldhouse and Mertens' estimates in Figure 2 (which compares each quarter's share of the total TFP effects in each of the cited papers) in order to keep the estimates as comparable as possible across papers.

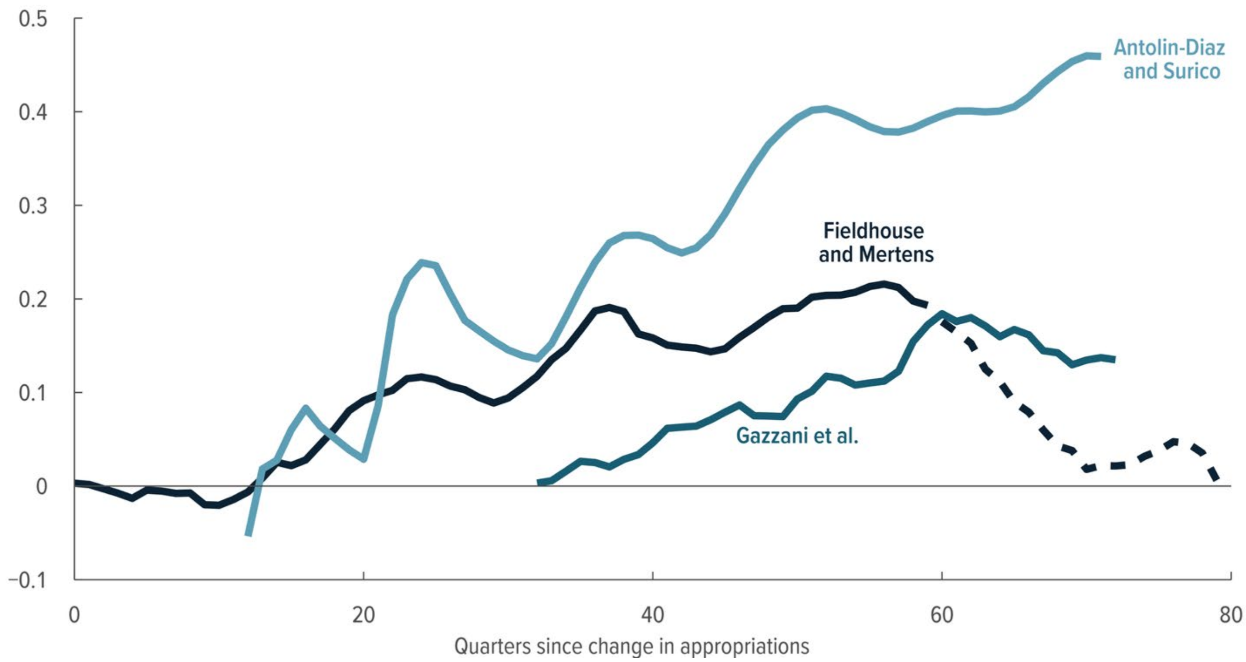
[13] Note that that timing is broadly consistent with what is implied by our estimated time lags between appropriations and outlays as discussed in Section 3.1.

[14] That time profile is also consistent with evidence presented in Jaramillo and Kim (2025), who estimate that additional R&D investment in South Korea raised patenting and exports in targeted patent classes and that the magnitude of the effects peaked at the end of the 15-year estimation window.

Figure 3.

Magnitude of Productivity Effects

TFP response (percent)



Data source: Congressional Budget Office, using data from the following sources: Antolin-Diaz and Surico (2025, Figure 10, adjusted TFP panel); Fieldhouse and Mertens (2026, Figure 6, business-sector TFP panel); Gazzani et al. (2025, unpublished results). See www.cbo.gov/publication/62387#data.

The extension of the Fieldhouse and Mertens line to 20 years is based on unpublished results shared with CBO. The start of TFP effects in the Antolin-Diaz and Surico series is delayed by three years to reflect the time between appropriations and spending. The Gazzani et al. series is delayed by eight years: three years for the time between appropriations and spending and an additional five years to reflect the time between spending and patent applications suggested by Li et al. (2017, Figure 1).

Figure 3, we plot the magnitude of the available estimates from those same three papers in comparable terms. Note that comparing the magnitude of the estimates in the three studies is challenging; for example, the Gazzani et al. estimates only capture the effects of federal funding for R&D that result in granted patents.

Of the three studies, Antolin-Diaz and Surico (2025)'s estimates of the response to a public R&D shock are the largest, and TFP increases by a growing amount over the 15-year response period. Fieldhouse and Mertens (2026) estimate smaller and more delayed responses, with a positive TFP response starting after 4 or 5 years. Fieldhouse and Mertens' unpublished 20-year estimates suggest that the effects on TFP decline after 60 quarters. Gazzani et al. estimate that the effects on TFP are smaller.

3.5 Depreciation of R&D Capital Stock[15]

Modeling of the economic effects of changes in the R&D capital stock in a classic capital accumulation equation requires an estimate of the depreciation rate of R&D capital.[16]

The depreciation of R&D reflects the rate at which new knowledge, ideas, and technologies become obsolete. The research literature, including Fieldhouse and Mertens (2026), generally applies the Bureau of Economic Analysis's standard R&D depreciation rate of 16 percent. Other work by BEA researchers (Crawford et al. 2014) has tabulated different depreciation rates for different categories of R&D spending: 7 percent for aerospace, 9 percent for health and energy, and 16 percent for other nondefense R&D. Weighted by their average share of federal spending for R&D by its different purposes from 1974 to 2023, their implied depreciation rate is 9.5 percent.[17]

However, both the 16 percent rate and the 9.5 percent rate are arguably intended to capture the *private* depreciation rate relevant to an owner of an R&D asset. For example, Li and Hall (2020) characterize depreciation rates for R&D as parameterizing the declining effect of R&D on a firm's profits over time. Such private depreciation rates exclude a key channel through which innovative activities affect productivity and other economic outcomes: The knowledge generated by previous innovations can lead to spillovers and follow-on innovations, including those by individuals and firms that do not own the rights to an R&D asset. The concept of depreciation that is relevant CBO's work is thus not the BEA concept of depreciation but rather the *economywide* depreciation rate for R&D spending. The economywide depreciation rate captures the decay in the contribution of past R&D to aggregate TFP though both the effect of the R&D asset on firms' profits and through any spillovers that accrue to other firms and individuals in the economy.

Griliches (1979) acknowledges that point, noting: "The only thing one might be willing to say is that one would expect such social rates of depreciation to be lower than the private ones. . . . It is hard to see, however, where one could get relevant evidence on this topic." We are unaware of any research on this topic since Griliches's paper. Our approach here draws on the work of

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[15] We thank Benjamin Jones, Donald Marron, Emi Nakamura, Daniel Sichel, and Timothy Simcoe for useful discussions and comments on the analysis in general and this section in particular.

[16] As detailed in this section, our R&D capital stock framework builds on the literature on the measurement of productivity and U.S. National Income Accounting, as measured by BEA. An alternative analytical approach that would be more closely connected to most standard models of economic growth would instead start with the idea that knowledge does not depreciate over time but rather—perhaps with rare exceptions—is useful in perpetuity. In alternative models based on that assumption, the key parameters would include the elasticity of productivity to R&D spending, as well as how a greater stock of knowledge generated by R&D affects the efficiency of future innovation. We thank Benjamin Jones for useful discussions on these points.

[17] The average spending shares are drawn from Table 9.8 of the historical tables from the President's budget for fiscal year 2025 (Office of Management and Budget 2024).

Klepper (1996), who emphasizes that innovative ideas tend to span several successive versions over a "product life cycle." The core idea behind Klepper's contribution was applied in work by Bilir (2014), who constructs an index based on the idea that the duration of citations received by patents reflects information about the useful lifetime of the technologies embedded in those ideas. That is, patent citations represent acknowledgement that a given idea (the cited patent) is useful for a new idea (the citing patent). For CBO's purpose of measuring the impact of ideas on TFP, the effects on TFP of those new (citing) ideas as well as the original (cited) ideas are both relevant.

In our modeling, we build on the work of Bilir (2014) by using the timing of patent citations to model and estimate the economywide depreciation rate of R&D capital. We use the National Bureau of Economic Research's patent citation database to directly estimate the decay of citations over time, which is how we infer the rate at which ideas become obsolete in the economywide sense described above. Specifically, we estimate patent-age fixed effects by estimating the following equation in a Poisson pseudo maximum likelihood (PPML) model:

$$y_{i,t} = \exp\left(a_t + \beta_{a(i,t)}\right) + \epsilon_{i,t}$$

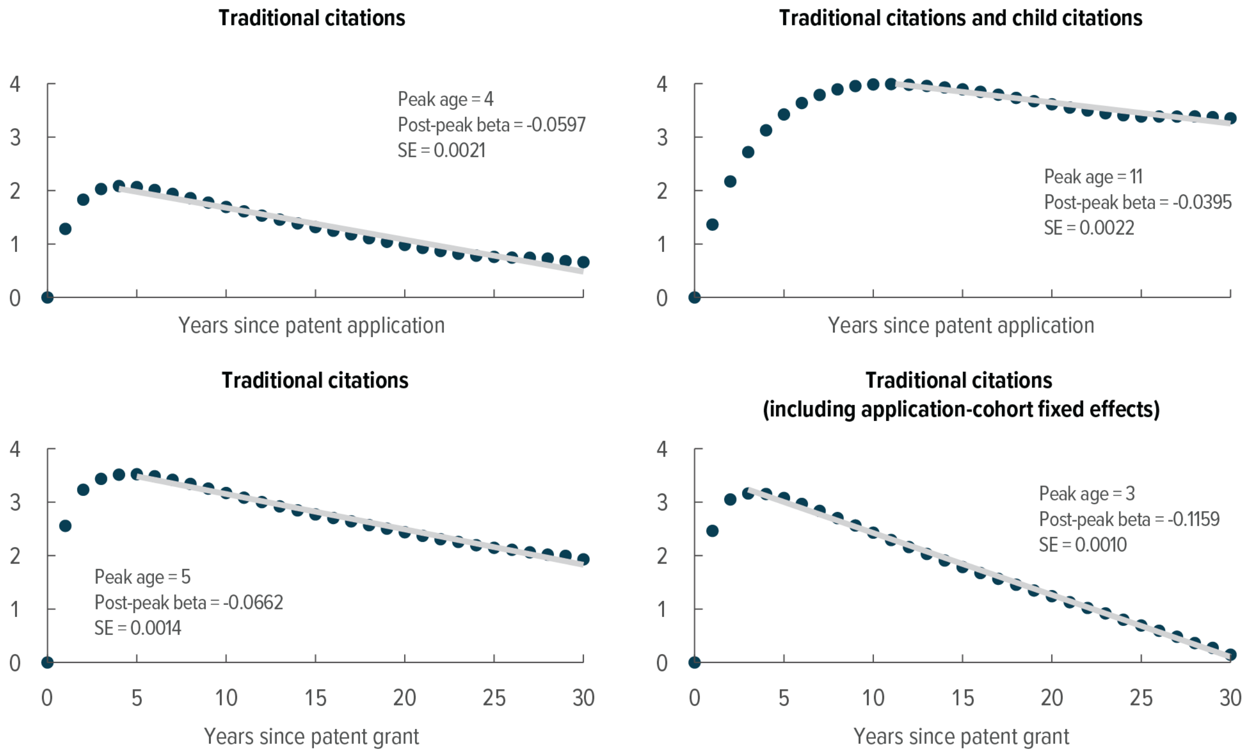
In the equation, the dependent variable, $y_{i,t}$ is the number of new citations received by patent i in year t. The primary coefficients are $\beta_{a(i,t)}$, which are the patent-age fixed effects. Those coefficients nonparametrically estimate how patent citations evolve as a function of the time since patent application. Figure 4 plots the estimated patent-age effects for our baseline specification (equation above). Patent age is based on the year of patent application plus patent-citing-year fixed effects to account for changes in patent citation rates over time. The top left panel shows the time path of patent citations, and the top right panel shows the time path of both traditional patent citations and child citations. (Child citations are citations to patents that cite the original patent, which might better reflect the cumulative nature of innovation.) Figure 4 also plots an estimate of the rate of decay of patent citations, estimated starting the year that patent citations reach their peak.

In our assessment, traditional citations (that is, not including child citations) peak around 4 years after the patent application is filed. After the peak, the rate of new citations decays at around 6 percent per year. Including child citations, new citations peak around 11 years after patent application. After that delayed peak, citations decay at a slightly lower rate as they do for traditional citations, at around 4 percent.

The two bottom panels of Figure 4 show two alternative specifications motivated by the work of Mehta et al. (2010). In both of those specifications, patent age is based on the year that patents were granted rather than the year the patent application was filed. (Mehta et al. 2010 show that lags between patent applications and grants are an important determinant of the age profile of patent citations). The bottom left panel plots the estimates with year fixed effects (defined based

Figure 4.

Patent Citations, by Patent Application Age and Grant Age



Data source: Congressional Budget Office, using data from the National Bureau of Economic Research's patent data project, available at https://sites.google.com/site/patentdataproject/Home. See www.cbo.gov/publication/62387#data.

SE = standard error of the post-peak line of best fit.

on patent grant date); the estimates in that panel are similar to those in the top panels. The bottom right panel plots the estimates with both year and application-cohort fixed effects. The addition of the application-cohort fixed effects raises the depreciation rate to about 12 percent.[18] Taken together, our results point to a depreciation rate for R&D of between 4 and 12 percent. In our analysis, we take the mean of the four post-peak beta coefficients in Figure 4, which is about 7 percent, and apply that as our R&D depreciation rate.

4. R&D Components Framework

Our second approach, the R&D components framework, begins with the observation that federal funding for R&D can be allocated to either labor or capital. As discussed in Subsection 2.2, we

[18] As noted in Mehta et al. (2010), age effects can be identified in this specification because of differences among patents in the lags between applications and grants. As a result, there is no mechanical age-time-cohort identification problem (Bruns-Smith et al. 2026).

estimate that, on average, 54 percent of federal funding for R&D goes to labor costs and 46 percent goes to nonlabor costs.[19] To estimate the effect of the capital component of R&D spending on GDP, we apply CBO's standard capital investment framework (Lasky 2018). That capital investment framework is not described further in this paper.

For the component of R&D spent on labor, we estimate effects through two channels: reallocation and training. The reallocation channel accounts for additional researchers that federal funding pays for. In our assessment, the research literature suggests that individuals who work as researchers generate spillovers to TFP beyond the economic contribution of their labor supply, meaning that the additional researcher-years supported by federal funding add to TFP. The training channel accounts for the education or training of additional researchers paid for by federal funding for R&D. The research literature suggests that more educated researchers contribute more to TFP; those education and training effects contribute to the economy over the entire working life of those more highly trained researchers. Because of the time associated with training, the lag between R&D spending and those training effects' contribution to TFP is longer than the lag for reallocation effects, but training effects affect TFP over a longer period than do reallocation effects. In essence, the reallocation effect represents an extensive margin increase in the size of the research workforce, whereas the training effect represents a more persistent change in the educational composition of the research workforce.

Estimating the economic effects of the reallocation and training channels requires careful consideration of counterfactual outcomes of the individuals whose researcher status, education, or training changes as a function of the change in federal funding for R&D. For example, if increases in federally funded R&D increase the number of STEM PhD recipients (as suggested by the estimates in Fieldhouse and Mertens 2026) by inducing individuals to complete a PhD who, *absent the policy change*, would have worked as a researcher with a bachelor's degree, then the per-person productivity effect for those individuals should reflect the *relative* TFP contribution between a researcher with a bachelor's degree and a researcher with a PhD. We emphasize the role of this type of counterfactual in our discussion throughout this section.

In this section, we start by describing the basis for our estimation of the reallocation and training effects and then describe how we integrate those estimates into our broader R&D components framework.

4.1 Reallocation Channel of Labor Component

We use the term reallocation to refer to the idea that changes in federal funding for R&D may induce some individuals to work as researchers who would otherwise have worked in a

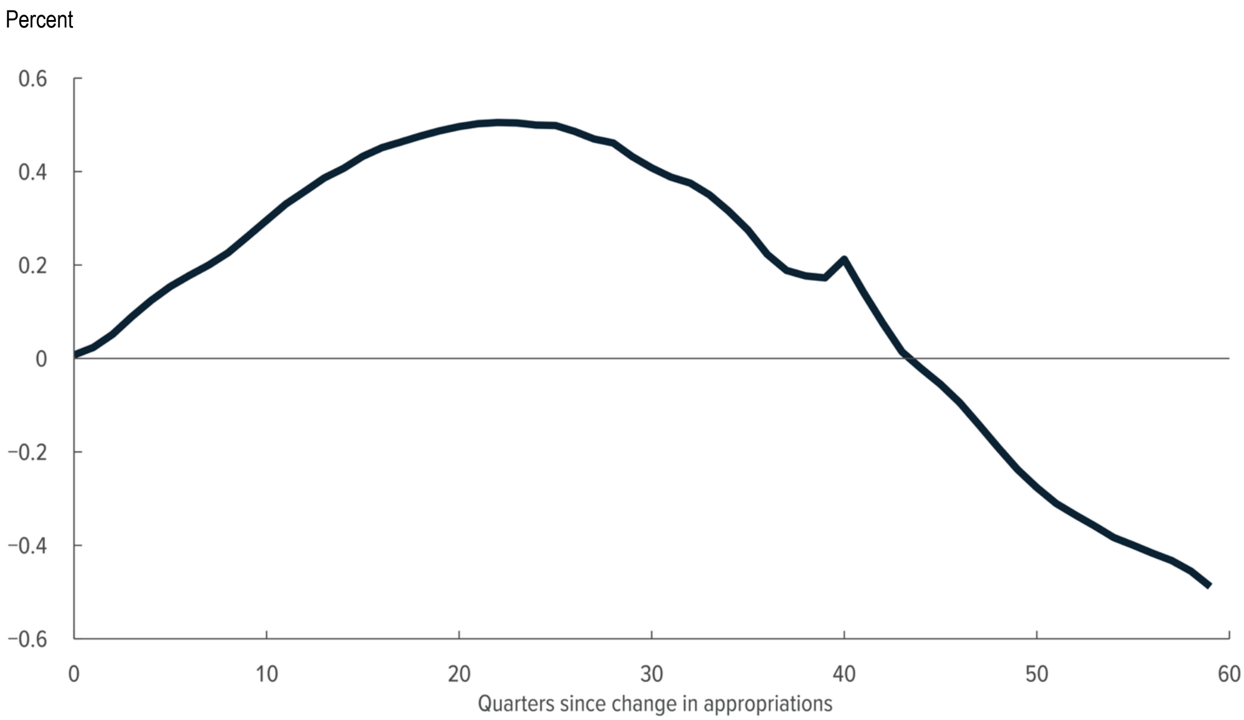
[19] That estimated share for labor is similar to the average share reported in Ekerdt (2024) over a similar time period, although that paper considers a longer time period (from 1963 to 2020) and documents more variation over time. That variation is less apparent in our data.

nonresearch position in the economy. In this subsection, we describe how we estimate the economywide change in the number of researchers resulting from a change in federal funding for R&D, how we allocate that change in researchers across different levels of educational attainment, and how we construct per-researcher-year estimates of the contribution to TFP for researchers of different educational attainment.

Estimating Economywide Changes in the Number of Researchers. To the best of our knowledge, the only available evidence about how changes in federal funding for R&D change the economywide number of researchers comes from Fieldhouse and Mertens (2026, Figure 7(e)). That evidence is reproduced here in Figure 5; the effects peak around year 5 and decline to zero around year 10.

Figure 5.

Change in the Number of Researchers Following a Change in R&D Appropriations



Data source: Fieldhouse and Mertens (2026, Figure 7(e)). See www.cbo.gov/publication/62387#data.

Taken at face value, Figure 5 implies a stark result: On the extensive margin, the size of researchers as a group in the economy is increased only temporarily by increases in federal funding for R&D. In Fieldhouse and Mertens' analysis (2026, Figure 7(e)), about 10 years after the shock, the effect on the number of researchers becomes negative. That path is consistent with their estimate of the effect of a change in appropriations on spending for nondefense R&D, which also becomes negative (Fieldhouse and Mertens 2026, Figure 8) about 10 years after the change in appropriations. That artifact of their analysis does not carry over to our analysis because, as described above, rather than relying directly on the impulse response functions presented in their paper, we use their replication files to estimate impulse response functions of real R&D spending to their identified shocks and generate estimates of changes in the number of researchers resulting from the changes in R&D appropriations represented by our policy experiment.

Allocating Changes in the Number of Researchers Across Educational Attainment. We map the economywide change in the number of researchers to changes by educational attainment (an outcome not reported in Fieldhouse and Mertens 2026) as follows.

First, we apply the estimates from Sattari et al. (2022, Figure 2) to allocate the total observed change in the number of workers across different types of workers who are paid on research grants, as shown in Table 3: faculty, postgraduate researchers, graduate and undergraduate students, research staff, and other staff. Because Sattari et al. (2022) tabulate information by headcounts rather than by a more continuous measure such as hours, our mapping is constrained to be based on a headcount distribution as well.[20]

Table 3.

Occupation of Researchers

Percent

Research staff	41
Faculty	28
Other staff	12
Graduate students	8
Postgraduate researchers	6
Undergraduate students	6

Data source: Congressional Budget Office, using data from Sattari et al. (2022, Figure 2). See www.cbo.gov/publication/62387#data.

The distribution in this table was estimated using the level-change coefficients in Sattari et al. (2022, Figure 2). We divided the level-change-in-employment coefficient for each occupation by the total-change-in-employment coefficient.

Second, we map this change in the distribution of occupations to a change in the distribution of education types. Table 4 shows the educational attainment distribution that we estimate for each of the occupations listed in Table 3. Although the UMETRICS data that underlie Sattari et al. (2022) do not directly include information on individuals' education, we are able to map the distribution of occupations shown in Table 3 to a distribution of educational attainment using the

[20] In their published paper, Sattari et al. (2022) describe Figure 2 as reporting estimates for full-time equivalent (FTE) workers; however, correspondence with the authors clarified that Figure 2 reports headcounts, not FTEs.

Table 4.

Categories of Occupation, by Educational Attainment

Percent

	Highest degree	Degree shares conditional on occupation
Faculty, postgraduate researchers	Doctorate	100
Research staff	Doctorate	14
	Professional degree	*
	Master's degree	47
	Bachelor's degree	39
Graduate students, other staff	Master's degree	31
	Bachelor's degree	69
Undergraduate students	Less than bachelor's degree	100

Data source: Congressional Budget Office, using data from the National Survey of College Graduates (2023). See www.cbo.gov/publication/62387#data.

This table maps occupation categories from Sattari et al. (2022) to degrees on the basis of descriptions of the UMETRICS occupation classifications in Ikudo et al. (2019) and Irhamy et al. (2024) as well as data from the National Survey of College Graduates (NSCG) on educational attainment among science and engineering workers. Faculty and postgraduate researchers are inferred to hold doctorates; research staff are inferred to hold a doctorate, professional degree, master's degree, or bachelor's degree, with shares assigned on the basis of the distribution of those degrees among science and engineering workers in the NSCG (see footnote 22 for details); graduate students and other staff are inferred to hold a master's degree or a bachelor's degree, with shares assigned on the basis of the distribution of those degrees among science and engineering workers in the NSCG; and undergraduate students are inferred to hold less than a bachelor's degree.

UMETRICS = Universities Measuring the Effects of Research on Innovation, Competitiveness, and Science; * = less than 0.5 percent.

descriptions of UMETRICS occupation classifications in Ikudo et al. (2019) and Irhamy et al. (2024) and information from the National Survey of College Graduates, or NSCG (NCSES 2025g).[21] For some occupations, the educational mapping is clear from the description. For example, faculty and postgraduate researchers generally hold doctorates. For other categories, that mapping is less clear; in those cases, we use the NSCG to fill in gaps. For example, the "research staff" category in Sattari et al. (2022) includes a variety of workers with a range of skillsets, including nonfaculty scientists and engineers who hold advanced degrees and work on "scientific aspects of research," as well as staff without advanced degrees, such as laboratory aides and research administrators. For this category, we use the educational distribution of

[21] The UMETRICS (Universities Measuring the Effects of Research on Innovation, Competitiveness, and Science) data, assembled by the Institute for Research on Innovation and Science at the University of Michigan, are an administrative, transaction-level dataset of payments charged to sponsored research grants at participating U.S. research universities. The data identify all individuals compensated from those grants (e.g., faculty, postdocs, students, and staff). The 2024 release covers 45 universities from approximately 2001 to 2024; see Irhamy and others (2024).

college educated STEM workers from the NSCG and descriptions of the UMETRICS data in Ikudo et al (2019) and Irhamy eta al (2024) to estimate the distribution.[22]

Finally, Table 5 shows the implied distribution of highest degrees attained by additional researchers. That distribution is based on translating the estimates presented in Table 3 through the mapping presented in Table 4. The distribution in Table 5 allows us to do two things: first, to disaggregate the total economywide change in the numbers of researchers into changes in the number of researchers with specific educational backgrounds; and second, to apply per-researcher effects on TFP that differ by educational attainment, estimated using the method described below.

Table 5.

Educational Attainment of Researchers

Percent

Doctorate	39
Professional degree	*
Master's degree	25
Bachelor's degree	30
Less than bachelor's degree	6

Data source: Congressional Budget Office, using data from the following sources: National Survey of College Graduates (2023); Sattari et al. (2022, Figure 2). See www.cbo.gov/publication/62387#data.

The distribution in this table is based on the occupational distribution in Table 3 and the mapping described in Table 4.

* = less than 0.5 percent.

Estimating Per-Researcher Effects on TFP by Educational Attainment. CBO has previously estimated the effects of changes in the number of foreign national (that is, immigrant) STEM workers on the economy and developed an estimate of the average TFP effect per researcher engaged in innovation-related activities (CBO 2024a). In constructing those estimates, the

[22] The "research staff" category in Sattari et al. (2022) is a composite of two underlying UMETRICS classifications, "research" staff and "research facilitation" staff, which their appendix (Table S1) reports as 43 percent and 57 percent of the composite category, respectively. We infer from the UMETRICS classification descriptions in Ikudo et al. (2019) and Irhamy et al. (2024) that research staff hold advanced degrees (that is, higher than a bachelor's), whereas research facilitation staff do not hold doctorates. We therefore assign research staff the NSCG degree distribution among S&E workers whose highest degree is a master's, professional, or doctoral degree, and research facilitation staff the distribution among S&E workers with no doctorate (a bachelor's, master's, or professional degree). To align with the composite "research staff" category in Sattari et al. (2022), we present the composite distribution using their respective proportions (43 percent and 57 percent, respectively). As a result, all doctorates in the composite category come from research staff and all bachelor's degrees come from research facilitation staff, and the master's and professional shares are a weighted average of the two subgroups.

agency considered a number of studies, including Prato (2025), Crane et al. (2021), Peri (2012), and Peri et al. (2015). The methodological approaches underlying those papers are diverse: For example, Prato (2025) estimates how the migration of inventors affects productivity growth in an innovation-based endogenous growth framework, identified from empirical event studies of cross-country moves of migrant inventors (patentors). By contrast, Crane et al. (2021) present a simple framework motivated by a Solow growth model in which the following is assumed: Innovation drives all increases in TFP, STEM talent working in the United States drives all innovation in the country, and foreign-born and U.S.-born STEM workers are equally productive.

Our comparison of their estimates suggests that despite their methodological differences, the implied TFP effects from Prato (2025) and Crane et al. (2021) are quite similar. Our estimates of per-researcher effects on TFP rely most directly on the estimates from Prato (2025). (The estimates from Peri (2012) and Peri et al. (2015) imply larger per-researcher effects on TFP.) Prato's empirical analysis focuses on foreign nationals who file patent applications, a sample in which she can observe—in administrative patent records—the cross-country migration that provides the basis for her core empirical estimates. We make a series of adjustments to map the evidence from her paper onto a schedule of per-researcher effects on TFP by education type.

First, not all researchers generate patents, so we extrapolate Prato's estimates to researchers who do not generate patents. On the one hand, because the process of filing and prosecuting patent applications requires time and resources, researchers who generate patents may be participating in innovative activities of higher economic value than are researchers who do not generate patents. On the other hand, some variation in the propensity of researchers to patent reflects cross-industry differences in the effectiveness of patent protection (see, for example, Levin et al. 1987 and Cohen et al. 2000) rather than differences in the economic value of innovative activity. In our assessment, the research literature offers little empirical basis for estimating the relative contributions to TFP of researchers who patent and those who do not; more evidence on this point would be helpful. In the analysis presented here, we adjust the per-researcher effect on TFP implied by Prato downward by 50 percent for nonpatenting researchers.

Second, Prato's estimates focus on foreign national researchers, so we extrapolate Prato's estimates to a representative sample of all U.S. researchers, including those born in the United States. Data from the NCSES suggests that, in recent years, about 22 percent of the STEM workforce in the United States was born in another country (NCSES 2026c). On the basis of evidence in the research literature, which suggests substantial positive self-selection of foreign-born PhD students (see, for example, Gaulé and Piacentini 2013) and researchers (see, for example, Bernstein et al. 2025), we adjust down our per-person productivity effects for non–foreign-national researchers. Our primary empirical basis for that adjustment is the evidence from Bernstein et al., which suggests positive self-selection of patenting migrant inventors of about 40 percent.

Finally, we need a basis for mapping the Prato-adjusted per-researcher effects on TFP onto a schedule of those effects by level of education. Evidence suggests that researchers with higher levels of education and training contribute more to TFP. For example, a replication and extension of the ordinary least squares estimates in Peri (2012) suggests that, in state-by-year panel data, changes in the number of foreign nationals are positively correlated with changes in labor productivity; that correlation is stronger for STEM workers and stronger for more highly educated foreign nationals.

In this analysis, we parameterize educational differences in the per-researcher effect on TFP on the basis of differences in rates of patenting by level of educational attainment. Because our framework assigns larger per-person TFP effects to patenting researchers than to nonpatenting researchers, the parameterization implies that educational groups with higher rates of patenting will contribute more to TFP.

Administrative data on patenting inventors generally do not include information on inventors' educational background, and work such as Akcigit and Goldschlag (2025), which has linked administrative patent data to survey and Census records, has unfortunately not disclosed tabulations of patenting by educational attainment. In our assessment, the best available data on patenting in the United States by educational attainment comes from the 2003 National Survey of College Graduates (NSCG), which included a series of patent-related questions, such as whether or not the individual was named as an inventor on a U.S. patent in the previous five years. We draw on that NSCG data to estimate the share of patenting researchers of different educational attainment (for example, whether a researcher has a bachelor's degree or a doctorate), and we use those shares as the basis for estimating the relative TFP contributions of different education groups. We subset the NSCG sample to "researchers," defined as NSCG respondents who spend at least 10 percent of their time on R&D and who hold a STEM occupation. That definition roughly aligns with the definition in the Organisation for Economic Co-operation and Development (OECD)'s Frascati Manual 2015, which forms the basis for the researcher variable analyzed in Fieldhouse and Mertens (2026).[23] Weighting that sample by the NSCG's population weights, we estimate that in the previous five years, about 19 percent of researchers with a doctorate, 10 percent of researchers with a master's degree, and 7 percent researchers with a bachelor's degree have been named on a U.S. patent application.

4.2 Training Channel of Labor Component

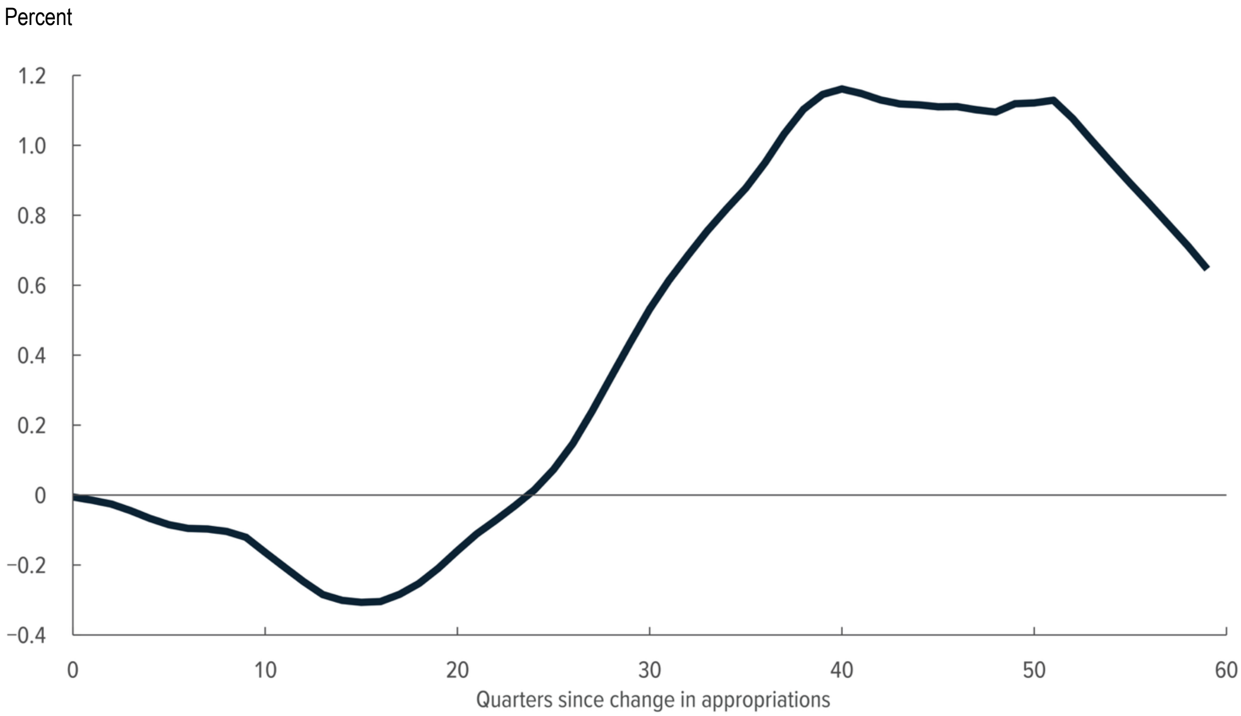
To the best of our knowledge, the only available evidence on how changes in federal funding for R&D change how much education and training researchers have in an economywide sense also

[23] The 10-percent threshold aligns with the "researcher" and "R&D personnel" concepts described in the OECD's Frascati Manual 2015, which states that "individuals spending less than 0.1 FTE [full-time equivalent] on R&D on an annual basis" should generally not be included in R&D personnel totals. Note, however, that "researcher" is a subset of "R&D personnel," and that distinction is not directly captured by the NSCG.

comes from Fieldhouse and Mertens (2026, Figure 7(d)). That data, reproduced here in Figure 6, plots the annual change in STEM PhD recipients on the basis of the NSF's Survey of Earned Doctorates. The number of PhD recipients in STEM fields remains relatively constant until about year 6. It then increases, peaking at about year 10. It begins to decline near the end of their 15-year sample but remains positive through the end of the period. It is notable that the timing of those effects roughly matches what might be expected if additional federal funding for R&D caused institutions of higher education to train additional PhD students, given the lags that would be expected from data on median time to degree (see, for example, National Research Council 2011).

Figure 6.

Change in the Number of New STEM Doctorate Recipients Following a Change in R&D Appropriations



Data source: Fieldhouse and Mertens (2026, Figure 7(d)). See www.cbo.gov/publication/62387#data.

The increase in the number of STEM doctoral recipients must account for a counterfactual of what level of education these individuals would have attained in the absence of the change in federal funding for R&D. On the basis of the evidence presented in Fieldhouse and Mertens (2026, Figure 7(e)), we assess that all the new STEM doctoral recipients would have been employed as (less educated) researchers in the absence of the policy change.

We map this change in new STEM doctoral recipients to changes in TFP on the basis of the per-researcher effects of TFP by education as described above. We model changes in TFP associated with changes in education and training as occurring at the time of degree completion. Because NCSES (2024, Table 2-5) suggests that the share of STEM doctoral students that are foreign nationals—around 42 percent—is higher than their share of STEM workers (of whom foreign nationals make up 22 percent, as noted above), we refine our adjustment for self-selection of foreign nationals to be based on data specific to this population. (Individuals holding temporary visas are used as a proxy for foreign nationals.)

We are currently unaware of evidence from the research literature that would allow us to estimate the economic effects of additional training beyond that estimate for additional STEM doctoral recipients. Any effects of postdoctoral training that increased the TFP contribution of researchers with STEM doctorates or the research experience gained by undergraduate and masters' degree researchers doing work supported by federal funding for R&D would be in addition to the effects described in this section.

4.3 Additional Factors in the R&D Components Framework

As in the R&D capital stock approach, we rely on several additional factors to round out the R&D components approach.

Time Between Funding and Outlays. Estimated lags between appropriation and spending of federal funds are an input into the R&D components approach in the same way they are an input into the R&D capital stock approach. As described in Subsection 3.1, we rely on data on historical spending rates to parameterize the timing between funding and outlays.

Response of Nonfederal Spending on R&D. Our assessment of how private spending on R&D responds to changes in federal funding for R&D under the capital stock framework applies to the R&D components framework as well. As described in Subsection 3.2, we estimate that an additional dollar of federal non-defense R&D increases nonfederal R&D by 25 cents. Our estimates of changes in spending on labor (via the reallocation and training components) incorporate this crowding-in effect by default because those estimates are built on the economywide estimates in Fieldhouse and Mertens (2026). Our estimates of changes in spending on capital incorporate this additional nonfederal spending response.

Lags Between Spending on Capital and Productivity Effects. This timing follows the standard relationships derived from CBO's capital investment framework (Lasky 2018). Following an increase in private investment, the productivity of labor immediately increases and potential GDP rises. Over time, as the capital stock depreciates, the effect of that increase in investment declines. After 10 years, the effect of a one-time increase in private investment on potential GDP is approximately half as large as the effect on potential GDP in the year immediately following the investment. After 30 years, the effect on potential GDP is less than one-sixth the initial size.

Lags Between Spending on Labor and Productivity Effects. Our modeling of the timing of when changes in the education and number of researchers lead to changes in economywide productivity draws on evidence from Prato (2025). That evidence suggests that researchers contribute to innovative activities, such as patenting, very quickly after they are added to the workforce. We build in a five-year lag between changes in patenting and changes in TFP, on the basis of the empirical relationship between patenting and TFP estimated in Kogan et al. (2017).[24] Overall, that structure implies that the economywide effect of new researchers on TFP phases in over five years.

We model the length of time that researchers contribute to innovative activities using estimates of the lifecycle productivity of patenting inventors from Bernstein et al. (2025). That study suggests that patenting inventors' productivity peaks when they are in their late 30s and then declines through their 40s and 50s. We model new researchers as entering the workforce close to peak productivity (with effects on TFP being phased in over five years as described above) and as contributing to TFP for a 25-year period. Figure 7 shows the overall timing of a researcher's contribution to TFP; the y-axis represents the share of the average researcher's lifetime effect on TFP occurring in each year since the individual entered the research workforce.

The components framework captures the idea that the effects on TFP of changes in federal funding for R&D depend not just on whether and how many individuals are brought into the researcher workforce but also on *which* new workers (for example, of what ages and levels of educational attainment) are brought into the researcher workforce, as those compositional differences affect when and for how long those people contribute to TFP. On the one hand, if increases in federal funding for R&D lead to more hiring of senior researchers who would otherwise have lived abroad, those individuals may contribute to TFP over a shorter time period than if the additional funding is allocated towards supporting graduate students. On the other hand, if the additional funding supports graduate students, the lag between initial spending and peak TFP effects may be longer than if it supports researchers who would have lived abroad. Empirically, Fieldhouse and Mertens (2026) estimate that changes in federal funding for R&D generate near-term increases in the overall number of researchers as well as more delayed effects on the number of PhD recipients in STEM fields, suggesting that the average response in historical data likely represents a mix of different cases. Consistent with the evidence from Fieldhouse and Mertens, Akcigit et al. (2025) estimate that higher R&D subsidies have relatively immediate effects on GDP, whereas education subsidies or increases in university slots have more delayed effects.

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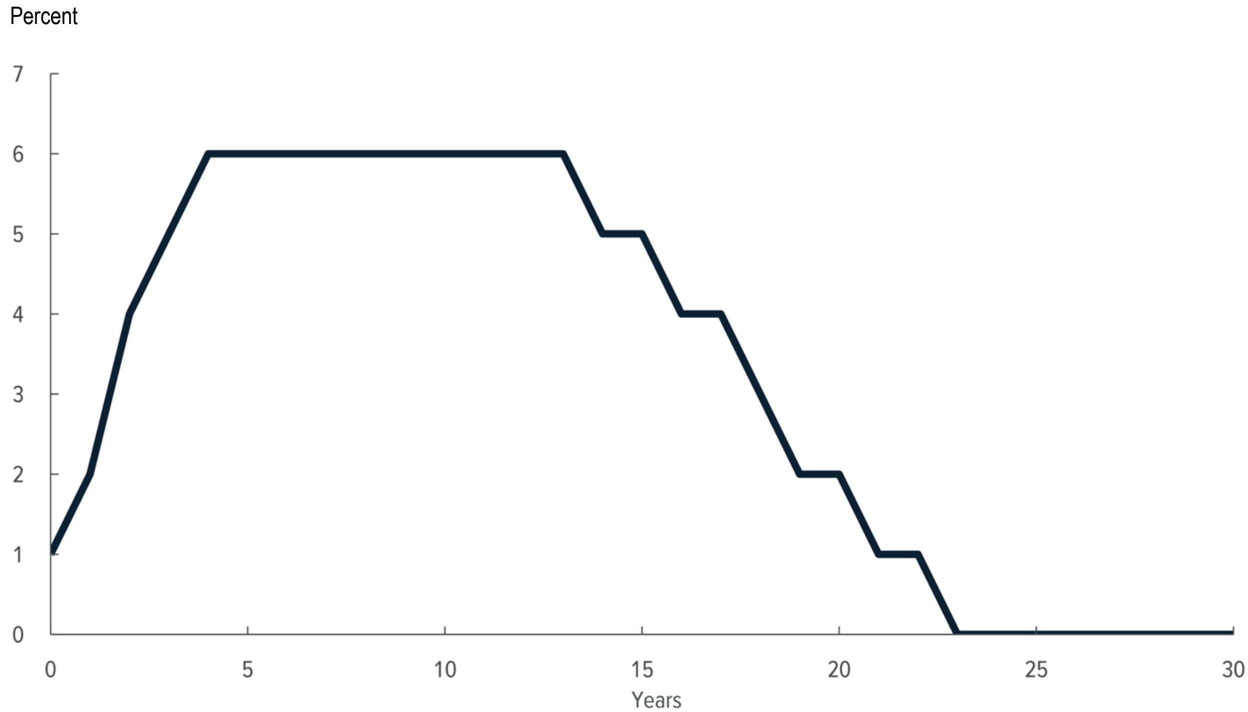
[24] Notably, that 5-year phase-in is roughly consistent with the estimates presented in Figures 6 and 7(c) of Fieldhouse and Mertens (2026): There, the patent innovation index impulse response in Figure 7(c) is positive and increases soon after the appropriations shock, and the TFP response in Figure 6 becomes positive just before quarter 20 (year 5), though neither response is statistically significant.

Figure 7.

Share of a Researcher's Lifetime Contribution to TFP Per Year Since Entering the Research Workforce



Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

5. Economic and Budgetary Effects of Changes in Federal Funding for R&D

This section presents the economic and budgetary effects of a set of illustrative changes in federal funding for nondefense R&D. Specifically, we analyze the effects of increasing federal nondefense R&D appropriations by $30 billion per year for 10 years (from 2027 to 2036) under four scenarios constructed using the capital stock and components frameworks and two financing mechanisms. The additional appropriations would be distributed among agencies according to their share of outlays for nondefense R&D over the past five years.

As context, the change in appropriations of $30 billion a year in our illustrative example is about one-third of spending on federal nondefense R&D in recent years. That amount was chosen to be roughly comparable to the percentage increase in funding for physical infrastructure that CBO analyzed in 2021. Because the implementation of our two analytic frameworks relies heavily on the estimates from Fieldhouse and Mertens (2026), it is worth noting that their analysis includes changes in appropriations of a similar scale in percentage terms, though the changes in levels are generally smaller than in our example.

Under the first financing mechanism, federal funding for R&D is deficit-financed—the change in funding is financed by borrowing. The second financing mechanism is deficit neutral—noninvestment government purchases are changed to offset the change in R&D funding before accounting for budgetary feedback resulting from changes in the economy. The economic and budgetary effects of changes in federal funding for nondefense R&D are roughly symmetric regardless of whether funding is increased or decreased, so for simplicity in exposition we focus only on the effects of increases; however, where relevant, asymmetries are discussed. For details on the suite of CBO's macroeconomic models used in this section, see CBO (2026).

5.1 Economic Effects

Increases in federal funding for nondefense R&D boosts actual and potential GDP. In addition, interest rates are affected by several factors—including changes in TFP growth, labor-force growth, and the debt-to-GDP ratio. The policies' effects on those factors vary across the two frameworks and financing mechanisms. This section summarizes our estimates of each of the economic effects relative to CBO's baseline projections.

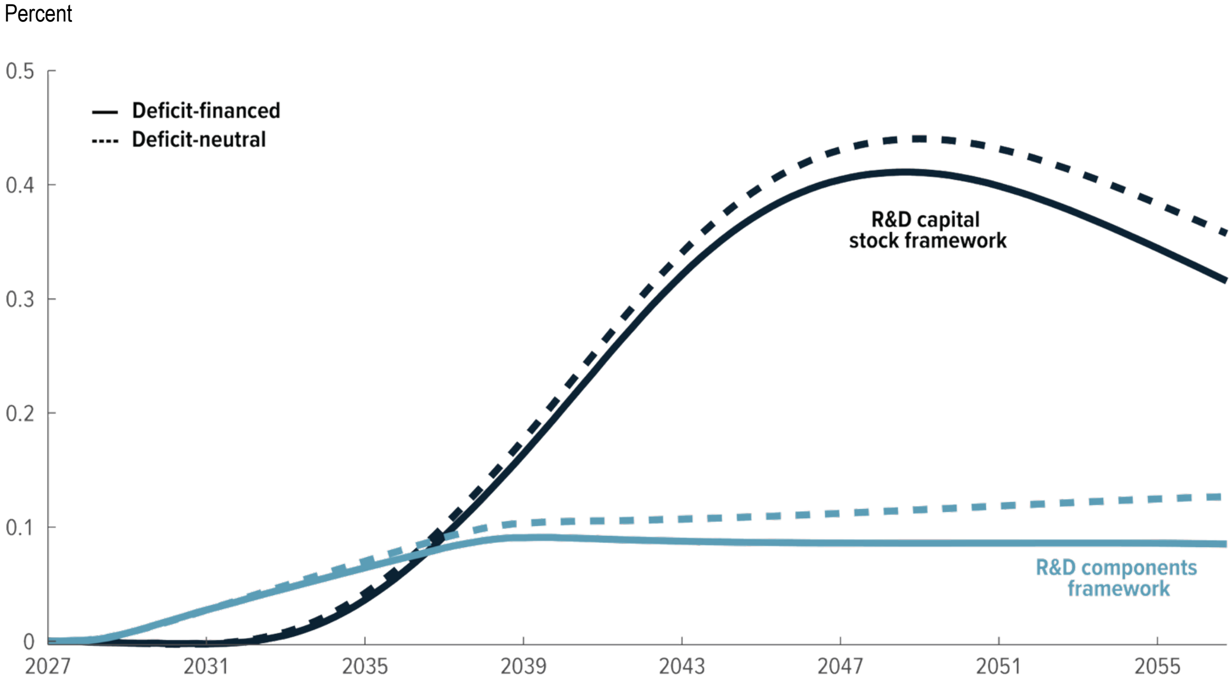
Potential GDP. Changes in federal appropriations for nondefense R&D affect potential GDP—a measure of the economy's maximum sustainable output—through three channels: total factor productivity, capital investment, and the supply of labor. Increases in federal funding for nondefense R&D would increase potential GDP—regardless of the means of financing—under both the R&D capital stock framework and the R&D components framework. At the end of the 10-year projection period in 2036, the effect on potential GDP would be similar under all four scenarios; however, beyond 2036 the effects differ between the two frameworks (see Figure 8). Under the R&D capital stock framework, potential GDP would be about 0.3 percent higher in 2056 than it was projected to be under CBO's baseline; under the R&D components framework, it would be about 0.1 percent higher.

Total Factor Productivity. Changes in the R&D capital stock (capital stock framework) or in the number and educational attainment of researchers (components framework) raise economywide TFP, thus increasing potential output. Consistent with the lags described in Sections 3 and 4, those effects phase in gradually after changes in spending. Those effects would not vary by financing method, and the effects would be symmetric whether federal funding increased or decreased.

Under the R&D capital stock framework, the change in the stock of R&D capital would evolve with federal spending for R&D; additionally, a 7 percent economywide depreciation rate is applied, as described in Subsection 3.5. The time path of productivity effects reflects both the accumulation of R&D capital and the lag between R&D spending and TFP, with the effect on the *level* of TFP reaching a peak of 0.4 percent in 2047 (see Figure 9). In CBO's estimation, the effect on TFP declines after 2047 but remains positive; it approaches zero beyond the 30-year period of analysis covered in this paper.

Figure 8.

Effects of an Increase in Federal Funding for R&D on Potential GDP



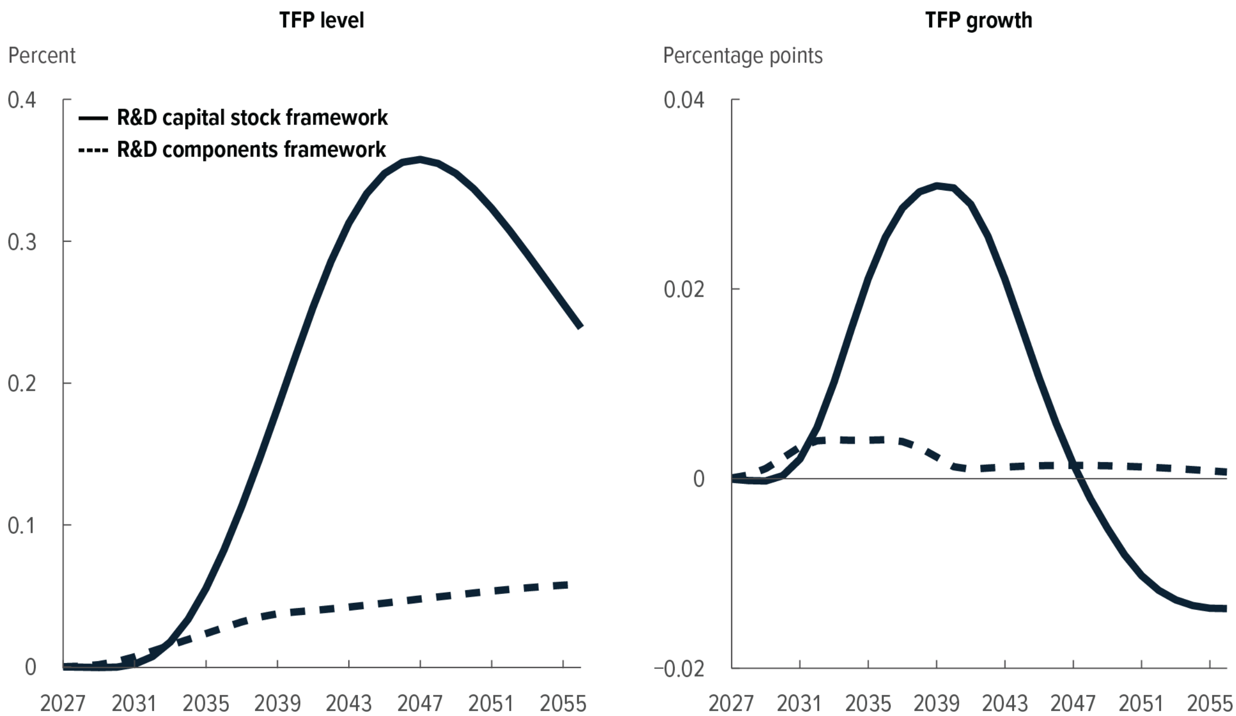
Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

Under the R&D components framework, the reallocation channel affects the number of workers participating in research; our estimates suggest that this effect would be temporary, occurring only while funding was available. In contrast, the training channel affects the education and training received by researchers and therefore induces more persistent effects on TFP. Increases in federal funding for R&D would increase TFP through both of those channels. The training effect would be smaller in the near term but grow over time. Together, the two channels would increase the *growth rate* of TFP through 2056 (see Figure 9). After 2056, TFP would be permanently higher because of the additional training, and it would continue to grow at a rate similar to that projected in CBO's economic baseline (that is, under current law).

Capital Investment. Three mechanisms would affect non-R&D capital investment after an increase in federal funding for nondefense R&D. CBO assesses that under all four scenarios, an additional dollar of federal nondefense R&D increases nonfederal R&D by 25 cents (see Section 3). On the basis of our assessment of the research literature, we model this change in nonfederal funding as a change in private funding for R&D (as opposed to, for example, R&D investments by state and local governments). In the R&D capital stock framework, the effect of private funding complementarity is implicitly incorporated in the empirical TFP estimates drawn from Fieldhouse and Mertens (2026). That private R&D complementarity is applied explicitly in the

Figure 9.

Effects of an Increase in Federal Funding for R&D on Total Factor Productivity



Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

R&D components framework as an additional capital accumulation effect because that framework splits R&D spending into labor and capital investment. Because changes in investment affect potential GDP almost immediately—in contrast with the effects of R&D on TFP, which occur with a lag as described above—the bifurcation of spending between labor and capital would result in an initially larger effect on potential GDP under the R&D components approach.

The second mechanism through which the policies affect capital investment under both analytical frameworks is their effect on interest rates. A change in federal funding for R&D would affect interest rates through a variety of channels (discussed below). The changes in interest rates would affect the user cost of capital and therefore firms' investment decisions. Crucially, the effect on interest rates—and the subsequent change in investment—would depend on how the policy was financed. Increases in debt as a percentage of GDP increase interest rates, all else held equal, which means that deficit-financed policies would tend to increase interest rates and crowd-out private investment more than deficit-neutral policies.

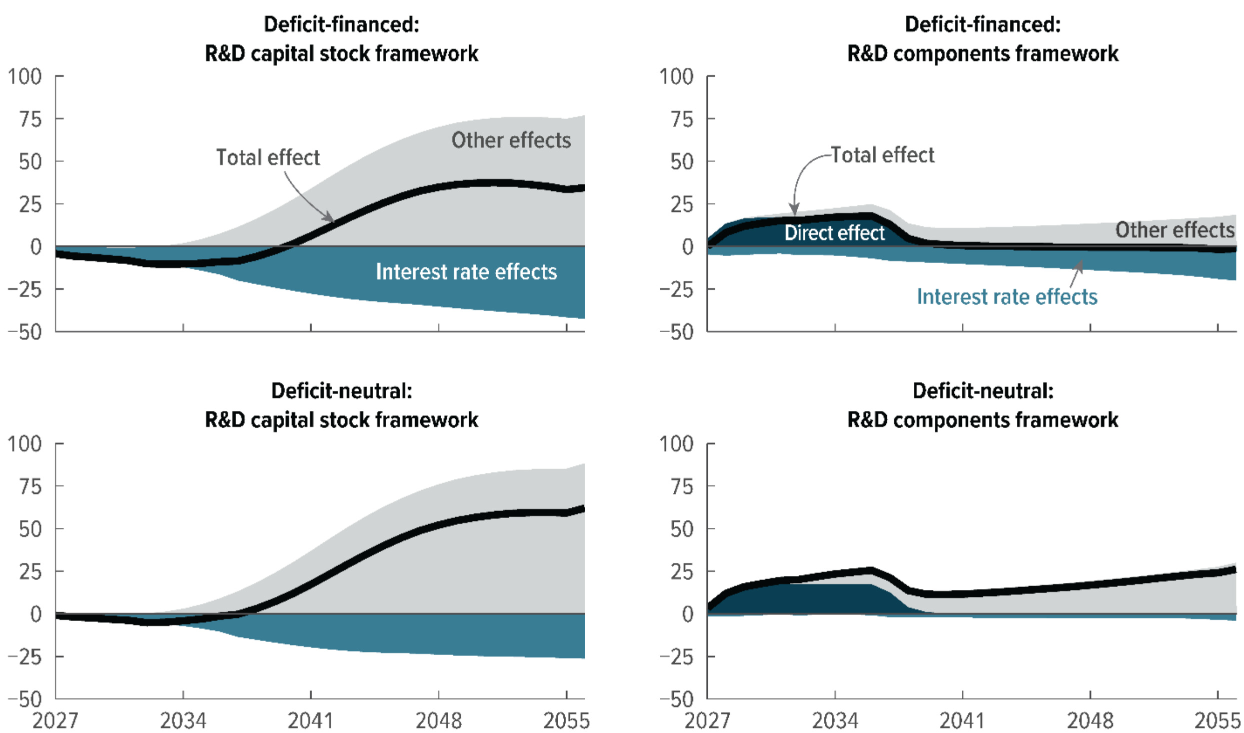
The third mechanism reflects how firms respond to increases in the supply of labor and the demand for goods and services. In CBO's assessment, when the supply of labor increases, businesses purchase additional capital for the new workers to use. Additionally, as the demand for businesses' output increases, firms add capital to meet that additional demand. Those investments then increase the potential output of the economy. Once businesses have invested enough to meet the additional demand and to supply workers with the necessary capital, the only further increase in investment comes from the need to gradually replace the additional capital as it depreciates.

Under the R&D capital stock framework, private investment would initially decline after an increase in federal funding for R&D because interest rates would be higher in anticipation of higher TFP growth. The decline would be larger if the increase in funding was financed by increased borrowing. Over time, however, increases in the supply of labor (discussed below) and in the demand for goods and services would increase investment. On net, private investment would be larger over the 2027–2056 period after an increase in federal funding for R&D (see Figure 10).

Figure 10.

Effects of an Increase in Federal Funding for R&D on Private Investment in Physical Capital

Billions of dollars



Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

Under the R&D components framework, private investment would increase over the 2027–2036 period regardless of how the additional funding was financed. The initial reduction in investment stemming from the interest rate effects would be more than offset by direct investment. As in the R&D capital stock framework, investment would increase over time as the supply of labor increased and the demand for goods and services grew. However, when the policy is deficit-financed, the effect on investment resulting from changes in interest rates grows over time and results in investment beyond 2036 remaining roughly unchanged.

Labor Supply. In addition to the effect that a change in federal funding for R&D would have on the size and composition of the research workforce—captured in the TFP estimates above—changes in the economywide wage rate would also affect the supply of labor more broadly. In the long run, wages reflect the marginal product of labor. All else being equal, higher wages induce workers to work more hours over their lifetime. Whereas increases in TFP boost wages, reductions in capital investment decrease them.

Under the R&D capital stock framework, wages would initially increase after a deficit-financed increase in federal funding for R&D. As the increase in demand attenuated following actions taken by the Federal Reserve, wages would decline slightly before rising again in the long run as the TFP effects discussed above increased the marginal product of labor. If the increase in funding was deficit neutral, wages would remain roughly unchanged through 2031 because the effect of the increase in TFP and the decrease in private investment roughly offset each other in terms of their effect on the marginal product of labor. After 2031, the TFP effect would dominate and wages would begin to rise, increasing the supply of labor (see Figure 11).

Under the R&D components framework, wages would rise from 2027 to 2056 regardless of how the funding is financed. The increase throughout the period would stem from the increase in TFP and the boost to investment, both of which would increase the returns on work and the supply of labor. We do not include effects on wages from additional education and training caused by changes in federally funded R&D. Incorporating such effects is a goal for future work.

Actual GDP. Under both frameworks, in the short run, an increase in federal funding for R&D financed through increases in borrowing (that is, deficit-financed) would increase the demand for goods and services before the supply-side effects reflected in the policy's effect on potential GDP materialized (see Figure 12). Under the R&D components framework, the effect on demand would be further boosted because the increase in federal funding would generate additional R&D investment in the private sector.[25] If the policy was deficit neutral, the direct

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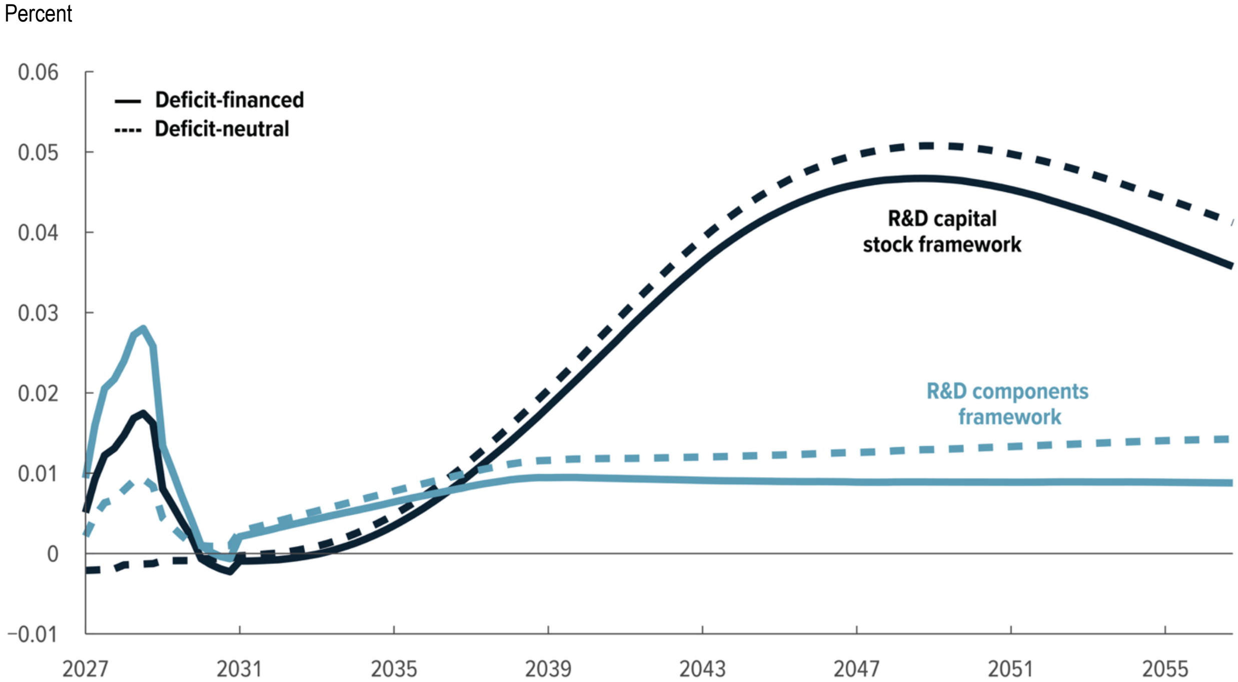
[25] We currently abstract from changes in aggregate demand that result from the crowding-in of private R&D investment under the R&D capital stock approach. However, the effects of those investments on productivity are captured in the TFP effect.

Figure 11.

Effects of an Increase in Federal Funding for R&D on Wage-Weighted Hours Worked



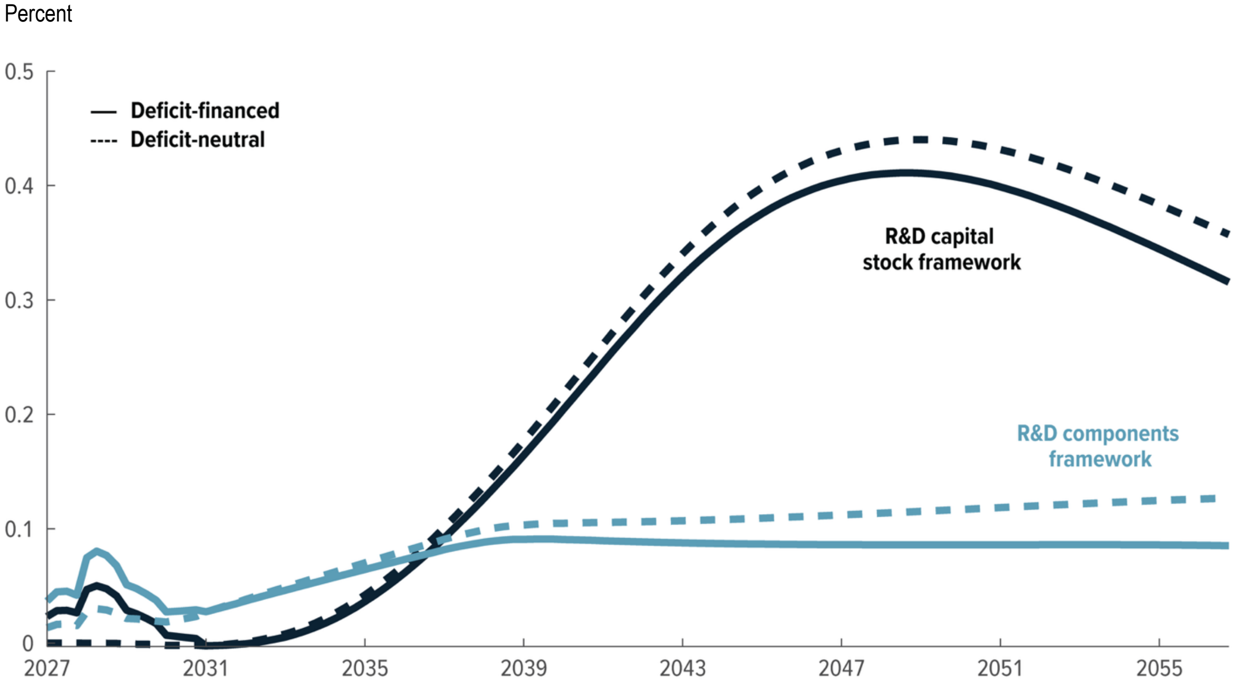
Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

effect on demand coming from federally funded R&D would be offset by an equal reduction in noninvestment government purchases; however, the effect coming from the private complementarity in the R&D components framework would persist.

The direct effect of a $30 billion increase in federal annual appropriations for nondefense R&D reflects the weighted-average spending rates across the seven largest nondefense R&D accounts (see Figure 1). The policy change's direct effect on output reflects changes in purchases by the government and by individuals and organizations receiving federal payments. In addition to the direct effects, policies have indirect effects that enhance or diminish the initial change in aggregate demand as the policy's direct effects on aggregate demand propagate throughout the economy (Whalen and Reichling 2015). These indirect effects can be summarized by a series of demand multipliers, which parameterize how total output is affected for each dollar of spending by the government at different horizons. CBO's central estimate of the demand multiplier—when the federal funds rate is *not* zero and the Federal Reserve is able to respond to changes in inflation and the labor market—has a cumulative effect on output of 1.15 over four quarters and 0.50 over eight quarters. Over time, as labor and capital markets adjust, actual GDP converges to its potential. In the illustrative policies considered in this paper, actual output would converge to its potential over five years.

Figure 12.

Effects of an Increase in Federal Funding for R&D on GDP



Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

To better account for the timing of the economic effects over a 30-year period, we estimated the present value of the future changes in GDP and compared the effects to the present value of federal dollars spent on R&D.[26] In present value terms, a $300 billion increase in federal funding for R&D would increase federal spending on R&D by $231 billion in 2027. Over the 2027–2056 period, an increase in federal funding for R&D—if financed by borrowing—would increase the present value of GDP by $5.15 per federal dollar spent on R&D under the R&D capital stock framework and by $1.98 under the R&D components framework. If financed by a reduction in noninvestment spending, the corresponding results would be $5.41 and $2.24.

Interest Rates. Changes in federal funding for R&D affect interest rates through two main channels. In CBO's assessment, over the first few years following the policy change, interest rates are primarily driven by the Federal Reserve's response to changing economic conditions, as

[26] A present value is a single number that expresses a flow of current and future income or payments as an equivalent lump sum received or paid at a specific time. CBO used a discount rate of 7.0 percent for the macroeconomic changes' effects on deficits; that rate is based on the rate of return on capital in the national income and product accounts data. For the direct effects on the deficit, which are not subject to market risk, CBO used maturity-matched Treasury borrowing rates as the discount rates. For more information about CBO's use of discount rates and the reasons for using Treasury rates and rates adjusted for market risk, see CBO (2024b).

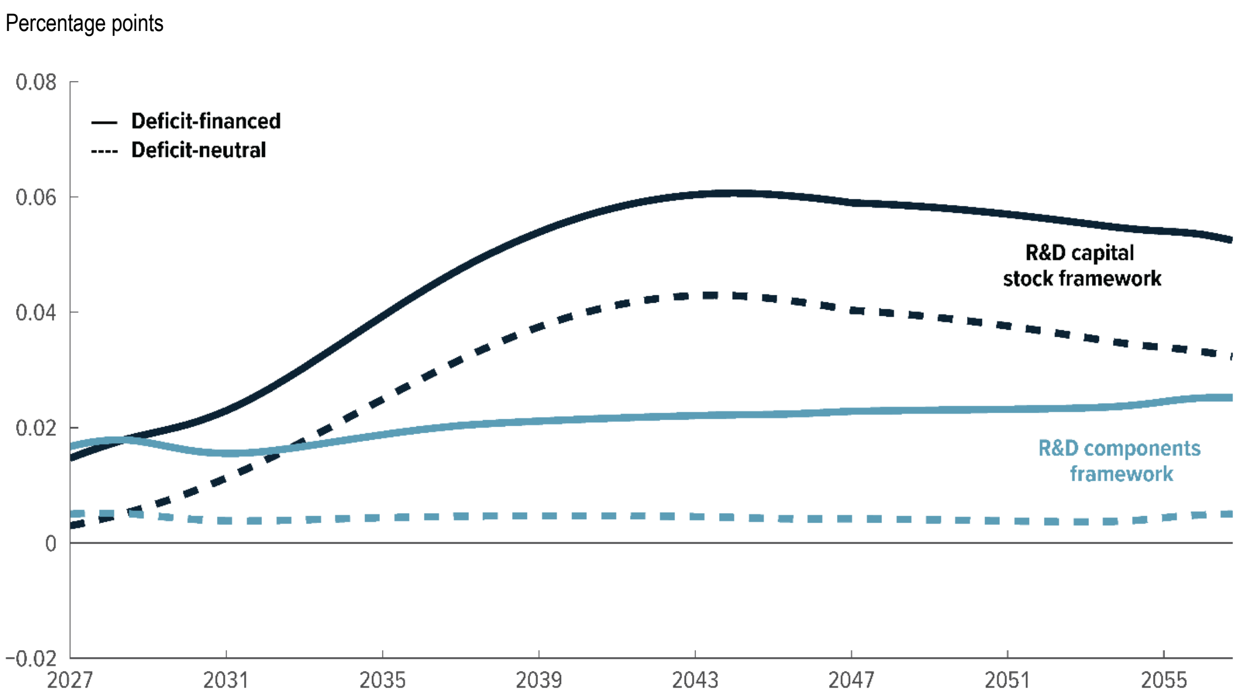
measured by inflation and the output gap (the difference between actual and potential GDP). For example, when an increase in federal funding for R&D is deficit-financed, the increase in government purchases raises demand relative to supply in the short term, increasing the output gap, to which the Federal Reserve responds by increasing interest rates.

In the long run, interest rates are determined by a policy's effect on the natural rate of interest (often referred to as r^*) and the term premium. Increases in TFP growth, the supply of labor, and the debt-to-GDP ratio increase the natural rate of interest. Additionally, increases in the debt-to-GDP ratio increase the term premium. (See Neveu and Schafer (2024) and CBO (2026) for details.)

Under the R&D capital stock framework, increases in federal funding for R&D would increase interest rates throughout the 2027–2056 period, primarily because of the policy's effect on TFP growth. If the policy was financed by an increase in borrowing, the policy's effect on demand—and therefore the monetary policy response—alongside the increase the debt-to-GDP ratio would further push up interest rates. If the policy was deficit neutral before accounting for economic effects, the effect on interest rates would be partially offset by a reduction in the debt-to-GDP ratio. Figure 13 plots the effect of the policy change on the 10-year Treasury note rate. If the

Figure 13.

Effects of an Increase in Federal Funding for R&D on the 10-Year Treasury Rate



Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

policy was deficit-financed, the effect on the 10-year rate over the 2027–2056 period would be about 5 basis points larger, on average, than it is in CBO's baseline projections.

Under the R&D components framework, an increase in federal funding for R&D would also increase interest rates; the magnitude would depend on how the policy was financed. If the policy was deficit-financed, the increase in TFP growth and the initial increase in demand due to higher government spending would slightly increase interest rates (because the Federal Reserve would raise rates in response to economic conditions); those increases would be partially offset by a reduction in the debt-to-GDP ratio later in the 30-year period. If the increase was financed by an offsetting reduction in other government spending, the decline in the debt-to-GDP ratio would offset the effect of faster TFP growth on the natural rate of interest and interest rates would be only slightly higher than projected in CBO's baseline.

New deficits are financed by issuing new government securities at new rates, so under both frameworks and financing methods, the effective rate on government debt would increase slowly over time. Under both frameworks, the effect on interest rates would be smaller if the policy was deficit neutral than it would be if it was deficit-financed (see Figure 13).

5.2 Budgetary Effects

This subsection presents the present value of the budgetary effects of each of the four scenarios over a 30-year window (2027 to 2056). The total change in the deficit can be decomposed into two components: the conventional deficit effect and budgetary feedback. The conventional deficit effect is relevant when a policy is deficit-financed; it includes any increase in outlays associated with an increase in budget authority—which can occur with a lag—including increases in net interest costs owing to the larger stock of debt. Budgetary feedback reflects changes in revenues, primary outlays, and net interest costs that result from changes in the economy. The subsection concludes by presenting the cumulative effect on the present value of the policy's effect on the total deficit and the change in the debt-to-GDP ratio over the 30-year window under both frameworks and financing mechanisms.

Conventional Deficit Effect. Over the 2027–2036 period, an increase in the annual funding for R&D of $30 billion would increase the primary deficit by $266 billion (with the remainder of the funds being spent beyond 2036), or $211 billion in present-value terms. The increase in the primary deficit would increase debt service costs by an additional $51 billion, for a total increase in the present value of the deficit of $249 billion over 10 years—before accounting for economic effects. In the deficit-neutral scenarios, the total deficit effect before accounting for economic effects is zero.

Budgetary Feedback Effect. The budgetary effects resulting from changes in the economy depend on the framework being applied and the policy's means of financing. In general, higher GDP increases taxable income, corporate profits, and consumption and it raises federal revenues through individual income, payroll, and corporate income taxes. Higher GDP, wages, and inflation also increase outlays for Social Security, Medicare, and Medicaid. Those effects are partially offset by a reduction in automatic stabilizers, such as unemployment benefits. Discretionary spending increases with inflation. The largest source of feedback to the federal budget—over the 30-year period—stems from changes in net interest costs. Changes in government borrowing rates apply not only to newly issued debt associated with the increase in funding for R&D but also to debt that already exists in CBO's baseline and would be rolled over at higher interest rates.

Over the 2027–2036 period, the budgetary feedback from an increase in federal funding for R&D would be relatively small because most of the economic effects would occur after 2036. From 2027 to 2036, revenues and primary outlays would increase by similar amounts under all four scenarios. Net interest costs would also increase, but the magnitude would vary across the scenarios. Under the R&D capital stock framework, a deficit-financed increase in funding would increase net interest costs by $48 billion over the first 10 years on a present-value basis. By contrast, under the R&D components framework, a deficit-financed increase in funding would increase net interest costs by $35 billion, in present-value terms, because of the smaller increase in interest rates.

Over 30 years, the budgetary feedback from an increase in funding would decrease the present value of the primary deficit regardless of the framework applied or the policy's means of financing. However, the effect on net interest costs varies across the four scenarios. If an increase was deficit-financed, the increase in net interest costs would be larger than the reduction in the primary deficit under both frameworks. If the policy was deficit neutral, the effect on net interest costs would be larger than the reduction in the primary deficit in the R&D capital stock framework but smaller under the R&D components framework. Under the R&D capital stock framework, budgetary feedback would lead to an increase in the total deficit whereas under the R&D components framework, it would depend on how the policy was financed.

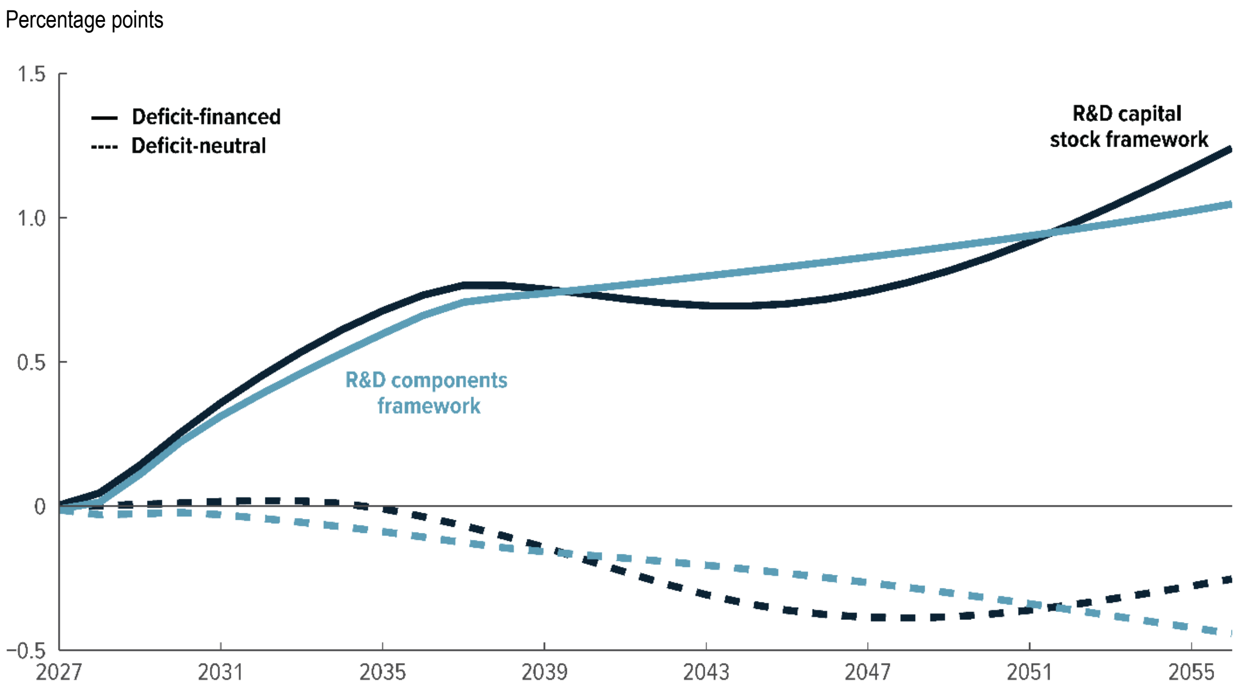
Total Effect on the Deficit. The total effect on the deficit over the first 10 years is driven mostly by how the policy is financed; deficit-financed increases in funding for R&D would increase the present value of the total deficit by $280 billion under the R&D capital stock framework and by $263 billion under the R&D components framework. Deficit-financed increases in funding would increase the present value of deficits over the 2027–2056 period by $609 billion under the R&D capital stock framework and by $463 billion under the R&D components framework. Under the R&D capital stock framework, a deficit-neutral policy would increase the present value of total deficits over the 30-year period by $97 billion. Under the R&D components framework, a deficit-neutral policy would decrease the present value of total deficit by $47 billion.

Across the two frameworks, in present value terms, each federal dollar spent on R&D financed by borrowing would increase the total deficit in the capital stock framework and the components framework over the 2027–2056 period (by $2.64 and $2.01, respectively). If the increase in funding was financed by a reduction in noninvestment spending, before accounting for economic effects, the present value of total deficits would increase by 42 cents per dollar of federal spending on R&D under the capital stock framework and would decrease by 20 cents per dollar under the components framework.

Total Effect on the Debt-to-GDP Ratio. The policies' effects on the debt-to-GDP ratio incorporates both the change in nominal debt and the change in nominal GDP. Under the deficit-financed scenarios, the initial increase in borrowing would raise the debt-to-GDP ratio; however, increases in GDP partially offset that effect. By 2056, the debt-to-GDP ratio would be 1.2 and 1.0 percentage points higher under the R&D capital stock framework and the R&D components framework, respectively, than that ratio is in CBO's projections under current law. If the policy was deficit neutral before accounting for economic effects, the debt-to-GDP ratio would decline over the 30-year period. Under the capital stock framework, debt-to-GDP would be 0.3 percentage points lower in 2056 than projected under current law; under the components framework, that ratio would be 0.4 percentage points lower than projected under current law (see Figure 14).

Figure 14.

Effects of an Increase in Federal Funding for R&D on the Debt-to-GDP Ratio



Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

6. Conclusion

In recent years, there has been Congressional interest in modifying R&D-related policies, including federal funding for R&D. This paper describes two analytic approaches that the Congressional Budget Office has undertaken in service of estimating the economic effects of changes in federally funded R&D: an R&D capital stock approach and an R&D components approach. We then apply these analytic frameworks to estimate the economic and budgetary effects of a set of illustrative policies that change federal funding for R&D by increasing appropriations by $30 billion per year for 10 years.

In this section, we summarize our estimates in terms of present-value effects of a change in federal funding for R&D and discuss sources of uncertainty in our analysis.

6.1 Present-Value Effects of a Change in Federal Funding for R&D

By law, when CBO provides an assessment of the effect of a change in policy on the economy and federal budget it must provide a point estimate. At the time of writing this paper, CBO places equal weight on the R&D capital stock and R&D components frameworks. Table 6 summarizes our takeaways from that combined approach and contains a summary of the present-value effects of an increase and decrease in federal funding for R&D over 10-year and 30-year horizons for both deficit-financed and deficit-neutral (before accounting for economic effects) policies.

Over a 30-year horizon, if federal funding for R&D was increased, the present value of GDP would increase by $3.57 or $3.82 for every federal dollar spent on R&D for the deficit-financed and deficit neutral scenarios, respectively. The effective rate on government debt would increase under both financing mechanisms but that increase would be higher if the policy was deficit-financed. The economic effects of a deficit-financed increase in funding would increase the present value of the primary deficit over a 30-year horizon by about 65 cents for every federal dollar spent on R&D; under a deficit-neutral policy, the primary deficit would be reduced by about 37 cents for every federal dollar spent. In other words, each federal dollar spent on R&D would cost the federal government about 65 cents if the policy was deficit-financed, not including any additional net interest costs. After accounting for the effect on net interest costs, the present value of the total deficit would increase by about $2.32 for each federal dollar spent on R&D if the policy was deficit financed and by 11 cents per federal dollar if the funding was deficit neutral. Taken together, each dollar spent on R&D would cost the federal government between 11 cents and $2.32 over a 30-year horizon, depending on how the increase was financed.

Those estimates highlight the importance of the means of financing, interest-rate dynamics, and the fiscal environment in determining a policy's effect on the federal budget. Over a 30-year horizon, the increase in GDP and other economic effects stemming from the boost to productivity reduces the primary deficit by about 65 cents per dollar of federal spending on R&D

Table 6.

Present-Value Effects of a Change in Federal Funding for R&D

	Increase in federal funding for R&D				Decrease in federal funding for R&D			
	Deficit-financed		Deficit-neutral		Deficit-financed		Deficit-neutral	
	10 years	30 years	10 years	30 years	10 years	30 years	10 years	30 years
Federal funding for R&D (billions of 2027 dollars)	211	231	211	231	-211	-231	-211	-231
	Total change (billions of 2027 dollars)							
GDP	102	823	75	882	-104	-841	-77	-900
Deficit								
Primary deficit	199	150	-9	-86	-167	-112	9	88
Net interest costs	72	386	15	111	-72	-379	-15	-108
Total deficit	**271**	**536**	**6**	**25**	**-240**	**-491**	**-6**	**-20**
	Change per additional federal dollar spent on R&D (2027 dollars)							
GDP	0.48	3.57	0.35	3.82	0.49	3.64	0.36	3.90
Deficit								
Primary deficit	0.94	0.65	*	-0.37	0.79	0.48	*	-0.38
Net interest costs	0.34	1.67	0.07	0.48	0.34	1.64	0.07	0.47
Total deficit	**1.28**	**2.32**	*****	**0.11**	**1.13**	**2.13**	*****	**0.09**

Data source: Congressional Budget Office. See www.cbo.gov/publication/62387#data.

* = between -0.05 and 0.05.

in present value terms when the policy is deficit financed. However, in the current fiscal environment—with federal debt projected to continue increasing—the policy's effect on interest rates and net interest would more than offset the effect on the primary deficit such that the total deficit would increase more than dollar-for-dollar over a 30-year horizon, on a present-value basis.

6.2 Areas of Uncertainty in Our Analysis

A major source of uncertainty in our estimates is that the evidence available from the research literature on many of the ingredients needed to implement our two analytic frameworks is thin on several dimensions. Dating back to work by Zvi Griliches and others, economists have looked to data such as patent statistics to provide a window into the relationship between R&D investments and economic activity. However, the available evidence linking changes in patents with changes in macroeconomic aggregates such as total factor productivity is quite thin (two examples we discussed here are Kogan et al. 2017 and Fieldhouse and Mertens 2026). Similarly, many research papers leverage local-area variation in federal funding for R&D to estimate the relationship between federal R&D investments and innovation outcomes; for example, Cook et al. (2026) analyzes changes in federal R&D investments and changes in STEM training. However, local-area variation in federal funding may result in, for example, local changes in the number of researchers that represent substitution from other geographic areas within the United

States but that do not represent economywide changes in the number of researchers. In implementing the two analytic frameworks presented here, CBO needs evidence connecting changes in federal funding for R&D to changes in economywide aggregate outcomes, such as the economywide number of researchers and the economywide numbers of STEM PhD recipients, estimates which—as far as we know—are only available from Fieldhouse and Mertens (2026).

Our analysis here relies heavily on Fieldhouse and Mertens' estimates, and it is worth saying a few words about the potential implications for our estimates of that reliance. For example, the authors note that the bulk of the identifying variation in their paper is driven by changes in appropriations for NASA, which in 2024 only accounted for about 13 percent of nondefense R&D outlays (as tabulated in Table 1). If there is substantial variation in the economic effects of different types of R&D spending (for example, if NASA's R&D spending has different effects than NIH's spending), the aggregate economic effects of policies that change spending across agencies in a manner representative of the current distribution of federal funding may differ from the estimates presented here. Fieldhouse and Mertens show in their paper that their estimated TFP responses are similar, although less precisely estimated, when NASA appropriations shocks are excluded from their analysis. One potential advantage of the R&D components approach is that, in principle, it allows us to more closely tailor our estimates based on the extent to which different types of R&D spending have differential effects on capital investment and the hiring and training of researchers.

In our work, we have tried to address the inherent uncertainty generated by our heavy reliance on the Fieldhouse and Mertens paper by cross-checking individual pieces of their evidence against the broader research literature. For example, as discussed in Section 3.2, we cross-checked Fieldhouse and Mertens' estimate of the complementarity between changes in federal funding for R&D and changes in nonfederal investments against a broader range of evidence and find that their estimate falls reasonably close to the center of the distribution of evidence from the literature. But additional research, particularly on the question of how changes in federal funding for R&D change the number of researchers and the education and training of those researchers at an economywide level would broaden and deepen our basis of assessment for this analysis.

Several additional areas of uncertainty in our two analytic approaches are worth highlighting as areas where additional research would be particularly useful. For the R&D capital stock approach, conceptual frameworks for and empirical estimates of the economywide depreciation rate for R&D capital would be helpful for our modeling of how the R&D capital stock evolves over time.

Our R&D components framework is in many ways built on a thinner basis of assessment than our R&D capital stock framework. Conceptually, the components framework requires us to model which individuals (researchers or other people whose work is supported by federal funding for R&D) contribute to innovative activity that has spillovers to total factor productivity and to estimate how the size and education or training of that group changes with changes in federal funding for R&D. As detailed above, given the thin evidence available on this point, we rely heavily on estimates from Fieldhouse and Mertens (2026), who document a stark result: Changes in federal funding for R&D result in changes in the number of researchers in the economy for only about 10 years after the shock (that is, temporarily). In contrast, the recent work of Cook et al. (2026) suggests that changes in federal research funding are likely to generate more persistent expansions in the supply of skilled labor because those changes increase, for example, the number of bachelor's degree recipients in STEM fields. Additional evidence on the magnitude and timing of those reallocation and training responses would deepen and broaden our basis of assessment.

Additional conceptual frameworks and empirical estimates of the relative TFP contributions of researchers with different educational attainment and training would be helpful. In this paper we quantify those training effects only for STEM PhD recipients, but additional training of undergraduate students, masters' students and postdoctoral researchers supported by federal funding may also contribute to TFP.

The economic effects of increases and decreases in federal funding for R&D are approximately linear and symmetric in both analytical frameworks presented here (capital stock and component), and additional evidence on the reasonableness of that assumption over the range of changes considered here would be valuable. Consider peer-reviewed grants from NIH. If peer review was successful at ranking grants on the basis of their expected TFP effects, one might expect nonlinearities in our estimates.[27] One test of whether linearity is a reasonable assumption is to ask whether the extrapolated effects of smaller changes in NIH funding from Azoulay et al. (2019) are consistent with the estimated effects of larger changes in NIH funding (a 40-percent change) from Azoulay et al. (2025).[28] To the best of our knowledge, the research literature has not yet generated that type of evidence. We are grateful to Fieldhouse and Mertens who provided us with some additional tabulations from their data, which—although statistically imprecise—did not provide strong evidence of nonlinear effects in their data. Taken together, our assessment of the available evidence is support for linearity in effects over the range of changes up to

[27] Although there is a statistically significant relationship between peer review scores and subsequent grant outcomes (see Li and Agha 2015 and Clancy 2023), several pieces of evidence in the research literature suggest that the outcomes of grant-funded research may be difficult to predict in advance, which could be interpreted as one factor pushing against the expectation of strong nonlinearities. For example, Azoulay et al. (2019, Table 9, Panel IV, columns 4 and 5) suggest that an additional dollar of NIH funding in a given area (such as cancer) is as or more likely to generate drug patents in other areas (such as heart disease) as it is to general drug patents related to cancer drugs. A second example is from Li et al. (2017), whose Figure 2 documents that "basic" and "applied" NIH grants—by a variety of definitions—are similarly likely to lead to drug patents with similar time lags.

[28] Although it is complicated to precisely construct this type of comparison solely on the basis of the published estimates in these two papers, we implemented a rough version of the approach. It suggested that a scaled-up version of the Azoulay et al. (2019) estimates would fall in the same range as the estimates in Azoulay et al. (2025), thus not providing strong evidence of nonlinear effects in this setting.

$30 billion per year, but we do not currently have a basis for extending beyond that size of change.

Beyond this linearity point, both the R&D capital stock approach and the R&D components approach would be improved by a deeper understanding of several other factors. For example, understanding how indirect costs can be decomposed into labor and nonlabor costs, both at higher education institutions and for other recipients of federal funding for R&D, would be helpful. In addition, research aimed at understanding how federal funding for R&D interacts with other areas of government action, including immigration policies and regulations, would provide additional insights into the economic effects of federal funding for R&D (see, for example, Tham et al. 2024). In addition to the sources of uncertainty that apply to the specific analytical frameworks developed in this paper, CBO has written separately about broader sources of uncertainty in the macroeconomic analytical frameworks that are applied in this paper. Those sources of uncertainty include how changes in factors, such as the federal debt and potential TFP, affect CBO's projection of the natural rate of interest; see CBO (2026) for one discussion of those issues.

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Appendix

This appendix provides additional details about the data construction underlying our research and development (R&D) components framework.

Estimating Labor and Nonlabor Cost Shares

We partition federal spending for domestic nondefense R&D into labor and nonlabor costs using data that record federal domestic nondefense R&D obligations and R&D spending patterns across R&D performers (higher education institutions; federal, state, and local governments; businesses; nonprofit organizations; and federally funded research and development centers, or FFRDCs). As detailed below, this part of our analysis primarily draws on National Center for Science and Engineering Statistics (NCSES) surveys from the National Science Foundation (NSF), along with R&D Satellite Account data from the Bureau of Economic Analysis (BEA).

Table A-1.

Average Shares of R&D Costs, by Type of Performer, 2010 to 2023

Percent

	Labor	R&D plant	Other	Share of total federal spending on nondefense R&D (weight)
Higher education institutions	61	7	32	0.37
Federal agencies	36	2	62	0.27
Businesses	65	7	28	0.15
FFRDCs	60	10	30	0.11
Nonprofit organizations	55	5	40	0.09
State and local governments	75	2	23	0.01
Weighted average	54	6	40	

Data source: Congressional Budget Office, using data from various sources (see appendix for complete list). See www.cbo.gov/publication/62387#data.

Labor, R&D plant, and other cost shares represent the composition of total R&D expenditures made by each type of performer over the years of the 2010–2023 period for which such composition data are available. The federal spending weight for each type of performer was calculated by dividing the cumulative federal obligations for nondefense R&D made to that type of performer over the 2010–2023 period by the total federal obligations for nondefense R&D over that period. The weighted average was computed using those federal spending shares as weights. See the "Data Sources" section for the corresponding sources. The appendix describes imputations and adjustments made to the underlying data.

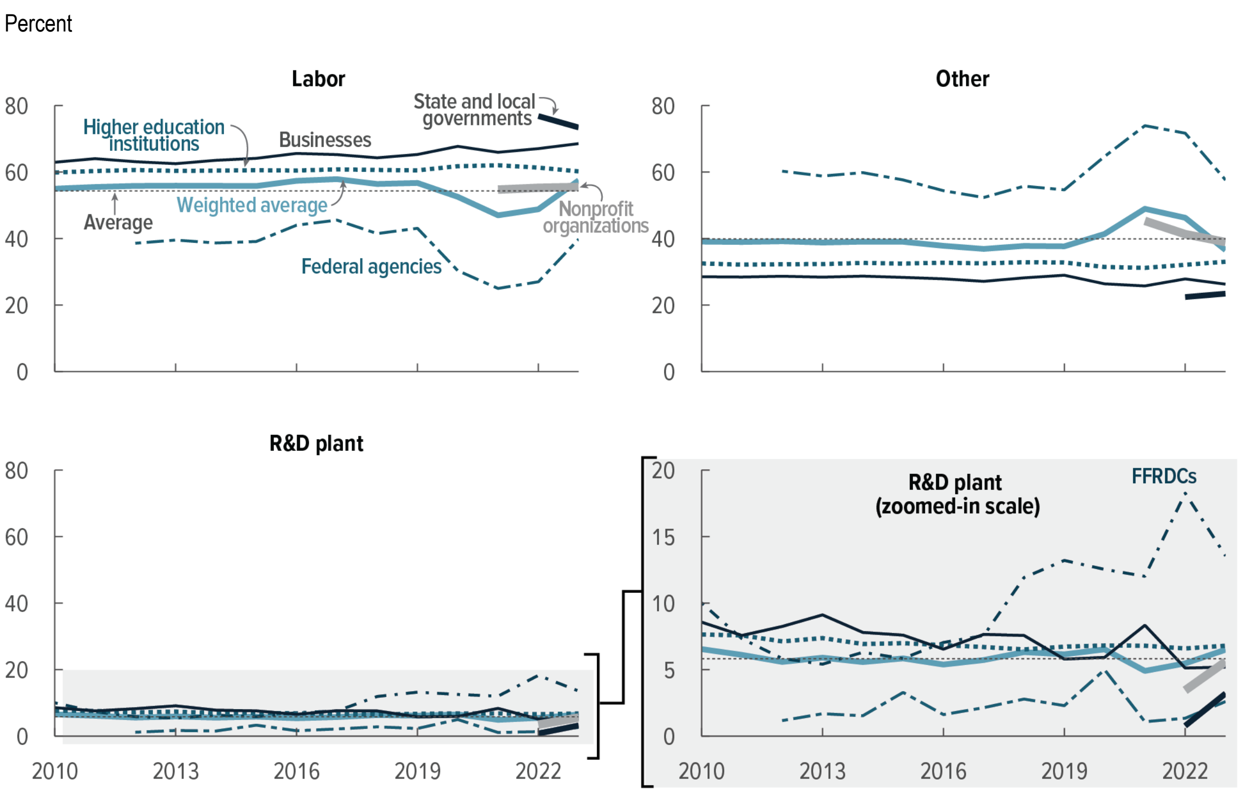
FFRDCs = federally funded research and development centers.

As displayed in Table A-1, we calculate these metrics separately for each type of performer, using available data over the 2010–2023 period, and then take a weighted average across performers, weighting by each performer's share of federal spending. Nonlabor R&D costs consist of "R&D plant" and "other costs," which in the R&D components framework we treat as capital. R&D plant (called "capital expenditures" in some surveys) includes investments in land, physical assets, and equipment that has a useful life of more than one or two years (depending on the survey). NCSES surveys typically list R&D plant or capital expenditures separately from other R&D costs, so we report them separately in Table A-1 for completeness. We calculate "other costs" as a residual, encompassing all nonlabor R&D costs not recorded as R&D plant or capital expenditures.

Figure A-1 displays some additional descriptive statistics about those data. In the labor panel, labor costs include salaries, benefits, and (for business performers) stock-based compensation of R&D employees. Costs for temporary and contract workers are also included for nonprofit, business, and higher education performers. In the other-costs panel, other costs are calculated as residual R&D costs after subtracting labor costs and R&D plant costs. The thick blue solid line in each panel represents the cost-type share for all domestic nondefense R&D spending, calculated as a weighted average of all performers, with each performer weighted by its respective share of federal domestic R&D spending in the given year. To construct the weighted

Figure A-1.

Annual Shares of R&D Costs, by Type of Performer, 2010 to 2023



Data source: Congressional Budget Office, using data from various sources (see appendix for complete list). See www.cbo.gov/publication/62387#data.

The panels show the time series underlying the average shares of R&D costs displayed in Table A-1 as well as the years for which such data are available for each type of performer.

FFRDCs = federally funded research and development centers.

average, we include the average over available years for years in which a performer's cost share data are unavailable. The thin black dotted line in each panel represents that weighted average aggregated over the entire period—which, for the labor share, is the 54 percent we rely on in the R&D components framework.

One source of uncertainty in this analysis involves interagency transfers, which in 2023 accounted for around 4 percent of total R&D spending (NCSES 2025d). Data on labor and nonlabor costs are not available for those transfers.

Overview of Data Sources

This section provides additional information about the data sources underlying this analysis.

Data Derived From NSF's NCSES Surveys

- Higher Education R&D Survey (HERD): Labor costs, capital expenditures, other costs, and total costs for higher education performers.
- Annual Business Survey (ABS): Labor costs, capital expenditures, other costs, and total costs for business performers with nine or fewer employees.
- Business Enterprise R&D Survey (BERD): Labor costs, capital expenditures, other costs, and total costs for business performers with more than nine employees.
- Survey of Federal Funds for R&D (SFFRD): Total costs and R&D plant for federal agencies and FFRDCs; federal spending on R&D by performer.
- Nonprofit Research Activities Survey (NPRA): Labor costs, capital expenditures, other costs, and total costs for nonprofit performers.
- Survey of State Government R&D (SSGRD): Total costs and R&D plant for state government performers.

Data Derived From BEA's R&D Satellite Account

- Research and Development Satellite Account (BEA R&D): Labor costs (referred to in the account as "compensation") to supplement data for federal and state government performers from the SFFRD and SSGRD, respectively. (See the "Other Imputations and Adjustments" section below for more details.)

Data Coverage

Because of data availability, coverage for performers and metrics varies. For higher education and business performers, we use data for 2010 to 2023 from the HERD and BERD surveys. For federal agencies, we use data for 2012 to 2023 from the SFFRD and BEA R&D sources; for FFRDCs, we use data for 2010 to 2023 from those sources for the R&D plant share metric but impute the labor share and other-cost share (see the "Other Imputations and Adjustments" section below). For nonprofit performers, we use data for 2022 and 2023 from the NPRA survey. For state government performers, we use data for 2022 to 2023 from the SSGRD and BEA R&D sources for the labor share, R&D plant share, and other-cost share metrics.

Data Sources for Federal Domestic Nondefense R&D Spending

To calculate federal spending for domestic nondefense R&D from the SFFRD data, we take total R&D obligations and subtract the Department of Defense's R&D obligations, the National Nuclear Security Administration's R&D obligations, and obligations to foreign R&D performers. We subtract R&D spent on foreign performers to be consistent with the way foreign R&D is treated in the Congressional Budget Office's tax and investment models.

Data Sources for Labor, R&D Plant, and Other-Cost Metrics

We collected data on R&D performer costs from 2010 to 2023, though the availability of data differed by data source and variable. BEA R&D provides data for 2012 to 2023. NCSES data coverage varies significantly, both among surveys and among variables. NCSES provides custom table-builder tools for the HERD, SFFRD, and SSGRD surveys. For other NCSES surveys, we downloaded relevant premade tables that NSF provides on a year-by-year basis to construct the time series of relevant variables.

For each performer, we calculate cost-type shares as a share of total R&D costs, defined as all R&D expenses, minus depreciation (if captured by the NSF survey), plus R&D plant (called "capital expenditures" in some surveys). Generally, R&D plant includes payments for assets with a useful life of more than one or two years (depending on the survey), such as land, structures, equipment, and capitalized software.[29]

Labor Cost Share

- For all performers, labor costs include spending on salaries, wages, and benefits of R&D personnel, including administrative and support staff.
- For business performers, labor costs also include stock-based compensation.
- For higher education performers, labor costs also include a portion of indirect costs, which NSF surveys do not disaggregate by cost type (see the "Other Imputations and Adjustments" section below).
- For state government performers, since SSGRD tables do not provide labor costs, we use BEA R&D compensation data. Specifically, we take state and local labor compensation and

[29] See the definition of "capital expenditure" in the description of the BERD survey methodology at https://tinyurl.com/2f2wyfxb or the definition of "R&D plant" in the description of the SFFRD methodology at https://tinyurl.com/2yh29vej.

subtract the public higher education component (line code 20 − (line code 21 − line code 14)) to obtain labor costs for state government performers.

R&D Plant Share

- For government performers and FFRDCs, we use “R&D plant” data from the SSGRD and SFFRD surveys.
- For higher education performers, we calculate R&D plant as the sum of “capitalized software,” “capitalized equipment,” and about 15 percent of “total indirect costs” from the HERD survey (see the “Other Imputations and Adjustments” section below).
- For industry performers (BERD and ABS surveys) and nonprofits (NPRA survey), the analogous concept is “capital expenditures.”

Other-Cost Share

- We calculate other costs as a residual: total costs minus labor and R&D plant. Other costs include expenses associated with R&D, such as materials and supplies; expensed (noncapitalized) equipment; royalties and licensing; lease and rental expenses; and other nonlabor indirect or overhead costs.
- When depreciation is reported as an expense in an NSF survey, we subtract it from total costs. That avoids double-counting capital spending, since depreciation represents previous capital expenditures expensed over time.
- For higher education performers, we also subtract “passed through to subrecipient” costs to avoid double-counting spending.

Other Imputations and Adjustments

Adjusting Federal Agencies’ Total R&D Costs in the SFFRD to Include Employee Benefits

Because labor costs exclude employee benefits in the SFFRD but include them in BEA R&D, we adjust the total costs from the SFFRD upward to account for the costs of employee benefits. Specifically, we calculate the difference between BEA R&D labor costs and SFFRD labor costs (which represents benefit costs) and add that amount to total R&D costs from the SFFRD. In addition, because the SFFRD does not report labor costs for 2022 and 2023, we impute benefit costs for those years by assuming that benefits’ share of total labor costs remains unchanged.

Allocating Indirect Costs for Higher Education Performers

NCSES tables provide disaggregated R&D cost-type data for higher education performers’ direct costs but not for their indirect costs. We therefore impute the labor, R&D plant, and other-cost shares of indirect costs using data from two sources: Table II.1 in Government Accountability Office (1995) and Tables 4.1 and 4.2 in Goldman et al. (2000). Those sources disaggregate indirect cost rates, which represent indirect costs as a percentage of direct costs, into various components. The sources differ by time period (1986 to 1995 and 1988 to 1999, respectively) and by sample of higher education institutions. We take the midpoint of the shares calculated from each source.

From those tables, we calculate the share of indirect costs devoted to infrastructure (called "use allowance and depreciation" in Government Accountability Office 1995) and the share devoted to administrative costs. We allocate the infrastructure share to R&D plant, the administrative share to labor, and the residual to other costs.

For example, Table II.1 in Government Accountability Office (1995) indicates that from 1986 to 1995, administrative costs made up about half of indirect cost rates (roughly 25 percentage points out of a total rate of about 50 percent). We allocate about 50 percent of indirect costs to labor, about 15 percent to R&D plant, and about 35 percent to other costs.

Imputing the Labor Share and Other-Cost Share for Federally Funded Research and Development Centers

Since the SFFRD reports R&D plant for FFRDCs but does not report labor costs, we impute the labor share and other-cost share. For context, FFRDCs are funded almost entirely by the federal government but are managed by universities, nonprofit organizations, or private-sector businesses. Reflecting that institutional arrangement, we impute the labor share for FFRDCs as a weighted average of the higher education, nonprofit, and business labor shares, weighting by the shares of federal funding to FFRDCs that are managed by universities, nonprofit organizations, and private-sector firms. The other-cost share is computed as a residual, ensuring that the labor, R&D plant, and other-cost shares sum to 1.