U.S. National Science Foundation
Evaluation and Assessment Capability

NSF Economic Impacts: Literature Review

March 2026

A report from the Evaluation and Assessment Capability of the U.S. National Science Foundation

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About this report

This report was prepared for EAC under contract number 49100421D0013, order number 49100424F0028. The views expressed are those of the authors and should not be attributed to NSF, nor does mention of trade names, commercial products, or organizations imply endorsement of same by the U.S. Government.

Preferred citation

Schnell, Joshua, Aviva Litovitz, Jeffrey Alexander, Adams Bailey, Carly Dotson, Joshua Fletcher, Lena Leonchuk, Jonathan Merker, Meaghan McGrath, Patrick McHugh, Jennifer Ozawa, Marwa Salem, and Amanda Walsh. 2026. *NSF Economic Impacts: Literature Review*. Alexandria, VA: U.S. National Science Foundation.

NSF Economic Impacts: Literature Review

Submitted to:

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ABSTRACT

The U.S. National Science Foundation (NSF) worked with Research Triangle Institute (RTI) International to identify rigorous methods for estimating the economic impact of NSF's funding for research via a systematic review of the literature on the theory and empirical work linking research to economic impacts. The review begins with descriptions of the research NSF supports. It continues with the theory underlying government support of research and development (R&D) and the links between R&D and economic growth. The review then explores empirical work on the relationship between R&D and economic impacts, including indicators and performance measures; the economic impacts of R&D awards themselves, independent of any impacts of discoveries; and the economic impacts of resultant discoveries. The review aims to present key strands of existing work and highlight the methods, data, and estimates most applicable to estimating the economic impacts of NSF's R&D funding.

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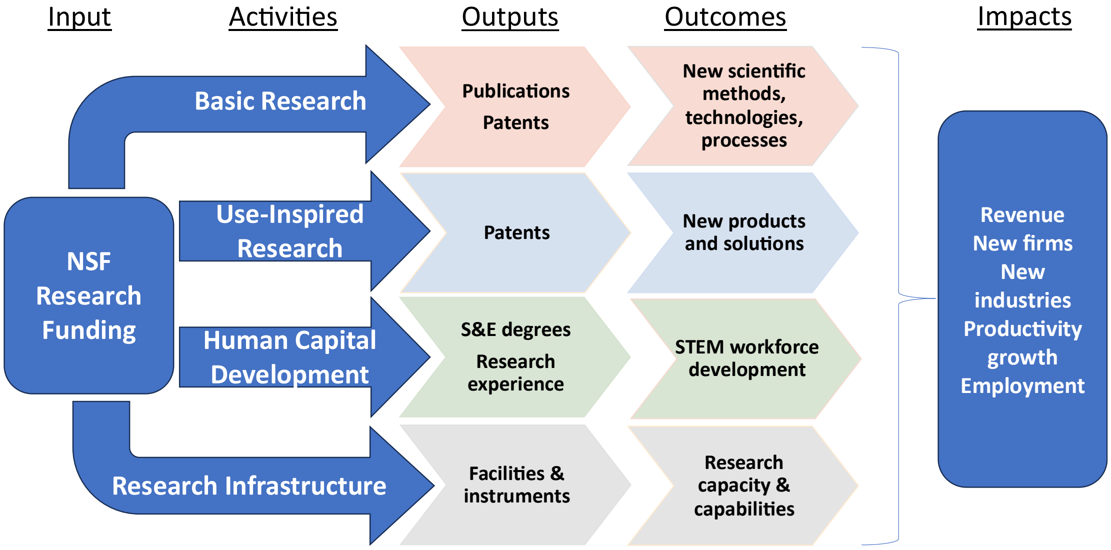
Executive summary

The U.S. National Science Foundation (NSF) is the only U.S. federal agency whose mission is to invest in basic research and human capital development across the full spectrum of science, technology, engineering, and mathematics (STEM) disciplines, excepting the medical sciences (U.S. National Science Foundation 2023). Congress established NSF in 1950 with the goals of advancing economic and other forms of well-being as well as securing the national defense (U.S. Congress 1950). In support of this mission, NSF awards are sizable, far reaching, and used to carry out research for public purposes, primarily through merit-based awards to educational institutions, businesses, nonprofit research institutions, and other organizations engaged in research.

To identify rigorous methods for estimating the economic impact of NSF's funding for research, NSF worked with Research Triangle Institute (RTI) International to examine the literature linking research to economic impacts. Exhibit 1 motivates possible impact pathways contributing to the economic impacts of NSF's research and development (R&D) funding with components that represent: a) the research activities enabled by NSF R&D support; b) the intermediate outputs and outcomes arising from those activities; and c) the varied economic impacts stemming from those outputs and outcomes, both for short-term R&D investments and from longer-term discoveries arising from that R&D.

Exhibit 1: Impact pathways for NSF R&D support



Note: Exhibit 1 is stylized to show the types of measurable outputs and outcomes that result from each type of NSF research award. Although represented as such, the achievement of research impact may not be a linear process. For example, outcomes from basic research such as new technologies and processes may beget other research, such as additional basic research or use inspired research, before downstream industrial outputs such as new firms, revenue, or employment are impacted.

In this report, RTI International provides a systematic review of the literature on measuring the economic impacts of R&D investments and related activities. Specifically, we document:

- The types of research supported by NSF,
- Theoretical justifications for government's role in R&D,

- Theories of change that relate R&D to economic growth,
- Indicators and performance measures of research investment, and
- Empirical literature examining the relationships between R&D awards and economic impacts.

Our review of the literature focuses on the data and approaches most often used as well as the most common measures of economic impacts (such as economic growth, productivity, and employment) and intermediate outcomes that have been tied to these economic impacts such as publications, patents, and the development of the STEM workforce. After, we highlight findings of particular relevance to NSF and the types of funding NSF typically provides. Next, we examine the literature on the economic impacts of research awards (e.g., the economic impacts of awards). Last, we examine the literature on the economic impacts of the research, discovery, or output from those research awards (e.g., the economic impacts of discoveries).

What types of research support does NSF provide?

NSF is the federal agency charged with funding research activities, resources, and people engaged in fundamental research across the entire range of science and engineering disciplines.

Most of the NSF's support for R&D is funded through its **Research and Related Activities** (R&RA) account. The Foundation distributes research funding awards to universities, nonprofit research institutes, and other performers through programs housed in its eight directorates (plus some programs within its Office of the Director). Award recipients are selected primarily from investigator-initiated proposals submitted to the NSF and subjected to rigorous peer review to support those representing high standards of intellectual merit while also generating benefits to the nation's economic and social well-being.

NSF supports **human capital development** by funding students through R&RA activities and through the Directorate for STEM Education (EDU). NSF R&RA funding prepares the next generation of STEM professionals, retains Americans in STEM careers, develops a robust research community, expands the population of Americans who can productively participate in an increasingly technological market, and increases the technological, scientific, and quantitative literacy of the United States. EDU supports science, technology, engineering, and mathematics at all levels, including both formal and informal educational settings.

NSF plays a key role in funding major **research facilities and equipment**. Infrastructure, facilities, and major equipment are often grouped together as providing the physical capabilities and environment necessary to conduct R&D.

What are the theoretical justifications for government's role in R&D?

Government is a major source of R&D funding, as well as an R&D performer in most industrialized countries, such as those in the OECD countries, and in rapidly industrializing countries, such as China. In 2022, the U.S. federal government provided approximately 18% of gross expenditures on R&D in the United States and nearly 40% of expenditures on basic research. The literature identifies several theoretical justifications for federal support of R&D, including creating positive externalities and spillovers, mitigating risk and uncertainty, supporting economies of scale, strengthening the United States global strategic strength, and supporting human capital development:

- **Positive externalities** occur when economic activity generates benefits that extend beyond the immediate participants. **Spillovers** are the unintended and non-compensated benefits that result from economic activity. Private actors may be disincentivized to invest in R&D, particularly basic research, which would result in an economically and socially sub-optimal level of funding for R&D. Public investment in research contributes to the stock of available knowledge, and scientific knowledge has economic value. Unexpected scientific discoveries may also provide insights for leveraging principles of nature to create novel and useful technologies.

- Government support for R&D can **reduce the risk** inherent in the process of bringing new technologies and products to market. Firms are generally risk-averse in selecting investments and risk-adverse capital markets often underinvest in innovation from small companies, missing opportunities that can disrupt existing markets and practices. By bearing part of the cost, the government reduces the risk facing private industry, allowing greater investment in projects with significant economic potential.

- **Economies of scale** occur when the average cost of production decreases as output increases, making large-scale investment in R&D more efficient than small-scale efforts. Government funding is key to achieving economies of scale because R&D investment exhibits increasing returns to scale, but private firms often lack the incentives to fund large scale research projects and infrastructure.

- In an increasingly globalized economy, maintaining a **strong national research base** is essential for economic and technological leadership. During the post-war era, increased federal R&D funding supported the development of the research infrastructure, both physical and human, that made the United States a global leader in developing new technologies and products.

- Government investment is key to **training the next generation of scientists and engineers**. Government-financed R&D contributes to the total size and geographic distribution of a country's science and engineering workforce. Science and engineering workers with previous experience on government funded research projects are particularly valuable to the private sector because they bring specialized knowledge, skillsets, and professional networks.

We also review how NSF supports basic research, use-inspired research, human capital development, and research infrastructure align with the theoretical justifications for governmental investments in R&D from the literature.

- While there is broad support among economists for NSF's basic research investments, the concerns for NSF reflect the need to assess the economic returns on investments, ensure that NSF awards complement rather than crowd-out private R&D investments, demonstrate that NSF awards contribute to the research talent base in the United States, and validate the economic impacts of R&D infrastructure.

What theories of change relate R&D to economic growth?

R&D is associated with long-run economic growth, or the increase in the total value of goods and services produced in an economy over time. Economic growth is measured by changes in real gross domestic product (GDP) and changes in real per capita GDP. Higher rates of economic growth are associated with higher levels of production, more jobs, higher incomes, and less poverty. Even small differences in growth over a sustained period can generate large differences in living standards.

There is a strong line of **macroeconomy theory** in the literature relating investments in technological change and R&D to economic growth. Modern economic theory treats R&D as endogenous to economic growth because it is the result of decisions made by profit-maximizing firms. R&D becomes embodied in the physical capital of machinery and equipment owned by firms that conduct R&D and the knowledge and experience of the human capital who perform R&D. Both forms of capital are factors of production that contribute to productivity gains and economic growth.

Microeconomic theory also associates R&D with economic growth through the productivity of firms. Discoveries from R&D can increase the efficiency of labor and capital in their production of industrial outputs. Microeconomic work has long focused on the spillover effects of federal research but also private research investment which contributes to productivity gains and economic growth beyond firms engaged in R&D.

As a federal research funding agency that invests in basic research, use-inspired R&D, human capital development, and research infrastructure, NSF contributes to the development of the physical and human capital required to achieve productivity gains and economic growth associated with R&D. NSF also supports the translation of R&D into commercialized technologies at the earliest stages.

What are the indicators and performance measures of research investment?

To measure the contribution of NSF support for research and related activities to economic growth, researchers rely on a variety of specific macroeconomic or microeconomic statistics, or "indicators." No single indicator fully captures the relationship between the different types of R&D performed in an economy and their economic impact. In particular, to capture the long-term economic impact arising from discovery, it is often necessary to rely on a series of indicators of intermediate outcomes that connect the original investments in R&D to their ultimate economic impacts. Some of these outcomes will be successful, and some will not.

Several types of indicators and the most prominent sources for these indicators are reviewed, including indicators of R&D investment, the development of knowledge capital, the development of human capital, the output of research commercialization, and finally of economic impacts. Common indicators of R&D investment include federal research funding levels and private and public research expenditures. Common indicators of knowledge capital include the net capital stock of structures and equipment, scientific publications, and patents. Common indicators of human capital include occupational employment, industry employment, and degree completion. Common indicators of commercialization include reported rates of innovation by firms, the creation of new establishments, and company sales related to new products and business lines resulting from innovation. Common indicators of economic impacts include total factor productivity, GDP, employment, and employee compensation.

Indicators of investment are often used in the literature as the control variable of interest and indicators of economic impacts are often treated as outcome variables. Indicators of knowledge capital, human capital, and research commercialization have been used in the literature as control variables predicting economic impacts and as outcome variables as indicators of the outcomes of research funding.

How does the empirical literature estimate the short-term economic impacts of R&D awards?

Regardless of any discoveries made, government investment in R&D impacts the economy through spending on labor, equipment, and supplies. The direct impact of R&D spending generates secondary and tertiary impacts in other sectors of the economy through the personal spending of science and engineering (S&E) personnel engaged in research. These spending impacts are likely to be relatively short term. Government investment in R&D can also stimulate co-investment and follow-on investment in R&D from other sources including private companies and research institutions. Federal R&D funding also contributes to human capital development and to scientific infrastructure such as equipment and facilities. We address two fundamental approaches to studying the impacts of R&D investments: **Input-Output (I-O) models** and **econometric methods**.

- The **I-O approach** is designed to trace the interconnections of economic impacts across regional and national economies. I-O approaches have been used to evaluate the economic impacts of government-funded research activities such as the economic impact of R&D performed by federal agencies, R&D funded by federal agencies but performed by others, investment in the construction and purchase of research infrastructure, and federally supported S&E student spending.

- **Econometric approaches** have been used to assess the economic impacts of federal investment in research activity, human capital, and research infrastructure; how federal awards act to stimulate non-federal R&D investments; and how awards contribute to human capital development. A review of the literature identified econometric approaches that have been used to estimate the impacts of awards on employment and GDP; however, fewer econometric studies were completed than the I-O approach. More econometric studies have been devoted to intermediate outputs of research activities, finding evidence that governmental awards can stimulate non-federal sources of research funding and contribute to human capital development.

The literature review demonstrates the applicability of both I-O and econometric approaches to several types of economic impacts and intermediate outcomes of NSF awards. Both I-O and econometric approaches can be used to evaluate the short-term economic impacts of NSF awards at the national, state, and local levels. Both approaches can also be used to evaluate economic impacts for specific funding programs and institutional economic impacts.

Based on the literature, it is likely that the I-O models represent the most practical approach to studying the short-term economic impacts of NSF awards due to their ability to estimate multiple types of economic impacts (e.g. contributions to GDP, employment, and employee compensation) in a single modeling framework where econometric approaches require separate models for each indicator of interest. Only I-O models were found in the literature to have been used to evaluate the economic impacts of construction and maintenance of research infrastructure and students spending.

Econometric approaches produce the leading approach to evaluating how NSF awards stimulate R&D investments from non-federal sources and contribute to human capital development including degree completion and post-degree job placement.

How does the empirical literature estimate the long-term economic impacts of discoveries?

R&D investment and activity can lead to inventions and innovations that contribute to productivity gains and fuel economic growth. The economic impact of R&D-financed technologies are generated when new technology is commercialized successfully—either by selling the product or service or adopting it into a production process or business process. However, economic impacts can also arise through technologies that are freely available for use.

Most scholarly studies on R&D investments focus on how they drive productivity gains, reduce costs, and generate returns on investment. Foundational economic studies found that R&D investment can explain differences in productivity growth across national economies and, because the benefits of discovery can spill over from one company or country to another, private actors often invest at a level that is suboptimal for society. Four approaches to evaluating the economic and societal impacts of R&D have generally been used: **production function**, **cost function**, **input-output (I-O)**, and **cost-benefit**.

- The **production function** approach is the most widespread approach to assess the economic impacts of R&D. In this approach, measures of innovation activity, including private and public investment in R&D, are treated as factors of production along with others like labor and capital. The most extensive literature using the production function approach examines the elasticity of production or total factor productivity to R&D funding and related activities. The production function approach has also been used to estimate the added value generated by federal research spending and the return on R&D investment of federally supported discoveries. Intermediate outcomes of investment in R&D have also been assessed, including the production of patents and sales of resulting products and services.

- The **cost function** approach focuses on how expenditure on R&D is driven by firms' efforts to minimize future production costs. The production efficiency of R&D is weighed against other factors of production, with the model identifying which factors of production would produce the greatest marginal returns. The cost function approach can only be used to estimate rates of return on privately funded R&D investments. Cost function approaches cannot be used to assess the returns to R&D performed by public research institutions or academia due to the cost minimization modelling approach that is used.

- Because **I-O** models cannot directly measure the economic impacts of discovery, they have been used instead to estimate the economic impact of sales generated by the goods and services that were developed with support from federal R&D. These studies have generally focused on NSF and other federal agency Small Business Innovation Research and Small Business Technology Transfer (SBIR/STTR) programs, which are commonly referred to as the federal government's seed fund. I-O modeling is feasible for measuring the impact of federal funding of basic research or research infrastructure, such as equipment.

- **Cost-benefit analysis** is used to estimate the private or social rate of return of investments in R&D activities and facilities. The cost-benefit approach has been used widely in the literature to evaluate the socio-economic impacts of specific portfolios of R&D awards, inventions, and major research infrastructure.

The review of the literature demonstrates how different approaches can be used to evaluate the economic impacts of discoveries emerging from NSF-funded R&D.

- The **production function** approach can be used to study the impacts of NSF-funded research and discoveries. The simplest production functions are used to measure the impact of R&D expenditures, primarily by private industry. Production function models include intermediate outputs, such as patents and capital stock, that can be used to evaluate the impacts of different types of funded research (e.g. basic research vs. use-inspired research), as well as spillovers across geographic regions such as states. The reviewed literature did not identify studies that use the production function approach to estimate impacts for specific funding programs. Production functions that use multiple stages of regressions to track the process from awards to commercialization may be particularly applicable to basic research where there are often multiple stages of research and development before products or services are brought to market.

- Because the **cost function approach** focuses on the cost-saving decisions of profit-maximizing firms, it has less applicability to the economic impact of NSF-funded R&D. The cost function approach has been used to evaluate the spillovers of R&D across industries and regions but is less applicable to many of the types of awards NSF makes for basic research, human capital development, and research infrastructure.

- The **I-O approach** has been used to study the economic impacts of SBIR/STTR-supported research commercialization activity (e.g., products or services brought to market whose commercialization was supported early on by NSF SBIR/STTRs). I-O models have more limited applicability to study the full range of impacts arising from NSF-funded research and related activities. Studies using the I-O approach to study the impacts of commercialization rely on extensive collection of sales data from companies that receive federal R&D awards, which significantly adds to the cost of using this approach. Moreover, for other types of NSF awards that support discovery such as basic research, research infrastructure, and human capital development, data on resulting sales from commercialized products is even more difficult or impossible to collect.

- The **cost-benefit analysis approach** can be applied to study the return on investment for all types of NSF-funded discovery, contributions of research infrastructure, and human capital development. Cost-benefit analysis is flexible and can be designed to assess the return on investment for different types of research activities, can be conducted at the individual program level, and for specific funding opportunities or technologies. Cost-benefit analysis can also be conducted at any desired regional level of disaggregation including at the state, county, or metropolitan statistical area. A central consideration in the potential application of cost-benefit analysis to the study of NSF-funded discovery is the selection of cases to study that would accurately reflect the full portfolio of NSF awards. Cost-benefit analysis does permit estimation of portfolio-level returns on investment, but this hinges on the selection of representative cases within a portfolio to include in the analysis.

What methods from the empirical literature are most relevant to estimating the economic impacts of NSF R&D support?

For estimating the impacts of research awards, the strengths of I-O models include estimating multiple types of impacts in one modeling framework (e.g., economic output, employment, employee compensation), the conceptual simplicity and breadth of use of I-O models, and the ready ability to compare results to other studies. However, I-O models are limited in their ability to account for opportunity costs, and the leading models do not differentiate between the impacts of different types of research activities (e.g., basic versus use-inspired, R&D performed by private industry versus R&D performed by academia, R&D differences by S&E field).

- It is possible to overcome the limitations of I-O modelling with additional analysis external to the models. For example, econometric approaches could be used to estimate the effect of NSF awards on stimulating research expenditures from private and other institutional sources. This could be used to calculate the total amount of research funding associated with NSF awards which could then be modeled using I-O tools.

There is no single recommended approach to estimating the economic impacts of discoveries produced by NSF funded research.

- Production functions and cost-benefit analysis (CBA) provide approaches that can be used to estimate the economic impacts arising from NSF-funded discoveries. These approaches differ in that CBA provides a general framework for case study analysis which can be aggregated up to create estimates of impact, whereas the production function creates aggregate estimates of impact from time series data.

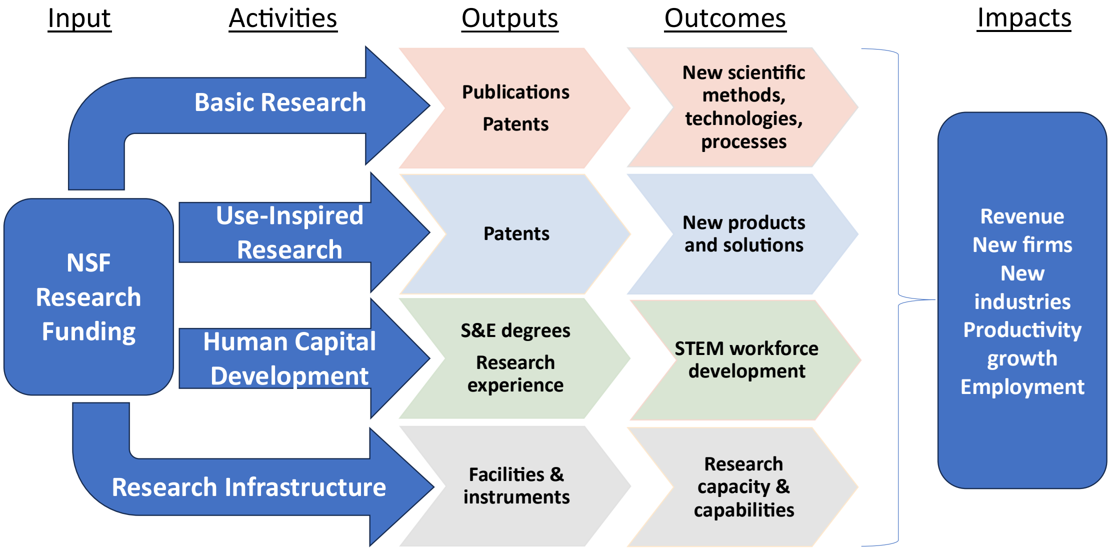
While both approaches to estimating the impacts of discoveries seem feasible, CBA is the more flexible of the two methods for meeting the diversity of NSF needs for economic impact statistics. The performance and aggregation of results from CBA case studies, can allow for simple aggregated estimates of NSF impact by type of research, geographic region, administrative unit or program (e.g., agency or program within agency), and performer type (e.g., type of institution such as academic or private sector).

1 Introduction

NSF is the only U.S. federal agency whose mission is to invest in basic research and human capital development across the full spectrum of STEM disciplines, excepting the medical sciences (U.S. National Science Foundation 2023). Congress established NSF in 1950 with the goals of advancing economic and other forms of well-being as well as securing the national defense (U.S. Congress 1950). In support of this mission, NSF awards are sizable, far reaching, and used to carry out research for public purposes, primarily through merit-based awards to educational institutions, businesses, nonprofit research institutions, and other organizations engaged in research. The NSF also funds educational programs and other forms of student aid along with research infrastructure (Harris 2021).

Exhibit 1 illustrates possible impact pathways contributing to the economic impacts of NSF's R&D funding. As an input, NSF research funding supports research activities, such as basic research, use-inspired research, human capital development, and research infrastructure. By activity, the outputs from research activities include publications and patents, which in turn yield outcomes such as new scientific methods, technologies, and processes as well as new products and solutions. The outputs from human capital development include research experience and increasing the number of science and engineering degrees, which in turn yield outcomes such as improvements to the STEM workforce. The outputs from research infrastructure investment include new facilities and instruments, which in turn yield outcomes such as an increase in research capacity and capabilities. The varied economic impacts stemming from these outputs and outcomes, both for short-term R&D investments and from longer-term discoveries arising from that R&D, include rising revenue, the creation of new firms, the beginning of new industries, productivity growth, and employment growth.

Exhibit 1: Impact pathways for NSF R&D support



Note: Exhibit 1 is stylized to show the types of measurable outputs and outcomes that result from each type of NSF research award. Although represented as such, the achievement of research impact may not be a linear process. For example, outcomes from basic research such as new technologies and processes may beget other research, such as additional basic research or use inspired research, before downstream industrial outputs such as new firms, revenue, or employment are impacted.

To better understand how NSF should best determine the economic impacts of its R&D awards, RTI International has been contracted by NSF to conduct a systematic review of the literature on measuring the economic impacts of R&D investments and related activities. Specifically, our review of the literature aims to document:

- The types of research supported by NSF,
- Theoretical justifications for government's role in R&D,
- Theories of change that relate R&D to economic growth,
- Indicators and performance measures of research investment; and
- Relationships between R&D awards and economic impacts.

Over 6,000 documents were collected in the search process. Team members initially screened documents to identify those papers of highest relevance for the literature review.[1] During screening, documents were assigned a broad topic area to allow for all documents with similar content to be further reviewed as a unit. In this further review, team members examined the documents more thoroughly to capture and summarize key approaches, data, and findings. The team then synthesized key themes across the literature within each of the sections, highlighting the estimates, data, and approaches most relevant for assessing the economic impacts of NSF's R&D investments.

Our review of the literature focuses on the data and approaches most often used as well as the most common measures of economic impacts (such as economic growth, productivity, and employment) and intermediate outcomes that have been tied to these economic impacts such as publications, patents, and the development of the STEM workforce. After, we highlight findings of particular relevance to NSF and the types of funding NSF typically provides. Last, we make a distinction between economic impacts from research awards (e.g., the economic impacts of awards)[2] and the economic impacts from the research, discovery, or output from those research awards (e.g., the economic impacts of discoveries).[3]

The literature review is structured as follows. Section 2 describes the types of research that NSF supports, highlighting key definitions and distinctions. Section 3 describes the roles for government in R&D, outlining the arguments for government funding of R&D. Section 4

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[1] For the screening process, team members used a combination of document titles, abstracts, authors, year of publication, and number of citations to identify papers of highest relevance. In cases where relevance was uncertain, screeners would briefly scan the full document.

[2] The section on the economic impacts of awards (Section 6) includes the impacts of R&D awards through spending on labor, supplies, and equipment. The effects of this spending ripple into the wider economy through impacts on those employed to do NSF-funded work as well as on suppliers and their employees. These impacts are likely to be relatively short term, constrained by the duration of the investment, and happen regardless of whether any scientific discoveries result and do not include the economic impacts of these discoveries. The impacts of awards also include impacts on human capital development and contributions to R&D infrastructure.

[3] The section on the economic impacts of discoveries (Section 7) focuses on the economic impacts of discoveries that arise through R&D. New discoveries allow developments such as the implementation of a new manufacturing process or the commercialization of a new technology, with economic impacts on the firm, consumers, and the broader community. Economic impacts from new discoveries may persist over the long term, far beyond the duration of the R&D award. The literature often does not distinguish between the economic impacts of awards and those from discoveries. In cases where the estimates include the impacts from discoveries, we include them in Section 7, regardless of whether they also include the economic impact of awards.

explores the theories of change linking R&D and economic growth. Section 5 describes indicators and performance measures for R&D. Sections 6 and 7 describe the empirical literature linking R&D awards and discoveries to economic impacts, with Section 6 focusing on the short-term impacts of R&D awards and Section 7 on the impacts of resulting R&D discoveries. Finally, Section 8 discusses the overall findings of the review, focusing on the findings most relevant to the types of R&D funded by the NSF.

2 What types of research support does NSF provide?

This section reviews the research activities supported by NSF and examines the literature to establish a definition of the types of research that may by supported by NSF awards. Specifically, we begin with an overview of NSF research awards in fiscal year (FY) 2024. From this we identified the following relevant research activities supported, including R&D, human capital development, research facilities, infrastructure, and major equipment. Consequently, we examine relevant literature that defines these terms to inform a working definition of the NSF research activities that may lead to economic impacts.

NSF is the third-largest federal funder of basic research after the Department of Health and Human Services and the Department of Energy (U.S. National Science Foundation 2024e), operating through directorates and offices representing the broad scope of NSF's mission.[4] NSF supports research through three broad activity types that are described as follows (U.S. National Science Foundation 2024a):

- **Research & Related Activities (R&RA):** "Invests in early-stage research and the development of a future-focused science and engineering workforce that can accelerate progress in fundamental and translational science and engineering research as well as support the private sector."

- **STEM Education (EDU):** "Invests in education and training programs to help prepare a diverse, domestic STEM workforce. These investments – spanning pre-K through graduate school and beyond – ensure pathways for people and ideas ready to solve pressing global challenges in science and engineering."

- **Major Research Equipment and Facilities Construction (MREFC):** "Supports the acquisition, construction, and commissioning of major facilities and larger mid-scale research infrastructure, providing unique capabilities at the frontiers of science and engineering."

In FY 2024, NSF had a $9.1 billion budget that was used across these activities: 79% R&RA, 13% EDU, and 3% MREFC (U.S. National Science Foundation 2024a), as well as administrative work and the National Science Board (U.S. National Science Foundation 2024b). Given that NSF's research investments are focused on these three broad activities, the rest of this section reviews the literature defining these activities and their component parts, specifically R&D, human capital, and infrastructure.

2.1 Defining R&D

The Organisation for Economic Cooperation and Development's (OECD) Frascati Manual is a standard reference for the definitions of R&D and its component parts (OECD 2015).[5] The Frascati Manual's definitions are adopted by the National Center for Science and Engineering Statistics (NCSES) at NSF (OECD 2015).[6] The definitions are used by a variety of U.S. federal agencies as well as in official U.S. R&D surveys, sometimes with additional detail to

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[4] As of FY 2024, NSF's directorates are: Biological Sciences (BIO); Computer and Information Science and Engineering (CISE); Engineering (ENG); Geosciences (GEO); Mathematical and Physical Sciences (MPS); Social, Behavioral, and Economic Sciences (SBE); STEM Education (EDU); and Technology, Innovation, and Partnerships (TIP). The Office of International Science and Engineering (OISE)is also involved in supporting scientific activities and actors.

[5] The Frascati Manual has substantive detail on R&D definitions and how to operationalize them.

[6] NCSES is a division of the Social, Behavioral, and Economic Sciences Directorate of NSF.

operationalize them for the specific task (Moris and Pece 2022). The Frascati Manual and NCSES define R&D as follows:

- **Research and (experimental) development (R&D):** "Creative and systematic work undertaken to increase the stock of knowledge—including knowledge of humankind, culture, and society—and its use to devise new applications of available knowledge" (OECD 2015).

Under the Frascati Manual's framework, R&D consists of three types of activity (OECD 2015):[7]

- **Basic research:** "Experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundations of phenomena and observable facts, without any particular application or use in view."
- **Applied research:** "Original investigation undertaken in order to acquire new knowledge. It is, however, directed primarily towards a specific, practical aim or objective."
- **Experimental development: "**Systematic work, drawing on knowledge gained from research and practical experience and producing additional knowledge, which is directed to producing new products or processes or to improving existing products or processes."

Along with an emphasis on basic research, the 1968 NSF Reauthorization explicitly authorized NSF support for applied research (Harris 2021).

Stokes (1997) describes a variant categorization of research, organized around two axes: the aim of fundamental understanding and the aim of practical utility. Three research categories emerge:

1. **Pure basic research** (Bohr's quadrant): directed toward fundamental understanding with no consideration of practical utility.
2. **Pure applied research** (Edison's quadrant): directed toward practical utility with no focus on fundamental understanding.
3. **Use-inspired basic research** (Pasteur's quadrant): combining the goals of fundamental understanding with considerations of practical utility.

A definition of use-inspired research arises out of this framework:

- **Use-inspired research:** Research performed with the desire to advance scientific understanding but may also involve commercial applications and engagement with the business sector (Tijssen 2018).[8]

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[7] The Office of Management and Budget (OMB) uses similar definitions, as does the Congressional Research Service (CRS) (Moris and Pece 2022).

[8] *Use-inspired research* is distinct from Stokes' notion of *use-inspired basic research* as it includes basic and applied research.

The literature generally focuses on basic, applied, and use-inspired research, but some R&D is distinguished further based on features of the problem under investigation, the approach to solving the problem, or the articulation of a deliberate process to produce economic or social impacts.

- **Convergence research:** "The merging of ideas, approaches, and technologies from widely diverse fields of knowledge to stimulate innovation and discovery" (National Science Board 2024).

- **Translational research:** "Translational research typically refers to converting discoveries, often made in a laboratory or other setting, into practical applications that can be deployed at scale. Opportunities for translation are often spotted first by those with intimate knowledge of a research project. The translation is successful when these opportunities lead to knowledge/technology transfer, commercialization, or transition to practice, resulting in tangible economic and/or societal benefits" (U.S. National Science Foundation 2023).

Synonyms may be used to describe research categories or subtle variations of them. For example, "fundamental" may be used instead of "basic." "Multidisciplinary" or "interdisciplinary" may be used instead of "convergence."

2.2 Defining human capital development

NSF supports STEM human capital development through EDU, as well as by funding students through R&RA activities. The goals of EDU are as follows (U.S. National Science Foundation n.d.):

1. Prepare the next generation of STEM professionals and attract and retain more Americans in STEM careers.

2. Develop a robust research community that can conduct rigorous research and evaluation that will support excellence in STEM education and that integrates research and education.

3. Increase the technological, scientific, and quantitative literacy of all Americans so that they can exercise responsible citizenship and live productive lives in an increasingly technological society.

4. Broaden participation (individuals, geographic regions, types of institutions, STEM disciplines) and close achievement gaps in all STEM fields.

STEM education is a set of tools through which NSF works toward these goals. It is defined by NSF's EDU directorate as:

- STEM education is pursued to support the development of a diverse and well-prepared workforce of scientists, technicians, engineers, mathematicians and educators and a well-informed citizenry that have access to the ideas and tools of science and engineering (U.S. National Science Foundation 2021).

STEM education is defined similarly by CRS, without specific reference to the goals:

- "Refers to teaching and learning in the fields of science, technology, engineering, and mathematics. It typically includes educational activities across all grade levels—from pre-school to post-doctorate—in both formal (e.g., classrooms) and informal (e.g., afterschool programs) settings" (Granovskiy 2018).

2.3 Defining research infrastructure

Infrastructure, facilities, and major equipment are often grouped together as providing the physical capabilities and environment necessary to conduct R&D. NSF's MREFC funding supports research infrastructure. The NSF's 2025 budget request describes research infrastructure as encompassing the following activities (U.S. National Science Foundation 2024b):[9]

- Operations and maintenance of major facilities
- Major research facilities construction
- Mid-scale research infrastructure
- Major research instrumentation
- Polar logistical and infrastructure support
- Networking and computational resources infrastructure and services
- Research resources
- Other research infrastructure

Relevant definitions of research infrastructure include the following:

- **Research infrastructure:** "Facilities, equipment, instrumentation, computational hardware and software, and the necessary supporting human capital," along with institutional research support and service capacity (U.S. National Science Foundation 2024d).
- **Research and development infrastructure:** "Facilities or systems used by technical communities to conduct research and development (R&D) or foster innovation" (Eop 2021).
- **Research facility physical capital:** Machines and equipment that are primarily used to support the generation of new scientific understanding (Beneito et al. 2015).

Research infrastructure includes physical resources such as facilities and equipment as well as other supportive systems including human capital. However, the literature notes that the definitions used for infrastructure and to discriminate between different types of infrastructure investments are often imprecise and inconsistent (Eggleton 2024).

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[9] The MREFC account typically funds larger projects, including the larger mid-scale research infrastructure projects with budgets over $20M. Smaller-level infrastructure support, such as for less expensive instrumentation, is typically supported through R&RA funds. Most of NSF's funding for infrastructure is supported through R&RA funds.

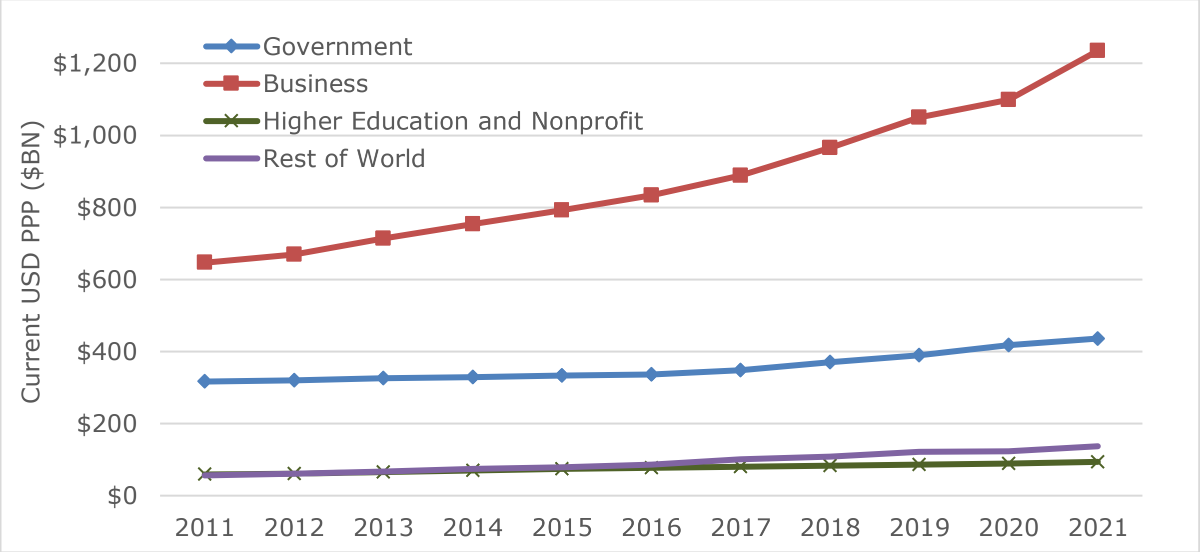
3 What are the theoretical justifications for government's role in R&D?

This section reviews the literature on the theoretical justifications for government support for R&D, including market failure and market correction arguments and normative arguments. We first review basic data on the scale of government R&D funding. Next, we discuss market failure and market correction theories applicable to those defined R&D activity areas and why government support for R&D is necessary. Then, we describe normative theories justifying government support for R&D. Last, we end with a literature-informed discussion on theories applicable to NSF's motivations for providing R&D support.

3.1 The scale of government R&D funding

Government is a major source of R&D funding, as well as an R&D performer in most industrialized countries, such as those in the OECD countries,[10] and in rapidly industrializing countries, such as China. As shown inExhibit 2Exhibit 2, government-financed R&D ($436 billion) represented 23% of gross expenditures on R&D (GERD) in OECD countries in current U.S. dollars adjusted for purchasing power parity (USD PPP) and 19% of GERD (or $144 billion) in China in USD PPP. In both the OECD and in China, government ranks second after business as a source of R&D funding. Business-financed R&D represented 65% of GERD in OECD countries and 79% of GERD in China (OECD 2024).

Exhibit 2: OECD gross expenditures on R&D by source of funds (current USD PPP, billions), 2011–2021



Source: OECD, Main Science and Technology Indicators (annual series).
Note: OECD spending is separated into government, business, and higher education and nonprofit groupings. Rest of world designates the total R&D spending of non-OECD countries.

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[10] The 38 OECD member countries are Australia, Austria, Belgium, Canada, Chile, Colombia, Costa Rica, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

Analyzing the type of R&D (e.g., basic, applied, experimental development)[11] and the type of R&D performer (e.g., business, higher educational, federal, nonprofit) that government funds relative to the private sector points to the role that government plays in the national R&D enterprise. In 2022, the U.S. federal government financed $159.8 billion of $885.6 billion in U.S. GERD, or approximately 18%. The U.S. federal government was the source of funding for approximately 52% of higher education R&D expenditures in the United States in 2022 and 5% of R&D expenditures by business (U.S. National Science Foundation 2024c).

Exhibit 3 shows the total amount of U.S. R&D funding that went to basic, applied, and experimental development in 2022 and the percentage of this R&D funding that came from government, business, higher education, and other (non-federal and nonprofit) organizations. Approximately 39.6% of this government-financed R&D supported basic research, 28.8% supported applied research, and 10.5% supported experimental development (U.S. National Science Foundation 2024c).

Exhibit 3: Percent of U.S. R&D expenditures, by type and funding source (percent of total among all funders and current dollars billions), 2022

Type of R&D	Federal government (%)	Business (%)	Higher education (%)	Other (%)	Total ($B)
Basic Research	39.6%	37.1%	12.5%	10.8%	$129.4
Applied Research	28.8%	61.8%	4.0%	5.4%	$159.9
Experimental Development	10.5%	88.2%	0.4%	0.9%	$596.2
All R&D Types	18.0%	76.0%	2.9%	3.1%	$885.6
Total R&D ($B)	$159.8	$672.9	$25.5	$27.3	$885.6

Source: U.S. National Science Foundation (2024c)
Note: Reported percentages are based on the proportion of total spending on each type of R&D by each type of funder. For example, 39.6% of all funding on basic research is provided by the federal government, whereas 18.0% of all R&D spending is provided by the federal government.

As the two largest funders of R&D expenditures, the interplay between the federal and private sector determines the total amount of R&D conducted in an economy and the incentives for performing different types of R&D (basic, applied, experimental development). It is important to note that while the federal government funds slightly more basic research, private industry contributes twice as much funding for applied research and nearly all funding for experimental development research.

Government support for R&D can impact the total amount of private R&D investment and performance both positively and negatively (Guellec and Pottelsberghe de la Potterie 2003). On the one hand, government support for R&D contributes to the scientific and technological base of ideas and knowledge that the private sector can build upon (Leyden and Link 1991). On the other hand, if government performs or funds R&D that the private sector would otherwise have funded or performed itself, or if government-financed R&D uses physical or

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[11] This section divides R&D into the three categories described by OECD's Frascati Manual as that framework underlies those statistics. Elsewhere we divide research into basic and use-inspired as they are the focus of NSF funding.

human resources that would have otherwise been used for private sector R&D, government funding can crowd out the private sector investment (David 2000).[12]

To justify the role of government in R&D, we draw upon three types of market failures that can result in a suboptimal level of private sector R&D investment: a) positive externalities or spillover effects from R&D, b) risk and uncertainty in R&D, and c) economies of scale in R&D. Government support for R&D can address these market failures.

3.2 Positive externalities and spillovers in R&D

R&D often results in spillover effects and positive externalities. Spillover effects are the unintended and non-compensated benefits or costs that result from economic activity, affecting parties that are not directly involved in the transaction. A positive externality occurs when an economic activity generates benefits that extend beyond the immediate participants, leading to a social return that exceeds the private return (Jaffe 1986). These effects can lead to a divergence between private and social returns to innovation.

For R&D, Griliches (1992) defines spillovers as the unintended diffusion of knowledge and innovations beyond the originating firm or institution, often benefiting competitors and the broader economy. For example, a company might engage in a series of R&D projects that result in the introduction of a better performing product. A competitor may reverse engineer that product and incorporate the innovations in its own product. In this way, R&D and the innovations that occur as a result, can have industry-wide spillover positive externalities or even interindustry spillover effects. This type of externality can also result from the movement of R&D workers between firms and the cross-fertilization of ideas between firms. Both types of positive externalities reduce the incentive to invest in internal R&D.

Additionally, R&D generated knowledge has characteristics of a public good. A public good has two properties: they are non-excludable (consumers cannot be excluded from using the good) and nonrival (consumption by one consumer does not reduce the amount available for others) (Arrow 1972). Among the types of R&D, basic research is closest to a public good.[13] As a result of these properties, private actors who invest in public goods may not recoup fully the economic or financial benefit of this investment. This may disincentivize businesses from investing in R&D at a level that is optimal for an economy or a society. Thus, private firms' investment criteria tend to limit their investments in basic research.[14]

From an economy-wide and societal perspective, there are many benefits to investing in R&D, and specifically basic R&D. Kuhn (1962) noted that new scientific understanding generates novel insights that undermine old assumptions, spurring "paradigm shifts" in science that in turn enable downstream innovation and commercial activity. While market

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[12] See Section 6.4 for additional discussion.

[13] As described in Section 2, the goal of basic research is to "acquire new knowledge of the underlying foundations of phenomena and observable facts" and help to advance society's scientific understanding (OECD 2015).

[14] Stephan (2012) notes that even when a firm invests in applied research, it is unlikely to appropriate all the potential benefits of this research as the results can often be used in multiple and unexpected ways. The use of the knowledge created through basic research by those who performed the research does not preclude use by others, and studies find that the overall benefits from R&D investment exceed the direct financial benefits to those directly investing in the research (Romer 1990; Solow 1957; Tassey 2004). Because the private sector chooses its investment level based on the benefits it can appropriate, spending on basic research will be below the socially optimal level (Bernanke 2011).

needs are a strong force that tends to “pull” innovators toward the development of new technology-based solutions (Schmookler 1966), many notable technologies have also arisen in the process of solving “extraordinary problems” related to social objectives such as space exploration, improved public health, and national security.

Unexpected scientific discoveries may also provide insights for leveraging principles of nature to create novel and useful technologies (Nelson and Winter 1982; Schumpeter and Backhaus 2003:193). These discoveries and the technologies they advance can have applications in multiple markets and can give rise to entirely new industries (Arthur 2009; Kuhn 1962). Indeed, breakthrough technologies can disrupt existing markets and create monopolistic advantages for firms and regions fueling innovation and economic growth (Christensen 1997; Schumpeter 1939).

3.3 Risk and uncertainty in R&D

Profit-maximizing firms must optimize any investments in workers, capital equipment, and R&D based on financial return. As a result, firms are generally risk-averse and short-term in selecting investments. Even applied research and experimental development projects are characterized by imperfect information about the outcomes. Firms may be hesitant to invest in R&D projects if they are not confident in the probability that they will recoup their R&D costs in a reasonable timeframe.[15] In addition, formal intellectual property (IP) protections, such as patents, are expensive and may be difficult and expensive to enforce. By contrast, government has a much longer-term outlook and may be able to diversify risk across a much larger portfolio, so the incentives facing government are more aligned with making research investments (Arrow 1972).

Jaffe (1998) explores the government’s role in reducing R&D risk within the context of the National Institute of Standards and Technology’s (NIST) Advanced Technology Program (ATP).[16] ATP adopted a model that jointly funded collaborative projects between private firms and government to pursue riskier R&D projects with significant disruptive potential in key industries. By bearing part of the cost, the government reduced the level of risk facing industrial partners and could engage multiple firms as co-sponsors, even though benefits would not be fully internalized by any single firm. Research priority areas and project proposals for the ATP were subjected to rigorous review to ensure that the funded research was likely to generate social benefits and would not replicate privately funded efforts.

Jaffe (1998) characterizes ATP’s projects based on both the gap between private and social returns to research as well as the commercial prospects for technology, illustrated in Exhibit 4**Error! Reference source not found.**. Here, hypothetical projects are plotted against two axes: the private rate of return on the x axis and the social rate of return on the y axis. Not only must technologies supported by ATP generate social returns (high value on the y axis), but they must also have sufficient commercial interests to ensure that research is translated into the marketplace (high value on the x axis). Policymakers should avoid project A, with social benefits but little commercial interest, and project D, with high commercial aspects but little social benefit. Project C is associated with high social benefit but its high private benefits suggest it may be funded independently by the private sector. Project B is likely to

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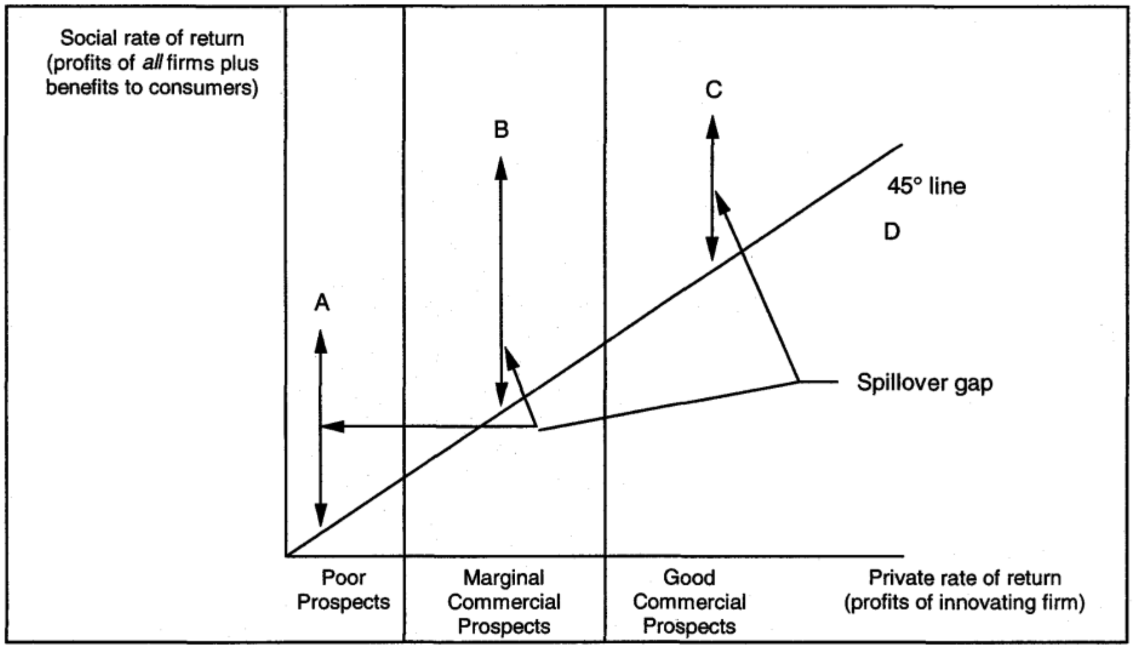
[15] Branscomb and Auerswald (2003) note this as a form of market failure in early-stage ventures. Risk-adverse capital markets are burdened by information asymmetries and therefore underinvest in innovation from small companies, missing opportunities that can disrupt existing markets and practices.

[16] The ATP was established by the Omnibus Trade & Competitiveness Act of 1988 and ended in 2006, when it was superseded by the Technology Innovation Program (Blevins 2022).

be the most appropriate target for funding because the gap between the social and private returns (spillover gap) is the largest. This is represented graphically by the vertical distance between Project B and the 45-degree line representing equal social and private returns.

Exhibit 4: Hypothetical gains to private and social welfare derived from ATP investments



Source: Jaffe (1998)
Note: Exhibit 4 presents four hypothetical projects, with varied private and social rates of return. Project B is a project with medium private rate of return and high social rate of return, which Jaffe asserts to be the type of R&D project that should be the subject of government intervention.

3.4 Economies of scale in R&D

Economies of scale occur when the average cost of production decreases as output increases, making large-scale investment more efficient than small-scale efforts. In the R&D landscape, this manifests in many ways: cost-sharing of infrastructure, knowledge accumulation, and network effects of innovation. Large research projects often require significant upfront investment in laboratories, equipment, and skilled personnel—costs that can be spread over a larger output base thus reducing the per-unit cost of innovation (Rosenberg 1990). These high fixed costs can also be prohibitive for some private firms, especially startups and small enterprises, necessitating government intervention to support large-scale, socially beneficial research endeavors.

A key challenge arises because R&D funding exhibits increasing returns to scale, meaning that as more resources are devoted to research, the knowledge generated can lead to further discoveries at an accelerating rate (Romer 1990). Private firms, however, lack the incentives to fund research of a larger scale due to the non-rivalrous and partially non-excludable nature of knowledge—once new knowledge is created, others can benefit from it without paying for the full cost (Arrow 1972).

The economic justifications for public investments in research and development infrastructure (RDI) are mostly pragmatic. If public investments in research are required to achieve a socially optimal level of scientific activity, then the government also needs to provide the infrastructure for that activity. This was the fundamental justification for RDI investment in the post-war era. As the United States pursued societal goals with a high degree of scientific and technological complexity, the government provided user facilities, equipment, and resources enabling related R&D. Modern science has advanced the frontier of inquiry to the smallest (microscopic) and largest (cosmic) scales, requiring new instruments for observation and measurement (Brooks 1994). This in turn drives the need for more sophisticated and expensive RDI.

For extremely expensive or unique infrastructures, such as radio telescopes and particle accelerators, no private entity can bear the whole cost of building and maintaining such facilities. Therefore, the government is the default investor. Likewise, no "market" exists for unique scientific facilities, meaning that the economic efficiencies generated by competition cannot be achieved. In such cases, the government is better suited for operating that infrastructure in the public interest.

Similarly, the benefits of RDI tend to increase with the number of infrastructure users due to resulting knowledge spillovers. Private ownership of RDI may create incentives by the owners to limit access to that infrastructure in hopes of appropriating a larger share of the benefits. This, in turn, would create a social loss as researchers needing access to that infrastructure would not be able to do their work. Public ownership is often the best way to achieve economically optimal use.

Without government intervention, many firms—especially in high-risk fields like quantum computing, materials science, or biopharmaceuticals—would struggle to reach the necessary scale of research to make meaningful breakthroughs. As more researchers, firms, and institutions engage in scientific discovery, the probability of significant technological advances increases, leading to broader economic benefits. Mowery and Rosenberg (1989) argue that public funding plays a valuable role in the formation of high-tech clusters, where economies of scale in knowledge creation drive long-term economic competitiveness. Without public support, industries reliant on advanced scientific research could face stagnation—ultimately hampering national productivity and global technological leadership.

3.5 Normative arguments for government funding for R&D

Positioning the U.S. on the global stage

In the "Endless Frontier", Bush (1945) pointed to the importance of basic research as a driver of long-term technological innovation and outlined for President Truman the need for public investment in scientific research and advocated for a peace-time science agency. He compared increasing the role of government in expanding basic science research to opening the western frontier for expansion and thereby providing new opportunities for economic growth. Through his recommendations, Bush helped to push for an active role for government R&D in both direct and indirect investments in research, particularly in academia.

During the post-war era, the increase in federal R&D spending was accompanied by large investments in:

> *Building laboratories and other facilities to accommodate the nation's growing R&D enterprise. These facilities, constructed at federal agencies and federally funded R&D centers (FFRDCs), included new laboratory buildings and specialized facilities and equipment, such as accelerators, ground- and space-based telescopes, reactors, and X-ray sources, to study fundamental and applied science.* (Whitman 2024)

The report further notes that these infrastructural investments enabled the United States to gain global scientific leadership and "led to technology breakthroughs that served as a foundation for the nation's economic growth and national security" (Whitman 2024*)*.

Human capital development

In the "Endless Frontier," Bush (1945) identified the training of the next generation of scientists and engineers as a core benefit of publicly funded research. More than half (52%) of higher education R&D expenditures in the United States in 2022 were financed by the federal government (Falkenheim and Alexander 2023). Government-supported R&D performed by higher education institutions supports the education and training of the next generation of scientists and engineers by sponsoring research and tuition for undergraduates, graduate students, postdoctoral researchers, and early-career faculty.

Government-financed R&D contributes to the total size and geographic distribution of a country's science and engineering workforce. This in turn expands the private sector's capacity to innovate and to adapt and integrate new technologies and scientific knowledge (Pavitt 1991). Rosenberg (1990) pointed out that scientific and technological knowledge are not "off-the-shelf" consumable items that are "costlessly available to all comers;" rather, they require a certain level of understanding and capacity to access and make use of this knowledge. Cohen and Levinthal (1990) have termed capability "absorptive capacity," or the ability of a firm to internalize new research findings and outputs. By employing trained scientists and engineers, firms gain the ability to understand and exploit new scientific knowledge and emerging technologies to enhance their market competitiveness. Differences in absorptive capacity across firms and geographies suggest that learning-by doing or "tacit knowledge" factor into how easily new scientific ideas and technologies can be transferred, underscoring that engaging students in research adds to their potential benefit to future employers (Polanyi and Sen 2009).

Science and engineering workers with previous experience performing publicly funded research are particularly valuable to the private sector for three reasons. First, workers who have previously engaged in government-financed R&D have specialized skillsets that are valued by firms that perform R&D.[17] Workers trained in research techniques, independent of the technical field of study, come to private-sector R&D more productive and efficient than those without this training and experience (Mamuneas 1999). Second, graduate-level and postdoc experience gained through government-financed R&D contributes to the development of specialized knowledge in particular science and engineering (S&E) fields. Scientists and engineers with this specialized training can understand published research; recognize the complexity of topics and the research that has led to the current understanding; and be in a better position to evaluate the usefulness and applicability of this scientific knowledge to private sector commercial applications. Third, scientists and engineers who have performed R&D in higher education, government labs, or nonprofit institutions typically develop and expand professional networks with other researchers. This network contributes to a firm's absorptive capacity since they can be leveraged to tap the specialized knowledge and experience of colleagues working in other firms and institutions (Rajkumar et al. 2022).

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[17] These specialized skillsets may include knowledge of how to frame and answer scientific questions, how to use specialized lab equipment and employ research techniques, and how to analyze and draw inferences from the resulting data.

3.6 Aligning economic theories with NSF R&D funding

Here we provide more detailed justifications for the types of R&D and related activities conducted at NSF, summarized in Exhibit 5. Beyond the general justification for government investment in R&D, economic studies explore some of the technical details specific to different types of R&D and related activities funded by NSF.

Exhibit 5: Economic justifications for NSF research support

Activity	Goal	Justification	NSF Evaluation Objective
Basic research	Create new knowledge of the underlying foundations of phenomena and observable facts and advance scientific understanding	Address market failures due to positive externalities and spillovers as well as risk and uncertainty	Show that economic return justifies the investment
Use-inspired research	Advance scientific understanding and have indirect or broad-based relevance to industrial needs	Address market failures due to positive externalities and spillovers as well as risk and uncertainty	Establish that investments support competitiveness but do not crowd out private R&D spending
Human capital development	Train the next generation of STEM workers at all levels including tech-based entrepreneurship training	Address market failures due to spillovers and positive externalities. Provide skills and talent to produce a competitive research and technical workforce	Show the value of the talent base built with NSF support
R&D infrastructure	Fund physical and other infrastructure required to conduct or facilitate scientific research and to strengthen national competitiveness in emerging technologies	Address market failures due to economies of scale and spillovers and positive externalities Provide systems and facilities needed to perform funded research	Demonstrate economic loss from absence of required infrastructure Demonstrate the contribution of research enabled by established infrastructure

Note: Exhibit 5 provides the goal of performance, justification for government intervention, and a corresponding need for evaluation for each type of research. Evaluation measures whether the government meets its objective in pursuing that type of R&D activity.

Basic research

The case for NSF's core funding programs focused on fundamental scientific research (primarily at universities) is the most well-established and is relatively uncontroversial. While critics of NSF may question the economic value of specific grants or funded projects, there is broad support among economists for NSF's basic research investments. The goal of NSF support for basic research is to create new knowledge of the underlying foundations of phenomena and observable facts and advance scientific understanding. This type of research exhibits positive externalities and spillovers (Arrow 1972; Bernanke 2011) and comes with a high degree of risk and uncertainty (Link and Scott 2011), resulting in under-investment among private firms. Federal investment fills the gap, providing a remedy for these market failures.

A potential challenge is the difficulty in predicting the long-term impact from discovery-focused R&D investments. One can argue that NSF support for basic research produces some number of discoveries with disproportionately large economic benefits that exceed the cost of all less-productive research. That assumption can only be proved by implementing rigorous assessment methods to measure the economic impacts of NSF R&D funding.

Use-inspired research

The goal of NSF support for use-inspired research is to advance scientific understanding and have indirect or broad-based relevance to industrial needs. As with basic research, use-inspired research displays spillovers and positive externalities (Jaffe 1998) and risk and uncertainty (Link and Scott 2012) that can lead to under-investment by the private sector. Federal spending on use-inspired research can remedy the resulting market failures and bring investment to the socially optimal level. However, federally funded or enacted use-inspired research also has the potential to crowd out private investment if conducted on research areas that would otherwise by carried out by private industry (David 2000).

Support for use-inspired research programs at NSF has increased recently, evidenced in part by the creation of the TIP Directorate in the CHIPS and Science Act. NSF has a long history of supporting this type of R&D, dating back at least to the 1960s (Teich 2018). However, similar investments at other agencies, such as the ATP, have faced strong opposition based on the assumption that such spending "crowds out" industrial R&D investment (Fong 2001).

Analytical justification for NSF support for use-inspired R&D needs to address both the economic case for this type of R&D investment and whether that investment duplicates spending that the private sector would have made on its own.

Human capital development

The goal of NSF support for human capital development is to train the next generation of STEM workers at all levels including tech-based entrepreneurship training. The literature on the economic returns of human capital development is well-established. Human capital development exhibits spillovers and positive externalities, resulting in under-investment from the private sector (Jaffe 1998). NSF's efforts to build a competitive research and technical workforce also reinforces the national effort to supply the nation with qualified talent capable of extracting the full value of investments in science and technology.

Government investment in research performed at higher education institutions and government labs supports knowledge diffusion and human capital development geographically. For example, the Established Program to Stimulate Competitive Research (EPSCoR) was created by NSF in 1979 to invest in and help build research capacity in states and territories that receive a lower-than-average share of competitive federal R&D funding. "Following World War II, federally funded research grew dramatically but only a small number of states benefited from the infusion of resources" (EPSCoR/IDeA Foundation 2015). In response to policymakers' concern about this geographic concentration of S&E talent production and research, the EPSCoR program was created and now operates across five agencies: NSF, National Aeronautics and Space Administration (NASA), DOE, Department of Defense (DoD), and National Institutes of Health (NIH) (known as the Institutional Development Award, or IDeA program). The EPSCoR program persists given the continued concentration of academic R&D expenditures in a relatively small number of institutions and geographies. In 2021, 3.5% of the 3,733 universities granting postsecondary degrees in the United States accounted for over 75% of academic R&D expenditures (Falkenheim and Alexander 2023).

Similarly, given the concentration of venture-backed start-up activity on the U.S. coasts, NSF launched the Innovation Corps (I-Corps) program in 2011 with the goal of training NSF-funded and other government-funded researchers in entrepreneurial skills—in particular, training in how to assess the commercial potential of early-stage technologies using intensive customer discovery to validate the business case for further development of the technology.[18]

To obtain socially optimal levels of science and technology-based entrepreneurship, government has a role to play in entrepreneurial training. Bozeman and Youtie (2017) evaluate several NSF initiatives such as EPSCoR and I-Corps and found that economic impacts often intertwine with social benefits. Continued analysis can confirm positive economic returns on NSF support across its human capital development initiatives.

R&D infrastructure

The goal of NSF support for RDI is to fund physical and other infrastructure required to conduct or facilitate scientific research and to strengthen national competitiveness in emerging technologies. RDI often displays economies of scale, negating the ability of private industry or academic institutions to be able to invest at economically optical levels (Rosenberg 1990). This makes the federal government the ideal investor for large-scale RDI. RDI also presents spillovers and positive externalities as long as access is not restricted (Arrow 1972).

Federally funded research equipment and facilities at government labs and higher education institutions may be used by a wide variety of performers (academia, industry, and government), maximizing the returns on investment. RDI investments are also clearly justifiable as the research funded by the NSF and others (including industry) cannot be performed without adequate and appropriate systems, equipment, and facilities (Brooks 1994).

These arguments highlight the value of NSF support for all forms of RDI, including mid-scale instrumentation, large-scale scientific facilities, and cyberinfrastructure. NSF can use

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[18] This might include speaking to dozens of potential customers and other stakeholders who bring an informed commercial perspective.

rigorous assessment methods to demonstrate economic loss in the absence of required RDI and the economic impact of the research enabled by its RDI investments.

4 What theories of change relate R&D to economic growth?

Government funding for R&D is valuable because it is associated with long-term economic growth which results in increased productivity, job creation, higher incomes, and reduced poverty. Economic growth, measured by changes in real per capita GDP,[19] has historically been influenced by technological advancements and R&D. After World War II, economists sought to understand the factors that explained differences in the observed economic growth rates across countries (Ricardo 1817; Smith 1776), considering historical events such as the second Industrial Revolution that occurred across continental Europe, North America, and Japan from 1870 to 1914 that highlighted this economic divergence (Mokyr 2005). The economic literature consistently links R&D to growth, demonstrating that technological progress plays a key role in shaping economic prosperity.

This section reviews the literature on the theories of change linking research and development to economic growth. We first discuss common frameworks of research and development. We then discuss the major historical economic theories, exogenous and endogenous growth theory, modern economic theories of change centered around accumulation theories, as well as microeconomic applications of growth theory. Last, we end with a literature-informed discussion on the economic theories of change most applicable to the NSF, given its established portfolio.

4.1 Linear and chain-linked models of innovation

One of the earliest models of research and development, Vannevar Bush's linear model (Exhibit 6), postulates a sequential process where basic research leads to applied research, which results in development that eventually culminates into commercial innovations (Bush 1945). The model emphasizes that basic research (scientific inquiry without immediate commercial applications) acts as the foundation for technological advancements. In this view, increasing public funding for basic research expands the pool of scientific knowledge, which fuels applied research and development efforts in both the public and private sectors.

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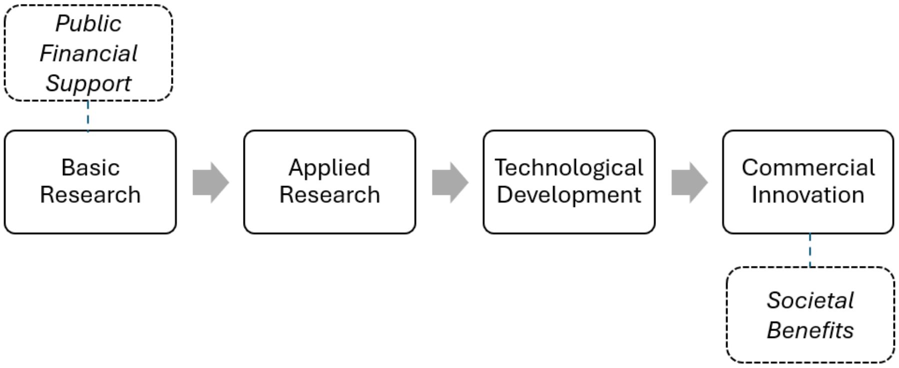
[19] Real GDP is the total market value of goods and services produced by a national or regional economy, adjusted for inflation. Real per capita GDP adjusts real GDP for the size of the population.

Exhibit 6: Bush's linear model of innovation



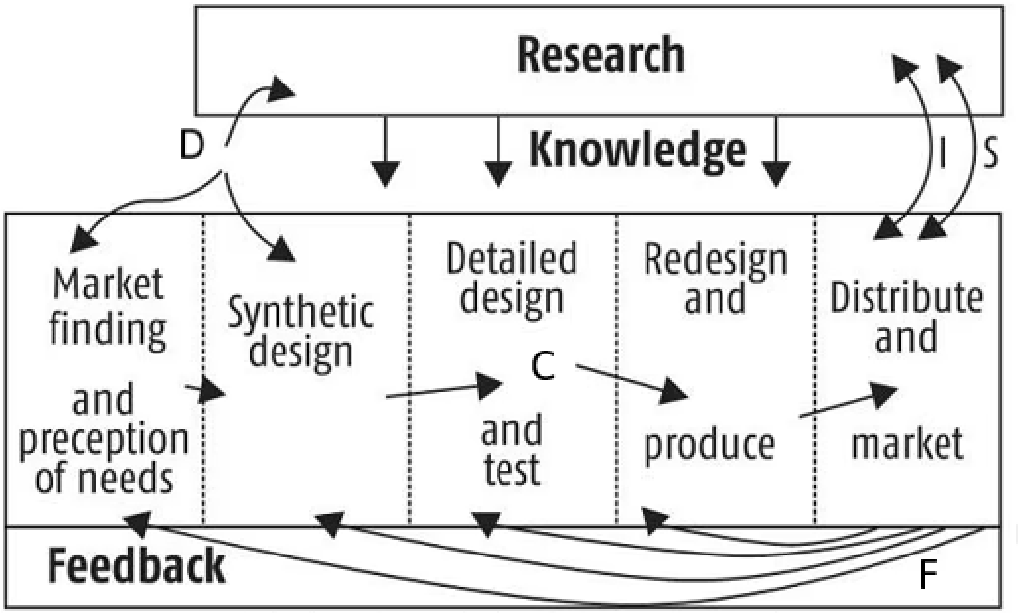
Source: Bush (1945)
Note: Exhibit 6 demonstrates the theory of Bush's linear model of innovation. In this simple model, innovation proceeds in steps, from basic research to commercial innovation. Despite its simplicity, the linear model highlights a natural lag in returns from R&D, due to the distance between R&D funding and societal benefits from R&D.

Tassey (1997) refined the linear model by examining the impacts of government-funded R&D, particularly the role of public research institutions in generating knowledge spillovers and enabling private sector innovation. He argued that public R&D is essential not only for advancing fundamental scientific knowledge, but also for creating the institutional infrastructure necessary to support technological diffusion across industries. This refinement underscored the important role of government intervention in knowledge-driven areas where the private sector tends to underinvest due to risk, long time horizons, or the non-excludable nature of knowledge production.

Tassey (2008) further extended the linear model by differentiating between three primary forms of research: a) fundamental (or basic) research, b) infrastructure technology research, and c) proprietary technology development. While basic research is the foundation of new scientific knowledge, infrastructure technology provides the tools, standards, and methods necessary for firms to translate basic science into practical innovations. Proprietary technology development involves firm-specific R&D investment in producing marketable products. While firms invest heavily in proprietary technology development, they often underinvest in infrastructure technology research, as the benefits are widely shared and not easily appropriated by any single firm. Consequently, public investment is required to develop shared technological platforms, such as advanced manufacturing techniques, measurement systems, and software frameworks, which facilitate private sector innovation. Tassey (2008) reinforces the importance of basic and infrastructure research as public goods that justify government support to maintain national economic competitiveness.

Kline and Rosenberg (1986) proposed the chain linked model of innovation (Exhibit 7) which is an instructive example that contrasts Bush's linear model. Their model described R&D as an interactive and iterative process where feedback loops exist between basic research, applied research, and development.

Exhibit 7: The chain linked model of innovation



Source: Kline and Rosenberg (1986)
Note: The chain linked model of innovation illustrates the non-linearity of the relationship between research and commercial processes. In this model there is a central chain of innovation that is linked to scientific research through processes of knowledge transfer. There are additional links between the central chain of innovation and scientific research from the introduction of commercial problems that can be solved by research (represented by D), the support of scientific research through finished commercial tools (represented by I), and industry support of scientific research (represented by S).

In this model, scientific discoveries often emerge from industry problems rather than following a strict top-down sequence. Increased public funding for basic research can stimulate applied research and development more dynamically than in the linear model, because scientific knowledge flows in multiple directions, including between researchers and industry stakeholders. For example, breakthroughs in materials science may arise from industrial challenges in manufacturing, and advancements in artificial intelligence can lead to new questions in fundamental mathematics and computer science. Kline and Rosenberg (1986) argue that public funding plays a vital role by bridging gaps between the different stages of innovation and by supporting the knowledge exchange necessary for technological progress.

4.2 Economic models and theories of change

Exogenous growth theory and prior theories

Early economic growth theories emphasized physical capital accumulation and investment rates as the primary drivers of national production functions (Domar 1946; Harrod 1939; Lewis 1954; Rostow 1959).[20] The Harrod-Domar model proposed that a nation's growth rate depends on its savings and investment levels, with economic growth occurring when all

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[20] A production function is an equation relating economic outputs to inputs such as labor, capital, and technology.

savings are efficiently invested in capital to maintain full employment (Domar 1946; Harrod 1939).

The Harrod-Domar equation suggests that increasing a country's savings rate (s) or improving capital productivity (c) can accelerate growth ($\dot{Y}/Y$), while capital depreciation (δ) slows it down. However, this model assumes a fixed marginal product of capital, meaning output growth is driven solely by capital accumulation without considering labor, technological progress, or productivity improvements. The Harrod-Domar equation is expressed as follows:

$$\frac{\dot{Y}}{Y} = sc - \delta$$

Rostow (1959) expanded on these ideas by outlining five stages of economic growth, where progress is driven by rising rates of investment that generate growth in manufacturing and industrialization: less than 5% investment rate in the traditional society stage, 5–10% in the pre-conditions to the takeoff stage, 10% in the takeoff stage, 10-20% in the maturity stage, and 20% in the age of high mass consumption stage.

The major criticisms of these classic theories of economic growth are their over-reliance on capital accumulation while neglecting factors like technological innovation, labor productivity, and human capital. The assumption of a constant capital-output ratio limits their explanatory power, as real-word economies experience diminishing returns to capital and are heavily influenced by technological change, which later theories, such as Solow's exogenous growth model, address.

Exogenous growth theory, primarily developed by Solow (1956) and Swan (1956), explains economic growth as the result of external factors such as technological progress, capital accumulation, and labor force expansion rather than being driven by internal economic mechanisms. In this model, long-term growth is primarily determined by technological advancements, which are considered exogenous—meaning they occur independently of economic activity and are not influenced by policy decisions or market incentives. Specifically, Solow's (1956, 1957) and Swan's (1956) contribution to economic growth theory was to demonstrate the very large role that technical change has played in the economic growth of the United States relative to the contribution of other factors of production. In the neoclassical production function, output, Y(t), is a function of capital, K(t), labor, L(t), and a "shifter" of the production function, technology, A(t). Time is represented by t. The equation is expressed as:

$$Y(t) = K(t)^{a}(A(t)L(t))^{1-a}$$

The Solow-Swan model suggests that while investment in capital and labor can drive short-term growth, diminishing returns eventually slow down growth rates, making technological progress the key factor in sustaining long-term growth. Technological improvements increase productivity, allowing an economy to grow even when additional capital or labor inputs yield decreasing marginal returns. Solow's (1957) regression analysis found that over the period of 1909–1949, output per capita in the United States doubled and the production function shifted upward by approximately 80%. He further found that one-eighth of the total output growth was driven by increased capital per labor hour, but the remaining seven-eighths was driven by a residual that Solow attributed to technical change, A.[21]

However, since the model treats technological change as exogenous (e.g., its value is determined outside of the model), it does not address how innovation occurs or how policies might influence it, leading to later developments in endogenous growth theory (Romer 1990). While limited, exogenous growth theory laid the foundation for understanding the role of research and development, education, and human capital in economic expansion.

Endogenous growth theory

In contrast to exogenous growth theory, Schumpeter (1939) earlier theorized that technological change is an endogenous characteristic of economic growth, because it is the result of the decisions made by profit-maximizing firms. Schumpeter (1939) theorized that entrepreneurial firms introduce new products and services with an eye toward capturing market share (e.g., monopolistic profit). This profit-maximizing, competitive behavior drives the innovation and technological progress that makes countries better off. In this process, which Schumpeter (1939) termed “creative destruction,” innovation and technological change can lead to the growth of new firms and industries along with the demise of others.

Romer (1990) published a paper based on Solow’s exogenous theory of growth but integrating ideas aligned with Schumpeter (1939); that technological change occurs as part of the profit-maximizing production behavior of firms. Romer (1990) theorized that technological change arises from intentional investment decisions in response to incentives (e.g., IP rights) and thus developed the endogenous growth theory.[22] In Romer’s model, knowledge is a byproduct of capital accumulation. It is another form of capital, and the stock of human capital determines the rate of growth. Romer (1990) defines human capital as a “measure of the cumulative effect of activities such as formal education and on-the-job training.” Public and private decisions to invest in factors such as education, training, and R&D impact the stock of human capital. International trade is a further factor and conduit for technological diffusion across countries. The ability of countries to adopt foreign technology is posited to also depend on the stock of human capital and physical capital.

Modern theories of technological change and growth

In recent work, economic theories and empirical analysis based on these theories have focused on two types of models to study the role of capital in technological change. Both build on the neoclassical theory of growth with modifications to the endogenous technological change variable. These models are physical capital accumulation and human capital accumulation.

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[21] Modern economists generally agree that the major driver of economic growth is technological change derived from industrial innovation by profit-maximizing firms and technology diffusion and adoption by firms (e.g., Aghion and Howitt 1992; Grossman and Helpman 1994).

[22] Endogenous growth theory is characterized by increasing returns on production, decreasing returns in the production of new knowledge at the firm level, and externalities or spillovers at the macro level. If returns on production are increasing, then different countries’ growth rates may diverge. If the returns on the production of knowledge are decreasing, a country may initially see rapid progress and growth due to the production of knowledge, but the same production of new knowledge will lead to increasingly lower output over time.

Physical Capital Accumulation

De Long and Summers (1991) revisited the Solow growth theory and posited that the knowledge gained by manufacturers or producers in countries that engage in R&D is embodied in machinery or equipment. Per the De Long and Summers theory, differences in the rates of equipment investment, rather than overall private investment, explain the observed differences in growth performance across countries.

The De Long-Summers model assumes positive externalities associated with equipment investment. That is, the resulting economic growth is higher than what can be explained by growth in investment in capital equipment. In the model below, DYL is the average annual growth rate of real GDP per worker over 1960–1985, i_E is the average share of real equipment investment in GDP over this period, i_S is the corresponding share for structure investment, GAP is the proportionate gap in real GDP per worker in the United States as of 1960 [$(YL_{US}-YL_m)/YL_{US}$ for country m], and DL is the average annual growth rate in the labor force over 1960–1985. c is the regression constant and ε is the error term. GAP and DL control for factors other than investment rates that could influence the growth of real GDP per worker.

$$DYL = c + b_E i_E + b_S i_S + q\,'\,GAP + g\,'\,DL + \varepsilon$$

Criticisms of the De Long-Summers (1991) model have questioned the assumed causal effect of equipment expenditures on economic growth and also whether there are positive externalities associated with this investment in equipment (Auerbach 1994).

Human Capital Accumulation

Other research has focused on the relationship between human capital, technological change, and economic growth. Arrow (1962) put forward the theory that technological change is knowledge; knowledge is accumulated through learning; and learning takes place through doing. In Arrow's model, learning takes place in the capital goods industry, and learning is subject to diminishing returns, growing rapidly at first and then more slowly over time.

Becker (1964) advanced human capital theory by positing that knowledge and skills are acquired through investment in formal education. He examined the microeconomic costs and benefits to individuals of pursuing formal education, with costs including out-of-pocket expenses and foregone earning and benefits including higher earnings later in life and higher employment rates.

Nelson and Phelps (1966) introduced a theory that posited that economic growth was driven by the rate at which a country can adopt advanced technologies that in turn, is a function of how educated production managers are. In the Nelson and Phelps model, the return on a country's investment in education is an increasing function of the rate of technological progress—that is, the rate of growth of educational attainment affects the rate of total factor productivity growth and economic growth.[23]

Lucas (1988) proposed an endogenous growth model, building on Uzawa (1965), that posited that human capital accumulation is the key driver of long-term economic growth.

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[23] Total factor productivity growth is the growth in output per worker beyond that attributed to increased capital.

Whereas the source of technical progress cannot be explained in the Solow model, Uzawa-Lucas theorized that optimal human capital accumulation can be explained by utility maximizing behavior.[24] In the Uzawa-Lucas model, Y is output, A is the amount of output for each unit of capital (A is exogenous and constant), K is capital, l is the proportion of total labor time spent producing final goods, h is the stock of human capital, ɑ is the share of capital in production, and L is labor. The equation is expressed as:

$$Y = AK^{a}(lhL)^{1-a}$$

Microeconomic models and theories of change

The shift to endogenous growth theory was pivotal within the macroeconomics literature. However, microeconomic growth theories had already been developed describing the same phenomena, with Griliches stating that the work of himself, Mansfield, and others was to "endogenize as much of technical change as was possible" (Griliches 1998).

There have been two main microeconomic methods used to evaluate the impact of research on economic growth:[25] production function-based approaches and cost function optimization approaches. The cost function is a variant of the production function with the difference being the use of different measures of productivity and optimization strategy. With the cost function being a later development from the production function, we focus on the connection between the production function and macroeconomic literature in this section. Both methods were developed from the Solow growth model with the basic premise that discoveries from research can increase the efficiency of labor and capital in their production of industrial outputs (Griliches 1963; 1964).

The most widespread microeconomic model for estimating the economic value of R&D is the production function. This model treats R&D as a factor of production alongside labor and physical capital. Whereas labor and physical capital determine productivity, R&D investment can lead to innovation and greater efficiencies in the usage of labor and capital in future periods, leading to long-term increases in total factor productivity (TFP).

As with endogenous growth theory, the production function literature stems from the theoretical works of Harrod (1939) and Solow (1957). Griliches (1963, 1964) developed the production function method that is used in much of the current literature, connecting R&D investment to the flow of industrial outputs.[26] Griliches (1963) focused on the influence of worker education as a factor of production among other factors including livestock expenses, machinery, land, building, and labor years. His 1964 paper revised the model to include R&D expenditures as another factor of production.[27]

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[24] Utility maximizing behavior includes that individuals choose between working in the production sector or going to school in the Lucas (1988) model and between working in the production sector and working in the education sector in the Uzawa (1965) model.

[25] These methods pertain to the effects of technical change on economic growth and are only applicable to measuring the benefits of NSF discoveries.

[26] The model consisted of a Cobb-Douglas production function that tested for the influence of factors of production of agricultural goods.

[27] The study examined agriculture output using data from the U.S. Department of Agriculture on agricultural inputs, including expenditure on labor, machinery, land and buildings, education, and R&D.

Mansfield (1965) tested a production function model using a standard Cobb-Douglas form with labor, capital, R&D, and non-R&D technical change as factors of production.[28] Mansfield (1965) noted that the rates of return from this study comprised private rates of return that were likely less than the full social rate of return. He wrote that the social rate of return would consider the "effects of increased R&D expenditures in one industry or firm on productivity in another industry or firm." This consideration is an early reference to spillover effects, which comprise much of the difficulty of measuring the full economic impact of R&D. Many later works in the literature focus on disentangling spillover effects and differential impacts of R&D between industries.

Other key developments came through the 1960s and 1970s from Griliches, Mansfield, and others. Terleckyj (1960) performed a study to determine which attributes of industry were related with interindustry differences in productivity growth, finding that research intensity was a significant contributor. Minasian (1962) developed a production function form including productivity as a factor of production, and found significant positive effects of R&D on productivity among a small sample of firms. Mansfield (1964) tested related questions of the year to year behavior changes of firms in investing in R&D, finding that firms increase R&D investment when experiencing high returns to R&D. Evenson (1967) discussed the role of research in agricultural production, produced a model of the production function that incorporated knowledge production, and tested for the best fitting lags for how research impacts agricultural production.

Griliches (1979) further advanced the field through the development of the knowledge production function, the main production function used in the subsequent literature. Along with treating knowledge capital as a factor of production alongside labor and capital, R&D investment from prior periods generates knowledge capital, which is used to produce knowledge.

Romer (1990) states the alignment of the Griliches (1979) knowledge production function with endogenous growth theory, agreeing on Griliches' assumption of R&D market effects hinging on dynamics of R&D producing excludable and non-excludable knowledge goods. In practice, Romer (1990) did not yield major change for users of the production function model, as authors in the microeconomic literature were already concerned with understanding the spillover effects of research investment such as in Levy and Terleckyj (1983), Lichtenberg (1984; 1987), and Link (1982). Later works such as Azoulay et al. (2019), Coe and Helpman (1995), and Dyevre (2024) expand on the connection of the literature, explicitly rooting themselves in endogenous growth theory and measuring spillovers that occur through the non-excludability of R&D produced knowledge.

4.3 The NSF and economic growth

From Schumpeter (1939) to Aghion and Howitt (1992), economists have observed that R&D, whether embodied in the equipment used to manufacture products or the human capital involved in finding solutions to technical challenges, plays a large role in driving technological change and the subsequent shifts in total factor productivity and economic growth in countries. Economic growth theory has focused on developing models that better explain and predict the process of technological change.

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[28] R&D in this model depreciates and output is dependent on R&D investment in prior periods. Total output was derived from Value Added. Prices of R&D used in the model were regressed from price increases of labor and capital over the same period.

Intellectual property frameworks provide the incentive for firms to invest in R&D because they enable firms to capture monopolistic profits for a set period. However, economists have also observed market failures that deter private investment at the socially optimal level (Bernstein and Nadiri 1991; Griliches 1992; Hall et al. 2010). The gap between the level of investment made by the private sector and the socially optimal level presents a role for government in remedying this market failure. By identifying the different types of market failures associated with R&D and the case for the role of government in addressing them as well as analyzing the ways in which economists believe R&D contributes to technological change and economic growth, NSF has a sound basis to continue to make targeted investments that support U.S. long-term economic growth. Chief among these are NSF's support for basic research, use-inspired research, human capital development, and research infrastructure.

The NSF's support for basic scientific research aligns strongly with Bush's (1945) linear model, which presents basic research as a critical throughline in the innovation process from the research itself, through its application, development, and eventual commercialization, emphasizing the importance of funding at this early stage. NSF research grants in physics, chemistry, and engineering at this fundamental stage have historically led to technological breakthroughs such as the internet, MRI technology, and nanotechnology (Nelson 1959).

While recognizing the key tenet of basic research in Bush's model, NSF support also reflects the dynamic nature of Kline and Rosenberg (1986) chain link model of innovation where R&D activities interact in a nonlinear, feedback-driven fashion. This recognition is apparent through the NSF's historical funding of multidisciplinary research centers, university-industry partnerships, and technology transfer programs. For example, the Engineering Research Centers (ERCs) and the Industry-University Cooperative Research Centers (IUCRCs) encourage continuous knowledge exchange between academia, government, and industry.

Similarly, while NSF's role in funding basic research supports exogenous growth theories, endogenous growth and accumulation theories tend to describe the larger role institutions such as NSF play in the arena of R&D and economic growth. NSF funding of R&D and human capital is consistent with a model of driving technological change from within the economy by funding STEM education, research infrastructure, and knowledge spillovers that fuel continuous innovation. For example, NSF programs that support graduate fellowships and early-career researchers contribute to human capital formation, ensuring that knowledge generation remains a self-sustaining driver of economic growth. Furthermore, NSF supported research often leads to intellectual property creation and start-up formation (Jaffe 1986), reinforcing the endogenous theory's assertion that knowledge accumulation is central to economic expansion.

Microeconomic models of innovation emphasize the role of market structure, firm behavior, and knowledge spillovers in driving technological progress. Schumpeter's (1939) theory of creative destruction suggest that new innovations disrupt existing markets, fostering competition and economic dynamism. The NSF facilitates this process by funding high-risk, high-reward research that may not receive private investment due to its uncertain commercial viability. Programs such as SBIR/STTR support early-stage technology startups, reflecting Schumpeterian dynamics where disruptive innovations create new industries.

5 What are the indicators and performance measures of research investment?

This section reviews indicators used to measure how R&D contributes to economic growth and productivity, including the indicator definitions, and leading sources for data in the United States. First, indicators of investment in R&D are reviewed, which are often causal variables of interest. Second, we list indicators of knowledge capital development which include the generation of new knowledge and research capacity that contributes to productivity growth. Third, we list indicators of human capital development which also contribute to R&D capacity and production. Fourth, we list indicators of commercialization which capture the translation of R&D into commercial goods and services. Finally, commonly used indicators of economic impact are reviewed, which often serve as the outcome variables of interest.

5.1 Indicators of investment

As noted in Exhibit 8, modeling the pathways that lead from NSF's funded R&D activities to economic impact requires the ability to link inputs and activities to their immediate outputs, and then demonstrate that the outputs contribute to various outcomes that generate economic impact. Many studies of the economic impact of R&D awards use R&D expenditure as the primary input.[29]

The primary indicator of investment is also represented by R&D expenditure and expenditure on R&D activities by federal agencies and private firms. Exhibit 8 includes relevant examples of indicators of investment, including a specific definition used in the literature and the leading data sources associated with that use. Indicators of investment include investment towards federal research funding, academic R&D expenditures, private R&D expenditures, and federal funding for R&D commercialization.

Indicators of investment are disaggregated by type of research, geographic region, administrative unit or program, and performer type. Annual values are most commonly reported, but more frequent time series data are also used.

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[29] See Section 6.

Exhibit 8: Indicators, definitions, and data sources for R&D investments

Indicator	Definition	Leading Data Source
Federal research funding	Federal funding for basic research, applied research, and experimental development activities in science and engineering (including administrative expenses, such as the operating costs of research facilities).	U.S. National Science Foundation (2024e), Office of Management and Budget (2025)
Academic R&D expenditures	R&D expenditure by academic institutions.	National Center for Science and Engineering Statistics (2023a)
Private R&D expenditures	R&D expenditures carried out by businesses by employment size, industry sector, and geographic location.	National Center for Science and Engineering Statistics (2023a), U.S. Census Bureau (n.d.)
Federal funding for R&D commercialization	Small Business Innovation Research/Small Business Technology Transfer funds early-stage technology development by small businesses.	U.S. Small Business Administration (2022)

Note: The included list of indicators and their leading data sources is not exhaustive. We report only the most common indicators from the relevant literature.

5.2 Indicators of knowledge capital

Indicators of knowledge capital act as proxies for the factors of technological production as inputs into R&D and as well as products arising from R&D. Exhibit 9 lists the indicators of knowledge capital that are commonly used as inputs, their definitions and data sources. As shown in the first row of the exhibit, *capital input* proxies the contribution to production from capital assets such as tools that are purchased for research and are reused.[30] Indicators of knowledge capital can be disaggregated by type of research, geographic region, and performer type, and annual values are most commonly reported.

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[30] The Bureau of Labor Statistics reports on this via the *TFP and Related Measures* data product.

Exhibit 9: Indicators, definitions, and data sources for knowledge capital (inputs)

Indicator	Definition	Leading Data Source
Capital input	Contribution to production from capital assets (productive tools that can be re-used in future time periods after they are purchased).	U.S. Bureau of Labor Statistics (2025b)
Labor input	A wage-weighted aggregate of hours worked that differentiates hours by the characteristics of age, education, and gender.	U.S. Bureau of Labor Statistics (2025b)
Total intermediate inputs	Total purchasers' prices of energy, raw materials, semi-finished goods, and services that an industry consumes in producing gross output, including inputs produced by domestic industries and inputs imported from foreign sources.	U.S. Bureau of Economic Analysis (n.d.)
Net capital stock of structures and equipment	Value of equipment and structures, adjusted for depreciation. Equipment includes tangible fixed assets (such as new machinery, furniture, and vehicles) that are used repeatedly or continuously in the process of production for at least a year. Structures are fixed assets (such as commercial buildings and highways) that are usually constructed at the location where they will be used and that typically have long economic lives.	U.S. Bureau of Economic Analysis (2024a)

Note: The included list of indicators and their leading data sources is not exhaustive. We report only the most common indicators from the relevant literature.

Knowledge capital outputs of R&D activities such as new or enhanced R&D processes and new knowledge, methods, or research tools that arise from R&D also serve as output indicators of knowledge capital. Exhibit 10 lists output indicators of knowledge capital along with specific definitions and data sources. *Publications* and *patents* describe and disseminate knowledge developed through R&D and both serve as common indicators of the knowledge capital output. Multiple propriety and free data sources exist for publications (Scopus, Web of Science, and OpenAlex) and for patents (U.S. Patent Office Patents View and TheLens.org).

Exhibit 10: Indicators, definitions, and data sources of knowledge capital (outputs)

Indicator	Definition	Leading Data Source
Publications	Publications describe and disseminate knowledge generated from R&D activities, including new theoretical and practical knowledge, new methods, processes, and tools.	Elsevier (2025), Clarivate (2025), OpenAlex (n.d.)
Citation counts	A measure of impact or influence of a scholarly work.	Elsevier (2025), Clarivate (2025), OpenAlex (n.d.)
Patents	Patents describe and protect new and improved knowledge and processes that result from R&D.	U.S. Patent and Trademark Office (2024)
Number of patent citations	Number of citations made to the patent.	U.S. Patent and Trademark Office (2024)

Note: The included list of indicators and their leading data sources is not exhaustive. We report only the most common indicators from the relevant literature.

5.3 Indicators of Human Capital

Broadly in the literature, the size of the S&E workforce is an indicator of the number of individuals trained and employed as a result of federal research and related funding of human capital development. For more specific indicators of human capital, there are distinctions for human capital working in firms (presented in Exhibit 11) and human capital active in higher education and research institutions (presented in Exhibit 12). In the economic modeling literature, human capital is treated as both a factor of production as well as a type of economic impact (e.g., growth in employment in R&D-intensive industries suggests successful commercialization and resulting economic activity).

Exhibit 11: Indicators, definitions, and data sources for R&D human capital in firms

Indicator	Definition	Leading Data Source
S&E workforce	U.S. population with bachelor's degree or higher by S&E field of degree and employment in S&E-related occupations.	National Center for Science and Engineering Statistics (2023b) developed by the OECD (Appelt et al. 2016)
S&E employment	The number of people employed in the U.S. workforce by STEM occupation group and educational attainment.	U.S. Census Bureau (2025a)
Employment, by industry	The count of filled jobs, whether full or part time, and temporary or permanent, by place of work.	U.S. Bureau of Labor Statistics (2025b)
Employment, by occupation	The number of part-time and full-time workers who are paid a wage or salary. Excludes the self-employed, owners and partners in unincorporated firms, household workers, or unpaid family workers.	U.S. Bureau of Labor Statistics (2025b)
R&D-intensive industry employment	A set of high and medium-high R&D intensity industries developed by the OECD.	OECD (2024), U.S. Bureau of Labor Statistics (2025b)
Wages, by industry	The total compensation paid, including bonuses, stock options, severance pay, profit distributions, the cash value of meals and lodging, tips and other gratuities, and, in some states, employer contributions to certain deferred compensation plans (such as 401(k) plans), during the calendar quarter, regardless of when the services were performed.	U.S. Bureau of Labor Statistics (2025b)
Wages, by occupation	Straight-time, gross pay, exclusive of premium pay. Base rate; cost-of-living allowances; guaranteed pay; hazardous-duty pay; incentive pay, including commissions and production bonuses; and tips are included. Overtime pay, severance pay, shift differentials, nonproduction bonuses, employer cost for supplementary benefits, and tuition reimbursements are excluded.	U.S. Bureau of Labor Statistics (2025a)
Job creation	Job creation is the sum of all employment gains from expanding establishments from year t-1 to year I including establishment startups.	U.S. Census Bureau (n.d.)
Job destruction	Job destruction is the sum of all employment losses from contracting establishments from year t-1 to year I including establishments shutting down.	U.S. Census Bureau (n.d.)

Note: The included list of indicators and their leading data sources is not exhaustive. We report only the most common indicators from the relevant literature.

Exhibit 12: Indicators, definitions, and data sources for human capital in higher education

Indicator	Definition	Leading Data Source
Staff salaries	Average salary equated to 9 months of all ranks of full-time non-medical instructional staff.	U.S. Department of Education, National Center for Education Statistics (2025)
R&D employment in academia	For 2019 and earlier, this measure (headcount) counts the number of "principal investigators" and "all other personnel" that received salaries, wages, and fringe benefits from R&D accounts. Starting in 2020, the survey was revised to ask for a headcount and full-time equivalents (FTEs) for three R&D functions: researchers, R&D technicians, and R&D support staff. The data for the revised questions are not available for 2020 and 2021 but are available for 2022 and later.	National Center for Science and Engineering Statistics (2023a)
S&E enrollment	Number of people enrolled for credit in the fall of the academic year.	U.S. Department of Education, National Center for Education Statistics (2025)
S&E degree completion	Number of degrees awarded.	U.S. Department of Education, National Center for Education Statistics (2025)

Note: The included list of indicators and their leading data sources is not exhaustive. We report only the most common indicators from the relevant literature.

5.4 Indicators of commercialization

In the literature on the economic impacts of R&D, indicators of commercialization are used to capture the translation of research into commercial goods and services. Exhibit 13 lists the definitions and leading data sources for indicators used to measure R&D commercialization. For example, indicators such as innovation rates track the number and share of companies by industry sector at the national level that report introducing a new or improved product, service, or business model to the market, the sources of funding for this innovation, and the source of intellectual property for this innovation. Other studies track commercialization outcomes through the identification of commercialized products followed by analysis of product specific sales-records and company records.

Exhibit 13: Indicators, definitions, and data sources for R&D commercialization

Indicator	Definition	Leading data source
Exports	The value of goods and services produced in the United States that are sold to buyers in other countries.	U.S. Bureau of Economic Analysis (2025)
Innovation rate	The introduction of new or significantly improved products and processes by U.S. businesses by size of company and by industry sector.	NCSES and Census, Business Enterprise R&D Survey (U.S. National Science Foundation 2024e) (U.S. Census Bureau n.d.)
Commercialization outcomes	Company specific outcomes related to the manufacture and sales of products arising from R&D activities.	Company Records, Sales Records
Price indices of net output	Measure of changes in prices received for the industry's output sold outside the industry.	U.S. Bureau of Labor Statistics (2025b)
Price indices of output	Price change for commodities sold as personal consumption, as capital investment, to government, and as exports.	U.S. Bureau of Labor Statistics (2025b)
Price indices of intermediate inputs	Price change for goods, services, and construction products sold to businesses as inputs of production, excluding capital investment.	U.S. Bureau of Labor Statistics (2025b)
Establishment entry	Establishment with positive employment in the current year and zero employment in the prior year.	U.S. Census Bureau (2025b)
Establishment exit	Establishment with zero employment in the current year and positive employment in the prior year.	U.S. Census Bureau (2025b)

Note: The included list of indicators and their leading data sources is not exhaustive. We report only the most common indicators from the relevant literature.

5.5 Indicators of economic impacts

Exhibit 14 reports commonly used indicators that capture the economic impacts of R&D and human capital and the leading sources for data on these indicators in the United States. Three indicators (total factor productivity, gross output, and value added) reflect either the value of goods and services produced or the efficiency with which inputs are used to produce final goods and services. *Total factor productivity* reflects the efficiency at which combined inputs are used to produce the output of goods and services (Bureau of Labor Statistics 2025c). *Gross output* is the value of goods and services produced, principally measured using industry sales or receipts, including sales to final users (GDP) and sales to other industries (intermediate inputs) (U.S. Bureau of Economic Analysis 2025).[31] *Value added* captures the current dollar value of output that has been adjusted for changes in

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[31] At the industry level, gross output is a measure of sales or revenue from production for most industries, although it is measured as sales or revenue less cost of goods sold for margin industries like retail and wholesale trade.

inventory (gross output) and the removal of intermediate inputs (energy, material, and services) (U.S. Bureau of Economic Analysis 2025).

Exhibit 14: Indicators and leading data sources for economic impacts

Indicator	Leading Data Source
Total factor productivity	U.S. Bureau of Labor Statistics (2025c)
Gross output	U.S. Bureau of Economic Analysis (2023), U.S. Bureau of Economic Analysis (2025)
Value added	U.S. Bureau of Economic Analysis (2025)
Industry earnings	U.S. Bureau of Economic Analysis (2025)
Taxes on corporate income	U.S. Bureau of Economic Analysis (2025)
Employment	U.S. Bureau of Labor Statistics (2025a), U.S. Bureau of Economic Analysis (2025)
Employee earnings	U.S. Bureau of Labor Statistics (2025a)

Note: The included list of indicators and their leading data sources is not exhaustive. We report only the most common indicators from the relevant literature.

A second set of indicators captures industry-level impacts resulting from economic activity. *Industry earnings* is defined as net income, before taxes, from current production of entities that are treated as corporations (U.S. Bureau of Economic Analysis 2025).[32] *Taxes on corporate earnings* include corporate income taxes paid to federal, state, and local government and taxes paid by domestic corporations to foreign governments on income earned abroad (U.S. Bureau of Economic Analysis 2025).

Finally, indicators of economic impact at the individual level are used to capture how economic activity produces benefits for individuals and households. *Employment* captures the number of jobs associated with economic activity, which is distinct from the number of employees and includes part-time positions (U.S. Department of Education, National Center for Education Statistics 2025). *Employee earnings* is the value of payment to employees before taxes, including overtime pay, commissions, and tips (U.S. Department of Education, National Center for Education Statistics 2025).

5.6 Applications of indicators

The indicators reviewed in this section comprise key inputs and outputs for the estimation of economic impacts of NSF research support.[33] While the primary input for estimates of economic impact from research is R&D expenditure, key differences exist between the indicators that are used in approaches for measuring short- and long-term economic

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[32] For corporate businesses, industry earnings is defined as gross output less the following expenses: intermediate inputs, compensation of employees, taxes on production and imports (less subsidies), consumption of fixed capital, net interest and miscellaneous payments, and business current transfer payments.

[33] More detail regarding the estimation of economic impacts from R&D is available in Sections 6 and 7. Section 6 contains additional details for the approaches used to estimate short-term economic impacts from NSF awards. Section 7 contains additional details for the approaches used to estimate long-term economic impacts from NSF R&D discoveries.

impacts from research, with a clear divide between control (independent) and outcome (dependent) variables used.

Short-term economic impacts typically involve the estimation of productivity increases, follow-on funding, and other intermediate outcomes that result from R&D expenditure. The input data that is required consists of sums of R&D expenditure and additional control variables. R&D expenditure is the common input for I-O and econometric studies of the economic impacts of awards,[34] with some econometric studies requiring other controls, depending on the outcome variables that are measured. Common controls include total government consumption and gross investment expenditures for non-R&D purposes; tax receipts excluding transfers, interest payments, and subsidies; private R&D investments; and national GDP. Common output data include indicators of economic impact and human capital such as gross output, value added, employee compensation, tax revenue, jobs created, degree completion, and crowded-in non-federal R&D funding.[35]

Long-term economic impacts typically involve the estimation of productivity increases, rates of return and intermediate outcomes from R&D discovery. Approaches to estimating the economic impact of research discoveries typically provide outputs in the form of rate of return statistics, based on productivity increases that result from the use of discoveries. These can be measured using R&D expenditure as the control variable and sales, value added, or TFP as the outcome variable. Additional input, output, and control variables differ widely by estimation approach. For example, econometric models may require additional data on the investment of research performers into other factors of production such as employment, wages, capital prices, and capital stocks.[36] Outcome variables can also differ among econometric models, with some models of knowledge production using patent counts, citation counts, and innovation counts as outcome measures for the measure of technological spillovers.

Lastly, indicators can be used for areas where economic impacts cannot be estimated. For example, indicators are commonly used in the cost-benefit literature to estimate benefits from projects that cannot easily be put in monetary terms, such as publication or citation counts for benefits from the value of acquired knowledge. Accordingly, indicators of impacts that emerge from NSF research can be used when there are no viable methods for converting data for those impacts into measures of economic return.

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[34] R&D expenditure may include R&D expenditure disaggregated by geographic region, administrative unit or program, or performer type.

[35] Selected output measures may differ by the type of research that is analyzed. While I-O provides estimates of GDP, value added, employee compensation, and employment regardless of input type (TechLink 2019b), econometric models may be designed around the outcomes most relevant to a type of research (Pallante, Russo, and Roventini 2023), such as the increases in employment that result from human capital investment. Similarly, the type of research can be included as a control variable in econometric models to assess the difference in outcomes between types of research.

[36] For disaggregation by research performer, econometric studies can require controls for industry, location, government spending shocks, technology area, and human capital.

6 How does the empirical literature estimate the short-term economic impacts of R&D awards?

This section reports on approaches used in the literature to estimate the short-term economic impact and intermediate outcomes of investments in research activities, research infrastructure, and human capital development. The discussion highlights the approaches that may be applicable to evaluating the impacts and outcomes of NSF awards.

We begin with a review of I-O modeling and how this method has been used to estimate the short-term economic impact of federal research awards and activities, research infrastructure, and student spending. This includes an overview of the logic of I-O modeling, the impact indicators that can be estimated, and the I-O tools that have been used most often to study the impacts of various federal R&D funding programs.

We then review econometric approaches that have been used to evaluate the short-term economic impact and intermediate outcomes of federal R&D and student funding. Econometric approaches have been used to study short-term economic impacts of federal research funding, including contributions to GDP and employment. Econometric approaches have also been used to estimate how federal research funding stimulates research funding from non-federal sources. Lastly, we review the econometric literature that estimates how federal R&D funding contributes to the production of human capital, including degree completion.

Lastly, we assess the practical applicability of I-O and econometric approaches for studying the short-term economic impact and intermediate outcomes of NSF awards. Specifically, we focus on data requirements and potential model specifications for estimating different types of impacts from NSF awards, including annual and quarterly impacts, state and local impacts, impacts and outcomes by type of research, geographic region, administrative unit or program, performer type, and funding opportunity.

6.1 Input-Output modeling of research, infrastructure, and student funding

Overview of I-O modeling approach

I-O models are designed to capture how changes in activity in a given sector will change economic activity across the entire economy. Relying on interindustry purchasing patterns, labor expenditures, and employment, I-O models capture the economic activity associated with a given amount of output in a specified industry. This includes the upstream effects created by the demand for inputs like raw materials and equipment, employment within the industry being studied, and downstream consumer spending supported by employee earnings.[37]

I-O models are widely used to study the impacts of a range of economic activities including manufacturing (Association of Equipment Manufacturers 2023), research infrastructure (Association of University Research Parks 2018), educational institutions (Beacon Economics 2021), and scientific R&D (Ohio University 2018; TechLink 2019b).

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[37] For additional detail on the background, structure, and data foundations for I-O modeling see Appendix D

The two most common I-O modeling tools in the United States are IMPLAN (IMPLAN 2024) and the Regional Input-Output Modeling System or RIMS II (Bureau of Economic Analysis, 2024). While these tools differ in the data used to create the modeling framework and in some of the estimates that can be produced, the underlying logic is the same: to model the ripple effects of production in a given industry through the broader commercial and consumer economy.

The model inputs correlate investments and spending with the corresponding change in the value of output (sales), employment, and labor compensation by industry. Based on these types of inputs both IMPLAN and RIMS II estimate the amount of output, value added, employee compensation, and employment associated with the economic activity that would be required to match the value of the inputs provided.

I-O studies of federal R&D funding

Most applications of I-O models in the federal R&D funding space have assessed the economic impact of SBIR/STTR awards. In the case studies of SBIR/STTR awards, these studies focus on the impacts of use-inspired research.[38] TechLink has conducted several studies evaluating the economic impacts of R&D activities funded through SBIR/STTR programs across multiple agencies including the Air Force from 2000–2013 (2014), the Navy from 2000–2013 (2016), National Cancer Institute in 2018 (2018), and DOD from 1995–2018 (TechLink 2019c). NASA (2017) also estimated the impacts of its SBIR/STTR R&D funding in FY 2016.

I-O models have also been used to estimate the national impacts of federal R&D spending outside of SBIR/STTR programs. Nadeau et al. (2021) estimated the employment, GDP, and earnings impacts of appropriations made in the 2012 Middle Class Tax Relief and Jobs Act for NIST’s Public Safety Communications Research Division. Zalalem et al. (2023) estimated the economic impact of climate change R&D funded by NASA in FY 2023.[39] United for Medical Research (2024) has released annual reports using I-O models to analyze the economic impact of NIH research funding for over a decade.

Exhibit 15 reports the summary estimates from 8 studies reviewed of the economic impact of extramural federal R&D funding, including the minimum, median, and maximum estimated value for five different output values reported by I/O models. In addition, the table reports which model provided the lowest or highest estimates. Results are generally expressed in terms of the value of the economic activity generated per dollar spent or household income per job supported by that activity.

The first notable feature of studies using I-O to measure the economic impact of R&D activities is the consistency of estimates across studies: an effect between $2.31 and $2.86 in additional output (sales) for each $1 in R&D funding. Estimates for value added resulting from R&D were similarly consistent, ranging from $1.46 to $2.00. Estimates of employee compensation were also tightly clustered with all but one falling between $0.94 and $0.98 for each $1 in R&D expenditure. Finally, there is notable consistency in estimates of the

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[38] For simplicity of interpretation, SBIR/STTR activities are considered to fall under use-inspired research for the purposes of this report. This categorization was made on the basis of SBIR/STTR activities for the NSF being housed within the Directorate for Technology, Innovation and Partnerships.
[39] The Zalalem et al. (2023) study is somewhat unique in that it combines the economic impacts of salaries and benefits paid to NASA staff conducting climate change research with the effects of procurement of goods and services to support climate change research.

amount of funding required to support one job, with most of the studies reviewed falling between $58,000 and $72,000.[40]

Due to differences the underlying data, assumptions, and methods for modeling regional monetary flows between industries (Bureau of Economic Analysis 2018; IMPLAN 2025b), RIMS II and IMPLAN will produce different estimates for the same set of economic inputs (Lynch 2000). Across all the outcome measures reported in Exhibit 15, the most significant variation in the magnitude of the estimates resulted from the RIMS II multipliers, while the estimates produced using IMPLAN were generally more consistent.[41] Limitations in the methodological descriptions provided for some of these studies makes it difficult to diagnose additional sources of differences between studies.

Exhibit 15: Summary of I-O Studies of Research Economic Activity Associated with Federal Research Funding

Estimate	Minimum	Median	Maximum	# of studies reviewed
Total output per $1 in funding	$2.31	$2.64	$2.86	8
Value added per $1 in funding	$1.46	$1.52	$2.00	5
Employee compensation per $1 in funding	$0.94	$0.96	$1.23	7
Tax revenue per $1 in funding	$0.33	NA	$0.36	2
Spending per job supported	$58,000	$72,000	$92,000	8

Note: This exhibit summarizes estimates from studies of the economic impacts of federal research awards and activities. Total output per $1 in funding reflects the estimated amount of GDP created by economic activity supported by federal research funding. Value added per $1 in funding reflects the estimated value of final goods and services supported by federal research funding minus the cost of inputs. Employee compensation per $1 in funding reflects the earnings and benefits received by employees from economic activity supported by federal research funding. Cost per job created reflects the amount of research funding divided by the total estimated number of jobs supported by federal research funding. Number of studies reviewed reflects the number of studies that produced each type of estimated economic impact. Minimum = smallest estimate from the literature; median = median estimate from the literature; maximum = the largest estimate from the literature.

I-O studies have been conducted on the economic impacts of spending on research infrastructure, including both federal and non-federal funding. Spending for construction and renovations are included in the estimated economic impact of the Pacific Northwest National Laboratory in the State of Washington (Battelle 2023). Construction of professional and scientific facilities factored into the estimated economic impact of developing the Research Park at the University of Illinois (Association of University Research Parks 2018).

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[40] The estimated impact of NIH (United for Medical Research 2024) generated the highest estimate of spending per job supported, reflecting the higher wages paid in many medical and medical research occupations. The median annual earnings for Medical Scientists in 2023 was $94,952, based on median weekly earnings of $1,826 (U.S. Bureau of Labor Statistics 2024).

[41] The lowest estimate for cost per job created of $58,000 (Nadeau et al. 2021) and the highest estimate of $92,000 (United for Medical Research 2024) were produced using RIMS II. The lowest estimate for output per $1 in funding, the highest estimate of value added per $1 in funding, and the highest estimate of employee compensation per $1 in funding were produced using RIMS II (Nadeau et al. 2021).

For NSF awards for *human capital* outside of funded research projects,[42] studies using I-O models to evaluate the economic impact from spending by university students may be applicable to direct student support from NSF (e.g., research fellowships). While not specific to federal funding for human capital development, example studies are included here that use I-O models to estimate the economic activity that occurs when students spend money in the consumer economy (for example, from salaries paid out of NSF funding).[43] A summary of the estimates produced by these studies, and a comparison to the magnitude of impacts driven by R&D awards is provided in Exhibit 16.

Exhibit 16: Differences in the estimated impacts of R&D funding and student spending

Estimate	R&D median	Student spending median
Total output per $1 in spending	$2.64	$1.58
Employee compensation per $1 in spending	$0.96	$0.70
Number of studies reviewed	8	2

Note: This exhibit compares the estimated economic impact of R&D funding and student spending. R&D median reflects the median estimated impact of federal research funding. Student spending median reflects the median estimated impacts of student spending. Total output per $1 in funding reflects the estimated amount of GDP created by economic activity supported by federal research funding and student spending. Employee compensation per $1 in funding reflects the estimated value of employee income and benefits supported by federal research funding and student spending.

The existing literature indicates that R&D funding often has a larger economic impact than student spending. While only a small sample of studies focusing on student spending were reviewed here, the estimates for the total output and employee compensation generated by each $1 in student spending was lower than the impacts estimated for R&D funding. The lower impacts reflect differences in the demand for R&D and labor compared to the economic activity associated with student spending.

6.2 Econometric modeling of R&D and student funding

This section reviews the literature that uses econometric approaches to estimate the short-run impacts and outcomes of R&D funding and student funding.

Overview of econometric modeling approach

The econometric literature examines outcomes and impacts of NSF funding that exceed those that can be evaluated using I-O models. While there are a small number of studies examining the stimulative effect of R&D funding on economic outcomes like employment and output (Chhabra et al. 2019; De Lipsis et al. 2023; Pallante et al. 2023), the literature is more developed for capturing other outcomes including the stimulation of additional non-federal R&D funding (Gonzalez and Pazo 2008; Guellec and Pottelsberghe de la Potterie 2003; Sussex et al. 2016; Wolde-Rufael 2009) and contributions of student financial aid to

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[42] In the case of R&D funding, consumer spending is estimated by I-O models based on the employee compensation that is generated by the economic activity being funded.

[43] An extensive literature exists using I-O models to evaluate the economic impact of colleges and universities. Two examples are included here that include student spending as one of the modeled types of economic impact (Anderson Consulting Group 2024; Beacon Economics 2021).

the development of human capital (Angrist et al. 2014; Angrist, Autor, and Pallais 2020; Bettinger 2015; Dynarski 2000). In addition to controlling for other macroeconomic factors that shape impacts and for confounding factors that mediate outcomes, estimation methods include quasi-experimental design (Howell 2017), regression with instrumental variables (Pallante et al. 2023), and structural vector autoregression (De Lipsis et al. 2023).

Econometric studies of the short-term economic impacts of federal awards

Econometric methods have been used to evaluate the short-term impacts of federal funding on economic output, employment, stimulating non-federal research funding, and the production of STEM graduates.[44] While most of the literature addressing the impacts of R&D funding on economic output focuses on long-term contributions to productivity growth, this review did identify two studies that assess the short-term impacts of a shock in federal R&D funding. De Lipsis et al. (2023) found that federal R&D funding has a significant short-term stimulative effect, particularly when the private sector anticipates forthcoming R&D projects, and that the multipliers associated with R&D funding outperform many other types of federal funding. Mitze and Makkonen (2023) found that a large increase in Finnish R&D funding during the COVID-19 pandemic had a stimulative effect on economic output.

Studies using econometric approaches have found mixed results on the effects of federal funding for R&D on private sector employment. Chhabra et al. (2019) found that R&D funding provided by the American Recovery and Reinvestment Act stimulated employment growth. Pallante et al. (2023) found that DOD R&D funding had a significant positive effect on employment within some high-tech industries, but the effects were not consistent across sectors.[45] Link and Scott (1981) found mixed results for the impacts of SBIR funding on the retention of employees for companies that received awards from different agency programs. The largest impacts tended to occur where projects resulted in IP including patents and trademarks and when the federal government created a market for products and services, such as DOD funding projects that produce technologies with military applications.

Econometric studies of the complementarity of federal awards

Economists have engaged in many studies on the extent to which public R&D funding complement (“crowd-in”) or substitute for (“crowd-out”) private sector investments in R&D. The field has not arrived at a single answer, and results indicate the answer is highly contingent on a number of factors, including: whether studies take a macroeconomic or microeconomic approach; the research funding mechanism (e.g., tax subsidies, grants or R&D performed by industry); or, the type of research being funded (David et al. 2000; Levy and Terleckyj 1983; Leyden and Link 1991; Lichtenberg 1984a; Moretti et al. 2019; Wallsten 2000; Zúñiga-Vicente et al. 2014).

While many studies have been performed cross-nationally or outside of the United States context (Gonzalez and Pazo 2008; Guellec and Pottelsberghe de la Potterie 2003; Sussex et al. 2016; Wolde-Rufael 2009), this review identified several studies that assess the impacts

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[44] This review did not identify studies using econometric approaches to evaluate the short-term economic impact of spending on research infrastructure.

[45] Pallente et al. (2023) estimate employment elasticities by industry where spending is occurring, which may be useful for estimating the impacts of NSF research funding because the study provides estimates of employment elasticities for a range of research-intensive industries and occupations.

of federal research funding on non-federal research investments that are applicable to NSF research support.

Elasticities from the reviewed literature range from 0.02 for non-firm private funding with respect to DOD R&D (Pallante et al. 2023) to 0.47 for federal funding with regard to private sector funding (Lanahan et al. 2016). Lanahan et al. (2016) also found positive and significant crowding-in effects for state and nonprofit sources of R&D funding. Lastly, Blume-Kohout et al. (2008) found that increases in NIH R&D funding boosted biomedical research funding from non-federal sources.

Econometric studies of human capital development

Studies that focus on funding for R&D human capital development are part of a broader literature on the role of financial and non-financial aid in educational outcomes. The efficacy of student funding in boosting educational outcomes is highly contested in the existing literature (Nguyen et al. 2019). While some studies have found little or no evidence that financial aid improves educational outcomes (Clotfelter et al. 2016; Sjoquist and Winters 2015; Zhang 2011), others have found evidence that scholarships can increase college attendance (Dynarski 2000), persistence (Angrist et al. 2014; Bettinger 2015), and degree completion (Angrist et al. 2020).

Econometric studies have found evidence of positive impacts for student funding aimed specifically at increasing the supply of STEM graduates. Graddy-Reed et al. (2021) found that the NSF Graduate Student Research Fellowship program increased degree completion by nearly 3% and postdoc position placement by 6%. Castleman et al. (2018) found that need-based financial aid increased STEM credit completion by 4% for academically prepared students and degree completion by 3%.

Student funding and employment on funded research teams have also been found to contribute to career advancement and employment in R&D positions. Zolas et al. (2015) found that two-fifths of federally and non-federally funded graduate students found private-sector employment, predominantly with large high-tech companies. While this study is not based on an econometric analysis that estimates the magnitude of impacts of working on funded academic R&D projects, it reflects the flow of researchers trained in academic setting like those funded by NSF into productive careers in private sector R&D.

Studies have also found that federal research funding can impact students' decisions about fields of study to pursue and creates opportunities for early-career R&D staff to gain experience. Freeman (1975) found that federal science funding influenced the rate of students entering and graduating from physics programs.[46] Wilson et al. (2018) found that participation in the NSF Research Experiences for Undergraduates program increased enrollment in PhD degrees, although the actual impact on the rate of degree completion was not analyzed. Funk et al. (2019) found that federally funded research groups tend to be larger and employ a higher share of graduate and postdoctoral students than research

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[46] Freeman (1975) explored how federal funding for physics impacted the salaries of working scientists, which was found to be a predictor of enrollment and graduation. Because of the lag between when students enter degree programs and graduate into the labor market, the paper argues for using salary levels rather than graduation numbers to predict entrants into science degree programs and uses a "cobweb supply relation model" for estimating supply responses to changes in salary. The analysis is also potentially useful in showing that labor market response elasticities differ between undergraduate and graduate students in ways that are logical given the different point students are at in making career path decisions.

groups that were more reliant on non-federal funding. Lane et al. (2014) found that research groups supported by federal grants tended to be larger and employ more researchers that would be categorized as “staff” and not faculty, suggesting that federal funding is particularly helpful for creating opportunities for early-career researchers.

6.3 Feasibility and data requirements for estimating economic impact from NSF awards

This section discusses potential practical applications of I-O and econometric approaches for estimating the economic impact and intermediate outcomes of NSF awards based on analysis that has been conducted in the literature. This section reviews model specifications and data requirements where the literature has demonstrated the potential to disaggregate NSF awards by type of research, geographic region, by sub-annual timeframes, research institution and type of institution, and administrative units including directorates, funding programs, and funding opportunities.

Exhibit 17 provides examples of studies using I-O and econometric approaches to estimate different types of impacts and outcomes that can provide guidance for estimating the impacts of NSF awards. For some types of impacts, a given approach is not applicable, such as using I-O models to estimate quarterly employment impacts. In others, such as estimating the impacts of basic research, no econometric studies were found in the literature, but the econometric approach could be used to estimate the economic impact of NSF R&D awards.

Exhibit 17: Example studies estimating different types of impacts and outcomes

Impact type	Input-Output	Econometric
Basic research	NASA (2017)	Not demonstrated
Applied research	NASA (2017); TechLink (2014; 2016; 2018; 2019a)	De Lipsis et al. (2023)
Research infrastructure	Battelle (2023)	Not demonstrated
National level	NASA (2017); TechLink (2014; 2016; 2018; 2019).	Pallante et al. (2023); Link and Scott (2012)
State level	TechLink (2014a2019c)	Chodorow-Reich et al. 2012; Pallante et al. 2023; Wilson 2012
Local level	Not demonstrated	Chhabra et al. (2019)
Program level	TechLink (2014; 2016; 2018; 2019)	Link and Scott (2012)
Government performed R&D	Nadeau et al. (2021); NASA (2017)	Pallante et al. (2023)
Academia performed R&D	Not demonstrated	Graddy-Reed et al. (2021)
Firm-performed R&D	NASA (2017); TechLink (2014; 2016; 2018; 2019).	De Lipsis et al. (2023)
Quarterly impacts	Not applicable	De Lipsis et al. (2023)

Note: This exhibit provides example studies using either input-output or econometric approaches to estimate the economic impact of different types of research funding (basic research, use-inspired research, research infrastructure, and human capital development), studies that have estimated economic impact at different geographic levels of disaggregation (national, state and local), studies that have estimated impacts for specific research programs, studies that have estimated impacts for different research settings (government performed, academia performed, and firm performed), and studies that have estimated quarterly instead of annual impacts. Not demonstrated = there were no studies reviewed for this report that estimated the impacts of a specific type of research funding. Not applicable = an approach cannot be used to estimate the economic impact of a specific type of research funding.

Applications of I-O approach

The literature provides approaches using I-O models to estimate the annual aggregate economic impact of NSF awards, including basic research, use-inspired research, research infrastructure, and human capital development. Based on the literature impacts can be estimated at the national, state, county, metropolitan statistical area, and congressional districts, levels. The literature also provides guidance on how to estimate the economic impact of NSF awards by institution, directorate, program, and funding opportunity. The literature demonstrates the ability of the I-O approach to model the short-term economic impact of NSF awards, including the amount of GDP, value added, employee compensation, and employment generated by economic activity supported by NSF awards.

The most basic application demonstrated in the literature is to estimate the annual impacts of aggregate NSF awards using funding as inputs (as was done for other agencies by Nadeau et al. (2021) and Zelalem et al. (2023)). The literature further shows that it is possible to model the economic impact for different types of NSF awards, including basic research (Zelalem et al. 2023), use-inspired research (TechLink 2019c), research infrastructures (Battelle 2023), and awards for human capital development (Beacon Economics 2021), separately.

Due to the different types of economic activity associated with each type of award, conducting separate I-O models for different types of funding will likely produce more accurate estimates of economic impact. For example, awards for basic research will produce different types of demand for raw materials, equipment, services, and labor inputs that will result from awards for STEM education, which will change the amount and types of economic impact generated by NSF awards for different purposes. While it was not done in literature reviewed for this study, it is possible to refine I-O models to reflect the specific mix of goods and services required to conduct different types of research (IMPLAN 2025a), which can impact the geographic distribution of impacts based on where industries that support research activities (Bureau of Economic Analysis 2018; IMPLAN 2025e). Different types of research will also create different labor demand based on the labor intensity of the research being conducted and the industries that are supporting research activities (Bureau of Economic Analysis 2018; IMPLAN 2025c).

It is not possible to produce estimates for timeframes shorter than one year using the leading I-O models. The I-O models used in the literature are designed to estimate annual impacts and therefore there are no examples in the identified literature of estimating impacts at shorter timeframes (IMPLAN 2025d). The inability of the leading I-O models to estimate impacts for less than a full year particularly applies to employment impacts which reflect the expected number of annual job years, both full time and part time, associated with a given amount of NSF funding (Bureau of Economic Analysis 2018; IMPLAN 2025c).

The literature demonstrates that I-O models can be used to estimate the economic impact of NSF awards at the state level (United for Medical Research 2024), and it is possible to produce estimates at more granular geographic levels. The leading I-O models can estimate impacts at the state, county, and metropolitan statistical area levels (Bureau of Economic Analysis 2018; IMPLAN 2025e), and IMPLAN can estimate impacts at the ZIP code and congressional district levels (IMPLAN 2025e). Disaggregating geographic impacts require annual NSF award amounts at the desired geographic level and separate I-O models for each geographic region.[47] More geographically granular estimates are possible where funding data can be disaggregated at the county, metropolitan statistical area, and congressional district levels.

The literature shows that I-O models can be used to estimate program-level economic impact (TechLink 2014, 2016, 2019b), which could be expanded to produce estimates of the economic impact for each NSF directorate, division, and funding opportunity. Conducting this analysis would require annual aggregate funding amounts for each administrative unit which can then be used as inputs for an I-O model evaluating the economic impact of awards made by each administrative unit. While I-O models have not been used extensively in the literature to estimate impacts from funding to specific institutions (e.g., impacts from awards to minority-serving institutions, impacts of EPSCOR grants, and impacts for non-R1 institutions), these types of analysis are entirely possible using annual NSF funding data broken down by type of institutional recipient.

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[47] For example, estimating the economic impact of NSF funding in Kansas would require annual NSF funding awards made to recipients in Kansas and an I-O model specific to the state.

Applications of econometric approaches

The literature demonstrates that econometric approaches can be used to estimate the annual economic impact of NSF awards, including short-term contributions to GDP (De Lipsis et al. 2023) and employment (Link and Scott 2012b; Pallante et al. 2023). Econometric approaches have also been conducted at the state and county levels and for quarterly economic impact. The literature also demonstrates that it is possible to estimate the intermediate outcomes of NSF awards including stimulating R&D investments from non-federal sources of funding (Blume-Kohout et al. 2008; Lanahan et al. 2016; Pallante et al. 2023) and contributions to the STEM workforce (Castleman et al. 2018b; Graddy-Reed et al. 2021).

The literature provides approaches to estimate the annual impacts of NSF awards on state-level employment (Chodorow-Reich et al. 2012; Pallante et al. 2023; Wilson 2012) and county-level employment (Chhabra et al. 2019), particularly in the wake of shocks to R&D funding levels such as when awards are used as fiscal stimulus. A cross-sectional model specification can be used, with instrumental variables to account for factors that impact the allocation of awards to states or counties (Chhabra et al. 2019). State-level fixed effects model specifications can be used to account for state-level economic dynamics that impact state and county-level economic outcomes (Pallante et al. 2023). The control variable of interest would be annual NSF funding amount granted to each state or county. Data for the dependent variable of total state or county employment can be taken from the Bureau of Labor Statistics, Quarterly Census of Employment and Wages (Bureau of Labor Statistics 2025d).[48] Data for the outcome variable of total state or county employment can be taken from the Bureau of Labor Statistics, Quarterly Census of Employment and Wages (Bureau of Labor Statistics 2025d).

At the county-level, employment in counties that neighbor counties that receive NSF awards can be included in the outcome variable to capture cross-county commuting patterns and procurement from outside of counties receiving NSF awards (Chhabra et al. 2019). To account for the fact that states and counties that receive larger amounts of federal R&D funding tend to have larger populations, changes in employment and funding levels can be divided by the population of each county.

Other factors that impact the allocation of NSF R&D awards can be captured through control variables including, the Quarterly Census of Employment and Wages data on the number of people employed in manufacturing to reflect differences in industrial structure across jurisdictions, the number of people employed in R&D and science from the U.S. Census Bureau County Business Patterns (U.S. Census Bureau 2022b) to capture differences in the total R&D intensity of each jurisdiction, whether a county is classified as urban or rural (U.S. Department of Agriculture 2025),[49] the presence or number of research universities in a state or county from the Carnegie Classification (Carnegie Foundation 2021),[50] the number of doctoral degrees conferred (National Center for Science and Engineering Statistics 2023b), R&D funding from non-federal sources including institutional funding and state

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[48] BLS employment variables can include total county employment and total county private sector employment.

[49] U.S. Department of Agriculture categorizes each county along a continuum from non-metro with fewer than 5,000 residents not adjacent to a metro area to metro counties with populations over 1 million. Using these data, it is possible to either divide counties into metro vs. non-metro or use the additional categories to draw more detailed distinctions.

[50] The Carnegie Classification was used to identify research universities.

funding (National Center for Science and Engineering Statistics 2023a), and the lagged level of NSF R&D funding.

The literature shows that it is possible to estimate the quarterly economic impact of NSF awards. A Structural Vector Autoregression (SVAR) time series model can be used to assess how changes in NSF award levels impact private investment in R&D and aggregate GDP at both short and long-run time horizons (De Lipsis et al. 2023). Specifying a SVAR model to capture how private R&D investments and GDP respond to change in NSF awards can be done using quarterly data on the level of NSF R&D awards and quarterly control variables including total government gross funding for R&D inclusive of grants, R&D procurement, and government-conducted R&D activities, total government consumption and gross investment expenditures for non-R&D purposes; tax receipts excluding transfers, interest payments, and subsidies; private R&D investments; and national GDP. De Lipsis et al. (2023) constructed a quarterly time series dataset for all these variables relying on data collected by the Bureau of Economic Analysis. A SVAR model can further be specified by including the next quarter's funding level as a variable to capture rational expectations of changes in funding levels which impact the timing and magnitude of private sector investment responses.

Only one study was found in the literature that evaluated the employment impacts of specific funding programs, which included estimating the impacts of NSF's SBIR/STTR program (Link and Scott 2012b). While this study indicates that econometric approaches can be used, the study relied on unique data that may not be possible to replicate for all of NSF's funding programs. Link and Scott (2012b) took data on the number of employees retained by SBIR/STTR recipients from a survey conducted by the National Research Council (Wessner 2000). Following this approach would require collecting similar data on employment levels and employee retention for NSF-funded awards.

The literature demonstrates that it is possible to estimate how NSF awards stimulate R&D investments from non-federal sources at the state-level (Pallante et al. 2023) and at the institution-level (Blume-Kohout et al. 2008; Lanahan et al. 2016) using cross-sectional time series data with an instrumental variable model specification.[51] The outcome variables can be constructed using non-federal research funding taken from the Higher Education Research and Development Survey (National Center for Science and Engineering Statistics 2023a), which provides separate data on state and local, private, and non-profit sources of R&D funding.[52] Control variables that can be used to improve the accuracy of estimated impacts include the outcome variable lagged by one year to control for prior capacity to secure federal funding, non-federal sources of R&D funding levels to control for changes to the broader R&D funding environment, the timing of macroeconomic shocks like changes to GDP that can impact R&D funding streams, and instrumental variables including the

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[51] A fixed effects model can account for time-invariant factors that are specific to each state or institution and year dummy variables can account for national shocks over time (Pallante et al. 2023). Clustering standard errors by state or institution can also account for geographic correlations in the structure of errors.

[52] The most commonly used approach examines the log change in funding from one year to the next (Lanahan et al. 2016; Pallante et al. 2023) for both the outcome variable of non-federal research funding and control variable of federal research funding. However, the literature indicates that it may be necessary to use the absolute level of annual funding to examine how NSF funding impacts universities that are less common recipients of federal funding given the significant number of institutions that record $0 in research funding in many years which cannot be transformed into log form (Blume-Kohout, Kumar, and Sood 2008).

outcome variable at multiple lags to control for potential omitted variable bias, measurement error, and endogeneity of explanatory variables.

The literature provides guidance on how to estimate how NSF awards contribute to human capital development.[53] GRFP administrative data can be used to identify the universe of recipients and honorable mentions, which can then be matched with Integrated Post Secondary Education Data System records to identify the institutions and fields of study for each individual, U.S. birth records to identify the gender of each individual, and the type of institution each individual attended from the Carnegie university classification (e.g., liberal arts, very high research institution). Using these criteria, GRFP recipients can be matched with honorable mentions to create a sample that controls for graduate training environment but varies by whether students receive NSF awards. Further matching to control for pre-award publication productivity can be done based on bibliometric data taken from Scopus.[54]

Outcome variables on graduate student outcomes can be taken from Proquest to identify the year in which students completed their dissertations and online searches to identify graduate students' first placement following completion of their Ph.D. Separate logistic regression models can then be used to estimate the impacts of receiving GRFP funding, controlling for factors used in constructing the matching sample including institution type, pre-GRFP publications, program rank, region, and the lagged institutional GRFP acknowledgement.

6.4 Conclusion

I-O models offer a practical approach to studying the short-term economic impact of all types of NSF funding. I-O models have a long track-record of being used to study the economic impact of research awards (Nadeau et al. 2021; TechLink 2014a, 2018, 2019c, 2019a; Zelalem et al. 2023). I-O models can estimate multiple types of economic impact including contributions to GDP, value added, employee compensation, and employment in one modeling framework based only on the value of research awards (TechLink 2019a). In contrast, econometric approaches require different models for each impact indicator being estimated and require additional control variables to estimate impacts (Pallante et al. 2023).

The advantage of only requiring award funding as inputs also makes I-O models practical for disaggregating estimates of economic impact by geographic region, NSF directorate, funding program, type of research, and research setting. Econometric approaches require that outcome and control variables are available at the level of disaggregation of the awards being studied, which can limit the types of disaggregation that are feasible using econometric approaches. The literature review identified examples of econometric approaches being used to estimate the short-term economic impact of awards at the state- (Pallante et al. 2023) and county (Chhabra et al. 2019) levels, and for funding programs at the agency level (Link and Scott 2012b), but not for other types of potentially valuable disaggregation. Because the I-O approach does not rely on control variables that match the disaggregation of the awards being studied, they can be applied to any type of awards where funding data is disaggregated.

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[53] A study of the NSF GRFP indicates that a quasi-experimental research design can capture the effect of receiving funding (Graddy-Reed et al. 2021). The study shows that by matching GRFP recipients with honorable mentions that did not receive funding, the impacts on GRFP on degree completion and post graduate academic placement can be estimated.

[54] Counts of publications can be derived using Scopus.

Disaggregating the economic impact of different types of NSF funding using the I-O approach would be improved with detailed data on the demand for labor, goods, and services generated by different types of NSF awards. For example, awards that support biological research will create demand for different types of equipment, materials, and labor than awards for computer and information science engineering research. This will then result in demand for different supplier industries and impact the geographic distribution of economic impact (IMPLAN 2025e). Using detailed data on the demand for materials, equipment, services, and labor generated by different types of NSF awards, I-O models can be refined to more accurately capture the mix of goods and services needed to conduct different types of research (IMPLAN 2025a). This would enable more detailed estimates of the geographic distribution of impacts, types of jobs that are supported, and the amount of employee compensation generated based on where industries that meet demand created by different types of NSF awards are concentrated.

Econometric approaches have been used to estimate how federal research funding stimulates funding from other sources, including the private-sector (Pallante et al. 2023) and other sources (Blume-Kohout et al. 2008; Lanahan et al. 2016). Traditional I-O models are not designed to capture how federal research awards stimulate research funding from non-federal sources, making econometric approaches the only way to estimate these types of intermediate outcomes of NSF awards.

Econometric approaches have been used to study how the NSF Graduate Student Research Fellowship Program impacts degree completion and postdoc position placement (Graddy-Reed et al. 2021) and a larger literature has studied the impacts of financial aid on educational outcomes (Angrist et al. 2014, 2020; Bettinger 2015; Clotfelter et al. 2016; Dynarski 2000; Sjoquist and Winters 2015). While the I-O approach can be used to estimate the immediate economic impact of NSF awards when students spend funds they have received in the consumer economy (Beacon Economics 2021), the approach is not designed to estimate how awards contribute to degree completion and other student outcomes. Therefore, econometric approaches offer the only way to estimate how NSF awards contribute to human capital development.

7 How does the empirical literature estimate the long-term economic impacts of discoveries?

This section describes the literature on measuring the economic impacts of the discoveries resulting from R&D awards.[55] We first introduce the foundational literature that assessed the economic impact of R&D discoveries. We then review four approaches that have been used for estimating the impacts of R&D discoveries: the production function, cost function, input-output analysis, and cost-benefit analysis. For each approach, we briefly summarize the method and describe data requirements. We conclude the section by assessing which approaches are most applicable to NSF's assessment of impacts from research discoveries.

7.1 Foundational literature on the impacts of research discoveries

Modern economic approaches to valuing research discoveries were born from the efforts of Zvi Griliches, Kenneth Arrow, and Richard Nelson. Griliches (1958) investigated the value of hybrid corn, tracing research through to market data and estimating return on investment.[56] Jewkes et al. (1958) authored the first study to look at commercialized inventions and trace them back to their source research.[57]

Theoretical work during this period was also formative in shaping concepts widely used in the empirical literature, including Nelson (1959) and Arrow (1962) on R&D spillovers. Spillovers describe the tendency for research efforts to be not fully excludable.[58] Many studies have found that a discovery results in economic benefits for others in the same discipline, industry, technology area, or geographic area due to the transfer of knowledge.[59] Spillovers are a key theme in the econometric studies on the value of discoveries, as they are necessary for assessing the total social returns to R&D.

Building from the theoretical contributions of Nelson (1959) and Arrow (1962), many empirical studies explored how to capture the economic impacts of research including spillovers (Griliches 1963, 1964, 1979; Mansfield et al. 1977; Pakes 1986; Pakes and Schankerman 1984; Schankerman and Pakes 1986). These early papers span the range of methods that will be reviewed in this section, aside from the modern, limited use of I-O methods for assessing research discoveries. Approaches by Griliches (1963, 1964, 1979) and Pakes and Schankerman (1984) inspired many follow-on econometric studies on the

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[55] The impacts of discoveries contrast with the impacts of R&D funding described in Section 6, as these economic impacts are typically generated when a new technology is commercialized successfully or is used to increase the efficiency of production processes. These economic impacts extend beyond the more immediate impacts of R&D awards on labor, supplies, and equipment and typically take longer to come to fruition and last longer than the more immediate impacts of funding.

[56] Griliches's hybrid corn paper applied methods that resemble modern cost-benefit analysis methods, using statistics on hybrid corn adoption and yield to argue that the innovation on hybrid corn was responsible for the growth of the American corn industry.

[57] The authors considered 61 important scientific inventions, including streptomycin, insulin, and the electron microscope, and found that the research performer was split between researchers operating individually and researchers funded by government and/or industry (Musson et al. 1970). Jewkes et al. (1958) was the first of many tech transfer tracking studies that have sought to directly connect commercial results to the underlying research.

[58] See Section 3.1 for further discussion on nonexcludability.

[59] E.g., David et al. (2000); Levy (1990); Leyden, Link, and Bozeman (1989); Lichtenberg (1984, 1987); Link (1982); and Robson (1993) for spillovers of public to private R&D.

impacts of research, generating subfields with many variations on research question and approach.

7.2 Production function modeling of discoveries

Overview of production function approaches

The production function is an approach to assessing the economic impact of R&D that comes from the Solow (1957) growth model. In this model, productivity increases in the economy are regressed using levels of investment. The main factors of production are labor and capital, however the production function adds R&D as a third factor of production, as Mansfield (1977), Griliches (1963; 1964) theorized that it is the source of technological progress, which was treated as exogenous by the Solow growth model.

The most basic form of the production function involves data on changes in the factors of production and outputs of industrial production. Outputs from the production function model include estimates of the elasticities of productivity to R&D and spillover effects such as spillover effects between public and private R&D, between basic and use-inspired research, and between and within industries. This model is flexible and can be used for basic, use-inspired, and research infrastructure as well as for R&D performed by public institutions, academia, and the private sector. However, a drawback of the production function is that it contains no explanation of the mechanisms of knowledge diffusion and technology transfer.

More advanced versions of the production function build from the knowledge production function developed by Griliches (1979), where R&D inputs lead to the production of knowledge, and then resultant knowledge is used in production processes alongside labor and capital. Models that use the knowledge production function involve the use of intermediate outputs such as patents (Jaffe, 1986, 1989; Myers and Lanahan 2022), patent citations (Jaffe et al. 1992; Akcigit et al. 2021; Dyevre 2024), and innovations (Feldman and Florida 1994; Anselin et al. 2000) to track knowledge as it is developed from R&D and used by industry. While this requires higher data requirements, the use of intermediate outputs creates causal estimates of productivity that results from R&D activities and allows for analyses at the state and local level. Simultaneous equation models and dynamic models of the production function that use intermediate outputs can also model complex spillovers between public and private R&D and basic and use-inspired research, which can enable greater understanding of the spillover effects from basic research and research infrastructure (Akcigit et al. 2021; Dyevre 2024).[60]

Production function studies of funded discoveries

The three most common production function estimates are TFP, sales, and value added, which all serve to measure increased output as a result of R&D increasing downstream industrial productivity. These economic impact measures can also be converted to an internal rate of return, thus matching estimates from cost function models, I-O models, or Cost-Benefit Analyses (CBA). Other estimates of economic impact can be applied to production function models including employment, patent, patent citation, and innovation outcomes. Production functions can also be modified to include spillovers between types of research, factors of production, technology areas, industries, sectors of R&D performance,

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[60] A historical review of production function approaches is provided in Appendix E.

and countries, which may allow for more accurate estimates of the social returns to R&D discoveries.

Exhibit 18 contains estimates of the elasticities of various forms of R&D on TFP. These estimates represent the percentage increase in TFP from a 1% increase in R&D expenditure. Estimates of TFP in Exhibit 18 are derived either from value added or sales.[61]

Exhibit 18: Estimates of the elasticity of TFP to R&D

Sector	Type of statistic	Estimates	Sources
Private sector	Elasticity of production to private research	.066-0.31	Altomonte et al. (2016), Coe and Helpman (1995), Crepon, Duguet, and Mairesse (1998), Cuneo and Mairesse (1983), Griliches (1964, 1980, 1985), Griliches and Mairesse (1984), Guellec and van Pottelsberghe de la Potterie (2001), and Mansfield (1980)
Private sector	Elasticity of TFP to basic research	1.78-2.31	Link (1981) and Mansfield (1980)
Private sector	Elasticity of TFP to use-inspired research	0.1-0.19	Link (1981) and Mansfield (1980)
Public funding	Elasticity of TFP to publicly funded use-inspired research	0.12	Mansfield (1980)
Public funding	Elasticity of TFP to publicly funded basic research	1.17	Link (1981)
Public funding	Elasticity of private sector productivity to government contract R&D	0.094-0.46	Elnasri and Fox (2014), Guellec and van Pottelsberghe de la Potterie (2001), and Levy and Terleckyj (1983)
Private sector	Elasticity of production to private R&D capital	0.073	Griliches and Mairesse (1984)
Private sector	Elasticity of TFP to foreign R&D	0.1 - 0.45	Coe and Helpman (1995) and Guellec and van Pottelsberghe de la Potterie (2001)
Public research	Elasticity of multifactor productivity to government and university-performed research	0.17	Guellec and van Pottelsberghe de la Potterie (2001)
Public sector	Elasticity of TFP to public infrastructure	0.17	Elnasri (2014)
Public sector	Elasticity of TFP to public research agency R&D	0.3	Elnasri and Fox (2014)

Note: All included estimates are in log-log form; thus, estimates can be interpreted as an elasticity from a 1% change in R&D. For example, Mansfield (1980) found that 1% increase in R&D yielded 0.12% increase in private returns. Some studies that disaggregated by types of research contained categories that did not correspond to the types of NSF-awards discussed in this report. In these cases, RTI revised the categories of author-imposed types of research for those used by the NSF.

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[61] See Appendix E for other estimates of the elasticities of TFP to R&D from the literature.

There is a consensus in the literature that R&D positively impacts productivity. Many of the early works look solely at the impact of private R&D investment on TFP, such as Griliches (1964, 1980), Mansfield (1980), and Griliches and Mairesse (1984). These results are in log-log terms, with the interpretation of regression coefficients thus being the percent increase in output resulting from a 1% increase in R&D. Estimates from the early literature find elasticities largely between 0.7-0.13 for private R&D – e.g., a 7%-13% increase in output per 1% increase in R&D. Mansfield (1980) is a notable outlier relative to other early studies, with an elasticity of 0.27, likely due to a narrow sample of chemical and petroleum firms in the 1940s-1960s.

Mansfield (1980) was also notable for providing model specifications testing for differential effects in basic, use-inspired, and government-funded research. When research is divided between basic and use-inspired research, basic research has been associated with much higher returns in productivity.[62] For Mansfield (1980) and Link (1981), the elasticities of TFP to basic research were 1.78 and 2.31. This indicates a 2% increase in downstream productivity for every 1% increase in investment in basic research. Estimates with similar magnitudes are found in Lichtenberg and Siegel (1989) and Fieldhouse and Mertens (2023), with rates of return of 1.338 from basic research and 2.13 from government R&D.

Although the production function literature is predominantly focused on firm R&D, there have been estimates of the public funding of firm R&D and the impact of publicly performed R&D in the literature. While positive elasticities have been found for publicly funded firm R&D, these elasticities are generally less than those of privately financed R&D. Mansfield (1980) found an elasticity of 0.10 of TFP to publicly financed R&D, compared to the estimate of 0.19 of TFP to privately financed R&D from Link (1981).[63] Link (1981) also generated estimates of elasticities of basic privately funded R&D and basic publicly funded R&D of 2.31 and 1.17, respectively, showing much higher returns for public over private R&D.

Of the estimates of elasticities of TFP to public research, largely positive results are found. These include 0.30 from public research R&D from Elnasri and Fox (2014b), 0.25 from Haskel and Wallis (2010), and 0.17 from Guellec and van Pottelsberghe de la Potterie (2001). While the above estimates come from diverse contexts (none directly including the NSF), they show positive returns to public research, all of which are toward the high end of estimates of productivity returns from private R&D.

Exhibit 19 includes estimates of rates of return from the production function literature. Rates of return are estimates of the annual return on investment from R&D. The estimates that do not include measures of uncertainty, such as Griliches (1958), Griliches, Pakes, and Hall (1986), and Griliches and Mairesse (1984), are estimates of rates of return that were derived from productivity estimates (Hall et al. 2010).

Some of the high estimates in Exhibit 19 are the result of the limited samples from which estimates were made. In the case of Griliches (1958), the estimate of a 0.37 rate of return on research comes from a limited sub-sample of research into hybrid corn agricultural research. Similarly, Griliches and Mairesse (1984), Cuneo and Mairesse (1983), and

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[62] Mansfield (1980) included disaggregation by the type of research categories of basic and applied research. In the main text "applied research" has been replaced with "use-inspired research" to correspond with the types of research used by the NSF.

[63] Link (1981) included disaggregation by the type of research categories of basic and applied research. In the main text "applied research" has been replaced with "use-inspired research" to correspond with the types of research used by the NSF.

Griliches (1985) used subsamples of firms focused on large manufacturing companies. Also, rates of return have generally decreased over time (Griliches 1985), implying that many of the estimates from Exhibit 19 may not be representative of modern rates of return.

Exhibit 19: Estimates of R&D rates of return from the production function literature

Sector	Type of statistic	Estimates	Source
Private sector	Total return on investment	0.37	Griliches (1958)
Private sector	R&D rate of return	0.18-0.90	Cuneo and Mairesse (1983), Griliches and Mairesse (1984), Griliches (1985), Jaffe (1986), Lichtenberg and Siegel (1989)
Private sector	R&D total rate of return	0.132	Lichtenberg and Siegel (1989)
Public funding	Rate of return for federally funded R&D	0.026	Lichtenberg and Siegel (1989)
Private sector	Rate of return for basic R&D	1.338	Lichtenberg and Siegel (1989)
Private sector	R&D rate of return for use-inspired R&D	0.108	Lichtenberg and Siegel (1989)
Public sector	R&D rate of return for government capital	2.13	Fieldhouse and Mertens (2023)

Note: All included estimates are in log-log form. See the note below Exhibit 18 for information regarding interpretation of log-log estimates. Some studies that disaggregated by types of research contained categories that did not correspond to the types of NSF-awards discussed in this report. In these cases, RTI revised the categories of author-imposed types of research for those used by the NSF.

Exhibit 20 provides estimates of intermediate outcome measures resulting from production function models. These models involved both an R&D input measure, such as R&D capital investment, and an R&D output measures such as patents or innovative sales. As a result, some of the models included in Exhibit 20 did not provide estimates of a final economic outcome elasticity, however others such as Jaffe (1986) and Crepon et al. (1998) estimated intermediate outcomes alongside final economic output estimates.

Estimates for the return on private R&D spending generally exceed those for the return on public R&D spending. These include:

- Jaffe (1986; 1989), where the elasticity of patents to industry R&D was 0.875, compared to elasticity of patents to academic R&D of 0.103.
- Feldman and Florida (1994), where the elasticity of patents to industry R&D was 0.190, compared to an elasticity of patents to academic R&D of 0.123.
- Acs et al. (1994), where the elasticity of innovative activity to industry R&D was 0.615, compared to an elasticity of innovative activity to academic R&D of 0.55.

Exhibit 20: Estimates of elasticities of intermediate outcomes to R&D

Outcome	Sector	Type of statistic	Estimate	Source
Patents	Private sector	Elasticity of corporate patents to R&D investment	0.875	Jaffe (1986)
Patents	Academic research	Elasticity of corporate patenting activity to academic research	0.103	Jaffe (1989)
Patents	Academic research	Elasticity of corporate patenting activity to academic research in drugs	0.385	Jaffe (1989)
Patents	Academic research	Elasticity of corporate patenting activity to academic research in chemicals	0.295	Jaffe (1989)
Patents	Private sector	Elasticity of patents to industry R&D	0.190	Feldman (1994)
Patents	Academic research	Elasticity of patents to university R&D	0.123	Feldman (1994)
Innovative sales	Private sector	Elasticity of innovative activity to industry R&D	0.615	Acs et al. (1994)
Innovative sales	Academic research	Elasticity of innovative activity to university R&D	0.55	Acs et al. (1994)
Patents	Private sector	Elasticity of patents to R&D	0.881	Crepon et al. (1998)
Innovative sales	Private sector	Elasticity of innovative sales to R&D	0.431	Crepon, Duguet, and Mairesse (1998)
Patents	Federal research	Elasticity of patents to R&D	0.223	Jaffe and Lerner (1999)
Patents	Federal research	Elasticity of patents to basic science share of R&D	-1.804	Jaffe and Lerner (1999)
Patents	Federal research	Elasticity of patent citations to patent count	-0.532	Jaffe and Lerner (1999)
Employment	Academic Research	Elasticity of private R&D employment in the drugs and chemicals industry to university research	0.24	Anselin et al. (2000)
Innovations	Academic Research	Elasticity of private innovations to university research	0.002	Anselin et al. (2000)
Innovations	Academic Research	Elasticity of private innovations to university research proximity	0.164	Anselin et al. (2000)

Note: All included estimates are in log-log form. See the note below Exhibit 18 for information regarding interpretation of log-log estimates. Some studies that disaggregated by types of research contained categories that did not correspond to the types of NSF-awards discussed in this report. In these cases, RTI revised the categories of author-imposed types of research for those used by the NSF.

7.3 Cost function modeling of discoveries

Overview of cost function approaches

The cost function approach contrasts with production function-based approaches in focusing on cost minimization rather than the productivity effects of R&D spending (Hall et al. 2010). Cost functions aim to reflect firms' decision-making as they allocate resources between the various factors of production. These models seek to measure the private return on investment in R&D relative to other factors of production (Levin et al. 1984; Mohnen et al. 1986). These models attempt to quantify the long-run benefits of R&D, measured by productivity benefits in the form of reduction of future production costs. The production of a base level of industrial outputs is held constant against future cost savings, with the goal of maximizing the present value of future profits. Cost function approaches can also be used to estimate R&D spillovers, as public and private R&D funding can reduce costs for firms (Mamuneas and Nadiri 1995; Mamuneas 1999).[64]

Cost function studies of funded discoveries

The primary objective of the cost function is to determine the optimal investment in factors of production for firms, given the many second order effects that are considered when trying to minimize cost for output. In Mohnen et al. (1986), such considerations include the adjustment costs of each factor of production, own-price elasticities of the factors of production, cross-price elasticities of the factors of production, and elasticities of the factor of production to technical change.

Most of the cost function literature estimates are intermediate estimates of the parameters for a firm making its ideal investment decision in factors of production. Thus, the estimates of the rate of return to the factors of production must be derived from different cases of the model. In the case of Mohnen et al. (1986), the rate of return comes from the difference between two scenarios: a scenario where the firm is allowed to optimally adjust all factors of production and a counterfactual scenario where the firm is not allowed to adjust for the factor of production that is measured. Due to this method, the economic impact estimates are much more restricted in the cost function literature compared to the production function literature. Estimates consist mainly of rate of return statistics derived in a manner such as described for Mohnen et al. (1986). Private rates of return consist of the benefits that accrue to the firm that invests in R&D, and social rates of return include any spillover benefits to other entities that result from investment in R&D.

In Exhibit 21, most of the estimates of economic impact from the cost function model are elasticities of the rate of return to private R&D investment. Among the estimates of rate of return, there are estimates of internal and social rates of return. Internal rate of return considers the position of the firm in making its investment choices by considering internal firm costs and revenues, whereas social return on investment also includes spillover effects of knowledge and productivity that accrue to other firms.

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[64] A historical review of cost function approaches is provided in Appendix E.

Exhibit 21: Elasticities of economic impacts to R&D from the cost function literature

Sector	Impact	Type of statistic	Estimate	Source
Private sector	Output	R&D share of annual output growth	0.11	Mohnen et al. (1986)
Publicly funded	TFP	R&D share of annual TFP growth	0.10-0.15	Nadiri and Mamuneas (1994a)
Private sector	Rates of return	Internal rate of return to R&D investment	0.12	Mohnen et al. (1986)
Private sector	Rates of return	Internal rate of return to capital investment	0.10	Mohnen et al. (1986)
Private sector	Rates of return	Internal rate of return to R&D investment	0.09-0.27	Bernstein and Nadiri (1988)
Private sector	Rates of return	Social rate of return to R&D investment	0.11-1.62	Bernstein and Nadiri (1988)
Private sector	Rates of return	Internal rate of return to R&D investment	0.12	Bernstein (1988)
Private sector	Rates of return	Social rate of return to R&D investment	0.19-0.26	Bernstein (1988)
Private sector	Rates of return	Internal rate of return to R&D investment	0.15-0.29	Bernstein and Nadiri (1991)
Private sector	Rates of return	Social rate of return to R&D investment	0.203-1.323	Bernstein and Nadiri (1991)
Private sector	Rates of return	Internal rate of return to R&D investment	0.08-0.50	Mamuneas (1999)
Publicly funded	Rates of return	Social rate of return to R&D investment	0.12-0.21	Mamuneas (1999)

Note: All included estimates are in log-log form. See the note below Exhibit 18 for information regarding interpretation of log-log estimates. Some studies that disaggregated by types of research contained categories that did not correspond to the types of NSF-awards discussed in this report. In these cases, RTI revised the categories of author-imposed types of research for those used by the NSF.

Among the estimates of rates of return, there is general consistency that private rates of return are roughly between 0.07 and 0.30. A notable exception to this is Mamuneas (1999), which looked at rates of return for R&D at the industry level, finding results as high as 0.805 the private rate of return. In Mamuneas (1999), there exist many industry estimates that are more akin to the normal range of estimates; however, there are outlier industries such as Scientific Instruments (0.209) and Fabricated metals (0.504).

Across the literature, there is more variation in the estimates provided for social returns from R&D. Generally, the social rates of return are between 0.1 and 1.6. The divide between studies with larger and smaller ranges are reflective of the divide in studies assessing social returns at the industry level or for the full U.S. economy.

The large ranges provided by Bernstein and Nadiri (1988; 1991) are reflective of their use of industry-level estimates, with the scientific instruments industry yielding the greatest social returns in both studies and transportation equipment and electrical equipment yielding more modest returns. In contrast, Mamuneas (1999) calculates economy-wide estimates of social rates of return for publicly funded R&D, with estimates for the decades of 1960-1969, 1970-1979, and 1980-1989 of 0.212, 0.115, and 0.131, respectively. These economy-wide estimates are more in line with a reasonable social rate of return and are similar to the economy-wide estimates of social return that are seen in the CBA literature.

7.4 Input-Output modeling of discoveries

Overview of I-O modeling of discoveries

Modern research approaches have used I-O models for the estimation of the impacts of research commercialization. These studies, all done in the assessment of SBIR/STTR award R&D, use downstream sales data from products that resulted from SBIR/STTR award R&D (Techlink, 2014, 2016, 2019a, 2019b; NASA, 2017). When sales data from downstream product sales are used as inputs to the I-O models, I-O models are in essence calculating the amount of production within the economy generated by prior R&D activity. While I-O models are not capable of estimating economic growth generated by future discoveries, the use of this approach allows for a retrospective analysis of growth that has occurred.

When using I-O models for measuring the benefits from research discoveries, it is insufficient to merely input figures of R&D spending into the model. Some approach must be taken which translates R&D spending into the commercial use of R&D discoveries, such as figures of productivity gains or the sales of new products that result from R&D. For example, the TechLink studies (2014, 2016, 2019a, 2019b) required an extensive survey apparatus to get estimates of the sales of products developed through SBIR/STTR funding. This is a clear limitation of the I-O method, as it is not built to account for the endogenous growth from R&D spending that is the driver of the benefits from research discoveries.[65]

Input-Output studies of funded discoveries

The data sources used by the reviewed I-O models are the administrative data regarding project or program spending and the I-O data built into the model that is chosen for analysis. The common models used for such analyses are the REMI, IMPLAN, and RIMS II models. These models assess how expenditure moves through industries to estimate total economic impact. I-O models can provide a range of economic outcome estimates to supplement final economic impact statistics, including total output, employment, value added, employee compensation, and tax revenue.

Exhibit 22 reviews estimates of the returns from R&D discoveries provided by recent I-O literature. The study results are consistent, with estimates of total economic multipliers from SBIR/STTR funding of between 2.52 and 2.69. These figures correspond to an annual return of $2.52 to $2.69 for each dollar spent on R&D.

It is also important to mention that I-O models are useful for distributional analysis of how spending differentially impacts industries. The IMPLAN model used in the TechLink studies can provide estimates of all the above statistics for each of the 536 industries contained within the model. The NASA SBIR/STTR study (2017) provided the most focus on the distribution of benefits by industry, with estimates of the top ten industries in terms of employment, employee compensation, value added, and output. The top industry for each of these categories was the scientific research and development services industry, which

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[65] A historical review of I-O modeling approaches on the impact of discoveries is provided in Appendix E.

was estimated to receive 27% of employment benefits, 40% of total economic output, 43% of employee compensation, and 37% of value added from NASA SBIR/STTR award spending.

Exhibit 22: Estimates of returns from R&D discoveries in the I-O literature

Impact	Type of statistic	Estimates	Source
Employment	Total employment resulting from DOD SBIR/STTR	94,180	TechLink (2019b)
Employment	Cost per job year	$71,683-$92,847	TechLink (2019a), NASA (2017), TechLink (2016), TechLink (2014)
Total output	Economic output multiplier from SBIR/STTR R&D activity	2.52x-2.74x	TechLink (2019b), TechLink (2019a), NASA (2017), TechLink (2016), TechLink (2014)
Employee compensation	Employee compensation multiplier from SBIR/STTR downstream sales	0.79x-0.86x	TechLink (2019a), TechLink (2019b), TechLink (2016), TechLink (2014)
Tax revenues	Tax revenues generated from SBIR/STTR awards and downstream sales	0.20x-0.33x	TechLink (2019b), TechLink (2019a), NASA (2017), TechLink (2016), TechLink (2014)
Value added	Value added multiplier from DOD SBIR/STTR downstream sales	1.28x-1.34x	TechLink (2019b), TechLink (2019a), TechLink (2016), TechLink (2014)

Note: Estimates are in monetary terms or represent multipliers of returns from investment in SBIR/STTR programs. For example, total output is estimated to increase by 2.52 to 2.74 times the amount invested in the SBIR/STTR programs that were reviewed.

7.5 Cost–benefit analysis modeling of discoveries

Overview of CBA modeling

Cost-benefit analysis (CBA) uses a variety of economic estimation techniques to weigh the total value of a project/program in monetary terms (Link and Scott 2012; Tassey 2003). The crux of CBA is the procedure of identifying all project costs and benefits, mapping cost and benefit streams to a time series of when they occur, and applying an inflation-adjustment or discounting procedure such that summary statistics of the project impacts and value for money can be derived (Tassey 2003; Walsh et al. 2022). This can involve many benefit streams across industries and spillover effects to other related industries. CBAs often strictly define the population that would bear the costs and reap the benefits of the project but are agnostic about who benefits accrue to and allow for judgment of alternative courses of action purely on monetary terms (Link and Scott 2012; Tassey 2003).

CBA methods have incorporated various benefits and cost streams, such as calculations of consumer and producer surplus via sales and licensing revenue (Allen et al. 2012), tax revenue as an estimate of commercialization value (Forster and Seeger 2014), estimates of value gained from basic research (Florio et al., 2016), cost savings from industrial process improvement (Link 2010), and estimates of decreased treatment costs, morbidity, and mortality from medical innovation (Weisbrod 1971). Moreover, studies in this literature have made different counterfactual assumptions of research funding to establish a baseline. Even though there are many possible techniques for the estimation of benefit streams in CBA, there are commonalities within the literature, including those with a particular focus on the value of public sector research.

Cost-benefit methods, in seeking complete estimation of impacts from a program, also include estimates of non-market benefits. Common examples of non-market benefits in CBA include the measurement of the value of decreased mortality or morbidity as well as the value of improved environmental quality and recreational benefits of parks or public infrastructure. Additionally, the theory of evaluation behind cost-benefit methods has been expanded in the literature to provide metrics pertaining to non-quantifiable benefits. This is important as often in CBA, there are benefits that are too uncertain, too difficult to predict, or too difficult to model to merit inclusion (Ruegg and Feller 2003).

The final goal of performing cost-benefit analysis is to obtain estimates of social return on investment. By including all known benefits that result from a given program, the result is a full social accounting of return from that program. This is identical to the goal of economists in attempting to endogenize growth through the accounting of various spillover effects. The econometric papers that have attempted to estimate social returns from R&D have, in essence, used the CBA case study by examining one or several individual products that resulted from R&D for their economic impacts.[66]

Cost-benefit analyses of funded discoveries

CBA approaches estimate the economic value that results from research discoveries. The most common statistics for CBA are net present value[67] (NPV) and the benefit-cost ratio[68] (BCR). While the BCR is a summary statistic that provides for simple understanding of total project value, it is time indeterminate and does not allow for understanding of the rate of return from project investment. Thus, some CBAs provide the internal rate of return (IRR), which is an annualized rate of return statistic.

The cost-benefit literature has a wide range of scopes and methods. Some deal with individual research projects and others entire research portfolios. Individual case studies can often yield great returns on investment when viewed in isolation due to biases in selecting successful case studies for review. Thus, portfolio-level reviews tend to indicate lesser returns.

Exhibit 23 contains BCR and IRR statistics from the CBA literature.[69] Across the CBA literature, there are a wide range of reported returns on investment. It is notable that none of the estimates in estimate 0% returns.

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[66] A historical review of CBA approaches is provided in Appendix E.

[67] NPV is the difference between the discounted benefits and costs for a project.

[68] BCR is the ratio of discounted benefits to costs.

[69] More estimates from the CBA literature, including NPV values, are available in Appendix E.

Exhibit 23: Selected estimates of economic impact from the CBA literature

Case study/portfolio	Type of statistic	Estimates	Source
U.S. Polio Research	Internal rate of return	4-14%	Weisbrod (1971)
Manufacturing Innovations	Median social rate of return	56%	Mansfield et al. (1977)
Manufacturing Innovations	Median private rate of return	25%	Mansfield et al. (1977)
CT Scanners	Increase in adoption for every $1 million investment	2.5%	Trajtenberg (1989)
CT Scanners	Total return on investment in tomography scanners	270%	Trajtenberg (1989)
NIST ATP Tissue Engineering	Internal rate of return for seven ATP-funded projects	116%	Martin et al. (1998)
NIST ATP	Social rate of return	80%	Tassey (2003)
NIST ATP Wavelength References	Internal rate of return	4400%	Link and Scott (2004)
NIST ATP Internet Commerce for Manufacturing	Internal rate of return	220%	Link and Scott (2004)
NIST ATP Polymer Composite Dielectrics	Internal rate of return	35%	Link and Scott (2004)
NIST ATP Injectable Composite Bone Grafts	Internal rate of return	230%	Link and Scott (2004)
Australian Research Council	Direct social rate of return	12.5%	Kanninen and Lemola (2006)
DOE Advanced Combustion Engine Program	Internal rate of return of the monetized economic and health benefits of the ACE R&D sub-program focused on heavy-duty diesel engines	63%	Link (2010)
DOE Photovoltaic	Internal rate of return	17%	O'Connor et al. (2010)
DOE Wind Energy Program	Internal rate of return	12%	Pelsoci (2010)
Saccharin Innovations	Internal rate of return	7.2%	Forster and Seeger (2014)
CERN LHC	Benefit-cost ratio	120%	Florio et al. (2016)
Economy-wide Innovation	Internal social rate of return to R&D	20%	Jones and Summers (2020)
Commonwealth Scientific and Industrial Research Organisation	Benefit-cost ratio of portfolio of 68 CSIRO case studies	840%	Walsh et al. (2022)

Note: Estimates are in the form of percentage increase relative to new investment. Internal rate of return estimates provide returns on an annualized basis and benefit-cost ratios provide the rate of return over the life of a project/program.

Across those reviewed in Exhibit 23, there exist more moderate estimates of returns such as Weisbrod who estimates a 4-14% return on investment from polio research and Forster and Seeger (2014), that reported a 7.2% return to saccharin research. Some of the more extraordinary rates of return estimated in the literature include estimates from Link and Scott (2004) of 4,400% rate of return to NIST ATP Wavelength References for Optical Fiber Communications and 220% to NIST ATP Internet Commerce for Manufacturing.

Most CBA studies are performed on projects that have yielded positive returns, due to selection bias against negative return projects. This provides opportunity for overestimation of rates of returns when case studies are aggregated to the portfolio level.

7.6 Minimum data requirements of approaches to estimating the economic impacts of discoveries

Production function

For analyses using the production function method, there are several approaches that can be taken depending on the type of research, performer type, and focus on intermediate versus final outputs. The simplest production function methods use data on factors of production and industrial output (such as costs or value added), to produce estimates of the elasticities of productivity to R&D. Other production functions focus on the production of knowledge by using data on factors of R&D production and R&D output data such as patents, patent citations, and innovations. Knowledge production function models may not always provide estimates of final economic benefit or return on investment but are useful for the measurement of spillover effects from R&D to production processes. Finally, multi-stage and dynamic production function approaches incorporate spillover effects into estimates of productivity from R&D. These models are highly varied but can incorporate multiple spillover effects into estimates of productivity such as spillovers across sectors of R&D performance, region, and type of research. Multi-stage production function models can also incorporate R&D outputs, allowing for estimates of elasticities of productivity to R&D that are robust to spillover effects between R&D performers and industrial production.

For simple forms of the production function, data for the other factors of production and data on industrial outputs are required. The simplest models are performed either at the firm or industry levels, with input data on the levels of labor, capital, and R&D expenditure, and outputs that provide measures of productivity estimates.[70] When done at the firm level, value added is a common output measure, or TFP at the industry level. Other common output data sources and types include industry sales data from S&P Compustat or Moody's, GDP, TFP, and output data from the BEA, and output, employment and value-added data from the BLS and OECD. Data on other factors of production are available from the BEA national income and product accounts at the industry level.

Examples of simple production function models include those of Griliches (1980) and Griliches and Mairesse (1984). Griliches (1980) performs a simple production function analysis of firms at the industry level, using R&D data from the NSF, and capital stocks and

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[70] In the simplest production function models, the main control variables are the variables for other factors of production. This can be seen in Levy and Terleckyj (1983), where the variables used for measurement of the private returns from public R&D are total government R&D, company R&D, and measures of labor and capital investment of fixed capital and unemployment, respectively.

output quantities and prices from the BLS.[71] Griliches and Mairesse (1984) perform similar analysis at the firm level including data on firm sales and factors of production data — including R&D expenditures — from S&P Compustat.[72] These models serve as a baseline for the data requirements of performing the production function approach, which involves R&D expenditure data, data for factors of production, a measure of industrial output at the firm or industry level, and possible controls for industry and time period.

The knowledge production function, espoused by Griliches (1979), has been used as a model for the tracking of R&D discoveries, which then serve as inputs into production processes. Studies that use such intermediate outcomes data include Jaffe (1986; 1989), Acs et al. (1994), Jaffe and Trajtenberg (1996), and Toole (2012), which perform analyses of the process of technology transfer using intermediate outcome data. These use various measures to assess knowledge produced from R&D such as patents, patent citations, product innovations and new molecular entities applications.

The seminal model of the knowledge production function with intermediate outputs is Jaffe (1986), which used patents as the output variable.[73] This model allows for direct calculation of the correlation of R&D to knowledge outputs, and Jaffe explored whether knowledge outputs differ by technology clusters. Data required for this model include firm-level R&D expenditures, patents, capital stock, market share, industry sales, and industry growth rate, with firm profits as the outcome variable.[74]

In addition to intermediate outputs, several models of the production function use multiple stages of regression to account for different stages of the pipeline of R&D to industrial outputs. Two formative macroeconomic papers, Aghion and Howitt (1992) and Romer (1990), perform multi-stage production function models, measuring intertemporal spillovers within the same industry, testing the theory of creative destruction from Schumpeter (1939). Commonly, these models contain equations for the spillovers between basic and use-inspired research, or equations between public and private research before private firms use research outputs in production processes. As the objective of these models is to include spillovers between types of research or sectors of R&D performance, there is no standard version of this model.

An example of a multi-stage function that assesses the spillovers between research areas is Akcigit, Hanley, and Serrano-Velarde (2021), which modeled the interaction of basic and use-inspired research by creating a three-stage model of the economy with upstream and midstream R&D performers, and downstream industrial production.[75] This includes a public sector that performs basic R&D, firms that perform basic and use-inspired R&D, and firms that produce commercial outputs. Firms in this model respond to the production of R&D

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[71] NSF data on R&D awards is expenditure by product fields at the industry level. Data from the BLS include output, manhours, and investments in capital stock at the industry level. Control variables include the average age of capital, manhours by industry and intercept and year dummies.

[72] Variables used from Compustat include sales, R&D expenditure, employment, and total capital expenditure. The only control variable used is a year dummy variable.

[73] Other specifications of the Jaffe (1986) use rate of return and Tobin's Q as outcome variables.

[74] R&D expenditure, profits, and patent information come from the NBER R&D database compiled in Bound et al. (1984), which is derived from S&P Compustat Firm data and matched USPTO patent data. Market share and sales data for firms are from Harvard's PICA database, and industry sales and growth rates are from the Census Bureau Census of Manufactures.

[75] Akcigit, Hanley, and Serrano-Velarde (2021) included disaggregation by the type of research categories of basic and applied research. In the main text "applied research" has been replaced with "use-inspired research" to correspond with the types of research used by the NSF.

outputs from the public sector and from other firms, thus allowing for a dynamic calculation of the resultant firm R&D investment decisions and estimates of public and private R&D returns that are controlled for public/private and basic/use-inspired spillover effects. To perform this model, several controls were needed at various stages. Data required for this model includes firm ownership information, market participation across industries including entries and exits, balance sheet data, firm growth, employment growth, firm age patent and patent citation data, and private and public R&D expenditures.[76]

Cost function

The cost function requires similar data to the production function. An example of the basic cost function is reported by Mohnen et al. (1986), who performed a model based on national-level manufacturing industry data from Germany, Japan, and the United States. The Mohnen et al. (1986) model estimated the returns to factors of production for the performance of firm R&D, with labor and energy as variable inputs and capital and R&D as quasi-fixed inputs. The data required to estimate the main factors of production are prices and quantities for labor, energy, capital, and R&D for all three countries, with gross value added as the output variable.[77] No additional controls are needed for the model.

Input-output

I-O methods require minimal outside data for performance of economic impact estimates. I-O models such as IMPLAN and RIMS II contain all necessary outcome variables including output, employee compensation, employment, value added and intermediate outputs. The only data required for operation of I-O models for the performance of estimates of the economic impact of research discoveries is data on downstream industry sales. The requirement of sales data is a limitation on the use of I-O for estimating the impacts of research discoveries as only use-inspired research performed by industrial R&D performers has a direct connection to downstream output.

Due to the difficulty of acquiring sales information for downstream products, the simplest I-O models are those performed on use-inspired industrial research. In the Techlink models that perform this procedure for federal agency SBIR/STTR programs, the accumulation of sales data involves the extensive collection of outcomes of participants in such programs. In (TechLink 2014b), this involved the surveying of 4,524 grants issued through the Air Force SBIR/STTR program which culminated in $14.6 billion in sales by the time of the survey.

Cost-benefit analysis

CBA methods require different data on a case-by-case basis depending on the impact of the R&D produced technology. Common data for all case studies include program cost data or

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[76] Data on firm ownership came from the "Enquete Liaisons Financieres" (LIFI) dataset. Balance sheet data comes from the LIFI and "Enquete Annuelle des Entreprises" (EAE) datasets and includes employment, fixed assets, sales, company location, and industry classification. Data on R&D expenditures come from the French Ministry of Research and include share of public R&D funding, university collaboration, and basic research intensity. Data on Patents and Patent Citations come from the NBER database and include patents, patent citations, and patent classes.

[77] Data for the United States in Mohnen, Nadiri, and Prucha (1986) include labor in the form of man hours from OECD labor force statistics, wages rates from the BLS handbook of labor statistics, capital user costs and net capital stock from the BEA Fixed Reproducible Tangible Wealth in the United States series, energy costs and prices from the OECD Energy Balances series, R&D stock and costs from OECD Science and Technology Indicators, and value added from the OECD National Accounts series.

project performance and inflation adjustment measures.[78] However, there are no common output data sources for CBA when analysis is performed at the level of an individual downstream product. Examples of the varied data requirements of CBA case studies include three case studies of DOE research outputs performed by Link (2010), O'Connor et al. (2010), and Pelsoci (2010). Despite these CBA case studies pertaining to similar research areas, different data sources were required to assess benefits across the case studies.

Link (2010) monetized the benefits from DOE advanced combustion research, monetizing economic benefits from increased fuel efficiency and health benefits from reduced pollutants. For fuel efficiency, required data included a time series of truck brake thermal efficiency from Aneja, et al. (2009), truck registration, miles-per-gallon and fuel consumption data from Davis et al. (2009), as well as expert estimates of the improvement of fuel efficiency attributable to DOE research. In addition to these data sources, the calculation of monetary health impacts required the use of the EPA's COBRA model, which produces estimates of avoided health incidents associated with emissions reductions.

O'Connor et al. (2010) performed a CBA case study on DOE investment in photovoltaic (PV) technologies, reviewing benefits including higher quality and lower cost PV modules in addition to environmental health benefits from reductions in adverse health incidences. Varied data sources were required for PV production including reports from the Flat-Plate Solar Array project, PV News, and the Energy Information Administration (EIA). Data on the energy efficiency of PV technologies included EIA reports and estimates provided by individual PV technology companies. Other required data included PV installations, attribution of efficiency increases to DOE research, estimates of production, and exports to foreign markets.

Pelsoci (2010) performed a case study of the DOE Wind Energy Program, including benefits of reduced pollution and increased energy production from various technologies. Data required for this case study included use of wind turbines and other energy production from the EIA State Historical Tables, volume of power from wind energy from the DOE Energy Efficiency and Renewable Energy Power Technology Energy Data Book, estimates of DOE attribution of increased energy efficiency of wind turbines based on historical R&D numbers, and estimates of reduced mortality benefits from the EPA COBRA model.

7.7 Additional data requirements for modelling economic impacts of discoveries

Disaggregations of interest

To provide NSF staff and stakeholders with understanding of the distribution of economic impacts of discoveries arising from NSF awards, estimates can be disaggregated by type of research, geographic region, funding program, and performer type. Based on the literature reviewed, these disaggregations present complications for estimating impacts of R&D discoveries. Disaggregation by type of research and by performer type requires the association of research inputs with industrial outputs. Disaggregation by geographic region or program requires the use of increasingly granular data on R&D awards.

Disaggregation by type of research is important due to the NSF's diverse support of R&D, ranging from basic research awards to support for large research infrastructures to use-

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[78] Common indices to convert nominal currency into real currency include GDP price indices (Link 2010) and consumer price indices.

inspired R&D.[79] Some use-inspired R&D produces technologies that result in commercial activity and economic value in the short term. In contrast, the impacts of basic research and funding for research infrastructure are more difficult to measure because economic and socioeconomic impacts are complex, diffuse, and long-term.[80] Thus, the estimation of economic impacts that result from basic R&D and research infrastructure require additional data including intermediate outcome data, such as patents, patent citations, and other innovation measures that connect research outputs to downstream industrial outputs.

Disaggregation by performer type similarly requires intermediate outcome data to connect R&D activities to industrial output. This is because academic and public research institution R&D does not often entail direct in-house research translation like privately performed R&D. The accurate measurement of spillovers from academia and public research institutions may require intermediate outcome data[81] to accurately assess their contributions to downstream output. However, the inclusion of intermediate outcome data can also provide clarity to private R&D output, as the inclusion of public R&D performance as a control variable may affect estimates of returns to private R&D.

Disaggregation by administrative unit or program and geographic region creates additional data requirements. These data requirements require additional granularity for input and output data for the disaggregation of estimates, such as by administrative unit or program or at the state or local levels. This is a common need when performing the production function at the state or local levels, which requires granular institutional R&D and industrial output data.

Disaggregation by temporal period (e.g., annual, quarterly, monthly time series data) was also considered when reviewing data requirements by approach. However, across the literature reviewed, most papers exclusively use annualized data, limiting the evidence available on temporal disaggregation to annual data. Because of this uniformity, disaggregation by temporal period is not considered in this section.

Exhibit 24 shows the applicability of each disaggregation across the four approaches reviewed for estimating the economic impact of discoveries. For each approach, citations are given for exemplar studies that include disaggregations. If no citations are available from the reviewed literature, it is noted if the disaggregation is thought to be feasible for that approach. For example, exemplar studies are included for the production function across most disaggregations, including Link (1981), Mansfield (1980), Leyden and Link (1989) for basic research and Link (1981) and Mansfield (1980) for use-inspired research.

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[79] The NSF award type that is not included in this section is NSF's investment in human capital investment. Human capital investment is a valuable investment that has effects on both downstream production and R&D. Human capital investments impact discoveries through a series of mechanisms including the initial human capital uplift effort, participation of uplifted workers in future R&D activities, production of R&D outputs, and use of R&D outputs to produce industrial output more efficiently. This is a notably long and complex impact pathway, compared to use-inspired research, basic research, and research infrastructure. From our review of the literature, human capital investment appears absent from approaches to measure impacts of discoveries, which may be attributable to the complex impact pathway through which human capital investment programs achieve impact.

[80] Examples include the Human Genome Project, the internet, and the Hubble Telescope.

[81] Such as patents, patent citations, or other innovation measures.

Exhibit 24: Applicability of disaggregations for approaches used to estimate the impacts of R&D discoveries

Disaggregation	Production function	Cost function	Input-output	Cost-benefit analysis
Basic research	Link (1981), Mansfield (1980), Leyden and Link (1989), Gersbach et al. (2018)	Not applicable	Not applicable	David et al. (1992) and Weisbrod (1971)
Use-inspired Research	Akcigit, Hanley, and Serrano-Velarde (2021), Gersbach et al. (2018), Link (1981), Mansfield (1980)	Bernstein (1988); Bernstein and Nadiri (1991); Mamuneas and Nadiri (1995); Mohnen et al. (1986); and Mamuneas (1994)	NASA (2017); TechLink (2014; 2016; 2018; 2019a)	Link (2012), Pelsoci (2010), O'Connor et al. (2010)
Research Infrastructure	Elnasri et al. (2014; 2015), Fieldhouse and Mertens (2023)	Not applicable	Not applicable	Florio et al. (2016)
National level	Coe and Helpman (1985), Guellec and van Pottelsberghe de la Potterie (2001; 2003), Altomonte et al. (2016), Bloom et al. (2016)	Nadiri and Kim (1996)	NASA (2017) and TechLink (2014, 2016, 2018, 2019)	Link (2010), O'Connor et al. (2010), and Pelsoci (2010)
State level	Aiello and Cardamone (2008)	Not demonstrated	(TechLink 2014a, 2019c)	Not demonstrated
Local level	Jaffe et al. (1992)	Not demonstrated	Not demonstrated	Not demonstrated
Program level	Fieldhouse and Mertens (2023).	Not demonstrated	Not demonstrated	Not demonstrated
Government performed R&D	Azoulay et al. (2019), Jaffe and Lerner (1999), Jaffe and Trajtenberg (1996), and Myers and Lanahan (2022).	Not applicable	Not applicable.	Link (2010), O'Connor et al. (2010), and Pelsoci (2010)
Academia performed R&D	Acs, Audretsch, and Feldman (1994), Anselin et al. (2000) Bacchiocchi and Montobbio (2009), and Feldman and Florida (1994).	Not applicable	Not applicable	Not demonstrated
Firm-performed R&D	Griliches (1980), Griliches and Mairesse (1984), Bloom et al. (2013)	Bernstein (1988), Bernstein and Nadiri (1991), Mamuneas and Nadiri (1995), Mohnen et al. (1986), and Nadiri and Mamuneas (1994)	NASA (2017) and TechLink (2014, 2016, 2018, 2019)	Forster and Seeger (2014)

Note: Studies cited in Exhibit 24 include the disaggregation that is indicated by the corresponding row header. Cells that are marked "Not demonstrated" or "Not applicable" did not have examples of studies that performed that disaggregation for that methodological approach within the performed literature review. Cells marked "Not demonstrated" are thought to be possible disaggregations for the corresponding approach whereas cells marked "Not applicable" are disaggregations that are not thought to be possible for the corresponding approach. Additional information about the data sources of reference papers are included in Appendix E.

Production function

The production function can be modified to provide estimates of economic impact for discoveries including all disaggregations relevant to NSF discoveries. Single stage production function models such as Griliches (1985), Link (1981) and Mansfield (1980) can evaluate R&D expenditure, regardless of type of research or research performer. Production function models have derived elasticities of productivity to basic research and use-inspired research (Leyden 1989; Link 1981; Robson 1993), publicly funded private research (David et al. 2000; Guellec and Pottelsberghe de la Potterie 2000; Levy and Terleckyj 1983; Leyden et al. 1989), public research performed by agencies (Anselin 2000; Jaffe 1989), publicly funded academic research (Adams and Clemmons 2013; Azoulay et al. 2019; Jaffe 1989), and research infrastructures (Elnasri and Fox 2014; 2015).

In addition to the disaggregations that are possible with the production function approach, there are production function approaches that use intermediate outputs for the measurement of spillover effects and multi-stage production function approaches that incorporate spillover effects into estimates of productivity from R&D. Due to these different varieties of the production function with different data requirements, we have separated the production function into three subsections.

Simple production function

The simple production function can be performed across disaggregations of type of research, geographic region, administrative unit or program, and performer type, with additional data requirements for each disaggregation.

Within types of research, the simple production function is tailored to providing estimates for use-inspired research. For simple production functions involving basic and use-inspired R&D, only data delineating the basic and use-inspired R&D expenditure are needed. Simple models are performed by Link (1981) and Mansfield (1980) who both use NSF data on government and private R&D expenditures by industry and by type of research, and value added data by industry from McGraw Hill's Business' Plans for New Plants and Equipment. Control variables in these models are the rate of unionization by industry, and the amount of R&D that is embodied in an industry's purchased inputs.[82]

Among the literature reviewed, we identified one example of a simple production function that included research infrastructure (Elnasri and Fox 2014). Research infrastructure is a lesser explored topic, and most authors analyze research infrastructure as a component of a multi-stage model. Elnasri and Fox (2014) use an intangibles model with public infrastructure at the national level for Australia. This adds several factors of production through the inclusion of non-traditional capital expenditures that may affect productivity such as scientific R&D equipment, computer software, databases, and economic competencies.[83] Standard input and output variables are used including market sector value added, total hours worked, and stocks on machinery and equipment.[84] Control variables

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[82] Both control variables are sourced as coming from calculations performed by Terleckyj.

[83] Sources on intangible capital include Australian business expenditure on R&D from the Australian Bureau of Statistics (ABS), computer software spending and economic competencies (estimated from marketing expenditures) from the ABS Australian National Accounts.

[84] Data on labor are from the ABS Labour Force releases. Data on capital and value added are from the ABS National Accounts.

include business cycle effects, energy prices, trade openness, and the ratio of export to import prices.[85]

The production function has been performed across geographic disaggregations at the local, state, and national levels. Production function studies such as Griliches (1980), Mansfield (1980) and Link (1981) use firm-level data for the production function, enabling analyses at the local level. Notable examples of simple production functions that have been performed with disaggregation by geography are Aiello and Cardamone (2008) and Coe and Helpman (1995).[86]

Aiello and Cardamone (2008) perform the production function for a set of Italian manufacturing firms including spillovers across Italian regions. Data include standard firm-level data on labor, capital, R&D investment, value added, as well as the location of each firm.[87] Elasticities in this model are calculated for spillovers by geography and by a measure of technological absorbative capacity derived from labor. While elasticities in this model are calculated for each Italian region, it serves as an example of the use of firm-level data which could be used for local or state-level analyses.

Coe and Helpman (1995) perform a similar analysis to Aiello and Cardamone (2008) at the level of international R&D spillovers. For this version of the production function, the factors of production are business sector capital, labor, and R&D expenditures with R&D capital stocks as a derived measure and value added as output data.[88] Control variables used in the model are bilateral trade shares and imports, accounting for other influences of foreign countries on production.[89]

Simple production functions with disaggregations by research performers may require alterations of the production function model to include R&D spillovers. For production functions for public sector R&D, models must include consideration of additional confounding variables that may affect the relationship between public R&D and private outputs. Like other production functions, production functions that model public sector R&D require data for the factors of production and an output measure. However, because public R&D does not directly lead to production, private factors of production must also be included so that the spillovers of public R&D to private production are assessed without significant bias. For Levy and Terleckyj (1983) the main model inputs include fixed capital per hour, unemployment, ratio of stock of private industry R&D capital to fixed capital, and the ratio of government R&D capital to fixed capital, with gross private sector output as the dependent variable. Additional control variables that are used in the calculation of returns to government R&D include corporate tax rates and prior year output (Levy and Terleckyj 1983). Other common control variables for the estimation of government R&D spillovers include political

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[85] The business cycle variable of Elnasri and Fox (2014) is derived from value added from ABS national accounts. The energy prices, trade openness, and ratio of export to import prices are taken from sources in the literature of Bolaky and Freund (2004), Connolly and Fox (2006), and Madden and Savage (1998).

[86] More examples of the modelling of regional spillovers with the production function are available in the subsections for production functions with intermediate output data.

[87] Firm data are from the "Indagine sulle imprese manifatturiere" surveys by Capitalia.

[88] Capital stock data are from the OECD Analytical Database for all countries. Labor data differ by country with the United States data coming from the BLS Monthly Labor review publication. R&D expenditures and derived R&D capital stock data are from the OECD Science and Technology Indicators.

[89] Bilateral trade shares are from the IMF Direction of Trade series and import volumes are from the World Economic Out Database.

engagement of private firms, whether government agencies monitor the private laboratory, if a private laboratory has inter-corporate laboratory cooperative research arrangements in place, government purchase of goods and services, private purchase of goods and services, firm size, research area, and industry (Leyden and Link 1991; Leyden et al. 1989; Lichtenberg 1984b; Lichtenberg and Siegel 1989; Robson 1993).

The production function can be performed at the program level if the input data regarding the investment of R&D at lower levels of disaggregation are provided. However, no examples of such a study exist in the literature. Production functions with intermediate outputs provide more clear examples of the use of production functions that may be relevant to disaggregation at the NSF program level.

Production function with R&D outputs

Use of intermediate outputs such as patents is robust for disaggregations by type of research, geographic region, administrative unit or program, and performer type. As with Jaffe (1986), the knowledge production function is used to measure the impacts of R&D processes on knowledge outputs. With added disaggregations, the knowledge production function can be used to assess spillovers across type of research, geographic region, administrative unit or program, and performer type.

The most common disaggregation of production functions with intermediate outputs are those that capture R&D output across performer type. Notable production functions of this type vary with some trying to measure spillovers between public research institutions and the private sector (Azoulay et al. 2019; Jaffe and Lerner 1999; Jaffe and Trajtenberg 1996; Myers and Lanahan 2022) and other seeking to measure spillovers between academia and the private sector (Acs, Audretsch, and Feldman 1994; Anselin et al. 2000; Bacchiocchi and Montobbio ; Feldman and Florida 1994). Within this literature, there is variation in the outcome variable used with some using patents (Anselin et al. 2000; Jaffe and Lerner 1999; Myers and Lanahan 2022), some using patent citations (Bacchiocchi and Montobbio 2009; Jaffe and Trajtenberg 1996), and some using innovation counts (Acs et al. 1994; Feldman and Florida 1994).

An example of the R&D output from public research institutions is Jaffe and Lerner (1999) who seek to determine spillovers from R&D performed by national labs to private sector patents. Information required for the national labs include dates of establishment, regional characteristics, lab budget and funding sources, annual R&D expenditures, cooperative research agreements, and engagement in technology transfer activities.[90] Patent information for the DOE was from a database compiled by the DOE's Office of Scientific and Technical Information, which was merged with the NBER/Case Western Reserve patent database to provide information for patent class, application year and inventor. Additional controls included lab fixed effects, technology area, laboratory contractor experience, a year dummy variable for patterns in patenting activity, basic science share of R&D, and national security share of R&D. This enabled estimation of patents resulting from public R&D

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[90] Most of these data come from a variety of sources. Dates of establishment were found on LEXIS/NEXUS and on facility websites, regional characteristics were found in the Venture Economics' Venture Intelligence Database and Census Bureau records, lab budget, funding sources, technology transfer activities and cooperative research agreements were obtained from the DOE, and annual R&D expenditures were from the NSF Federal Funds for Research and Development series.

activities, taking into account several factors including exposure to private sector cooperation, technology area, and researcher quality.

Examples of the use of intermediate outputs for measurement of spillovers across geographic areas include Acs et al. (1994), Audretsch and Feldman (1996), and Jaffe et al. (1992). Jaffe et al. (1992) performed a knowledge production with patents and geographic data to identify geographic spillovers from R&D. This model uses data for the R&D and patents of private firms and universities. Analysis of the geographic spillovers is done at the country, state, and Metropolitan Statistical Area (MSA) levels, using data on inventor location. In addition to the patents from target R&D, patent data were needed for a set of control patents in the same technology area, and patents that cited and were cited by the target and control patents. Other controls include citation lags, corporate origination, matching patent classes, exact geographical matches and self-citations.[91]

Less common is the use of production functions with intermediate outputs to determine spillovers across types of research. This is not because production functions with intermediate outputs cannot measure these spillovers, but rather because the line between basic and other types of research is difficult to assess for the purposes of attributing patents. A study that attempted to infer type of research from patents is Trajtenberg et al. (1992), which measures for differences in the basicness of research between university and corporate R&D. The unique data requirement for this paper is the need for a measure of the "basicness" of R&D, which is a derived measure from patent citations, non-patent citations, patent class, technological field and class, and the lag between application date and citations.[92] Trajtenberg et al. (1992) shows both the difficulty of a derived measure of basicness, however, the knowledge production function should have no difficulty if the categorization of basic, applied, and research infrastructure support is pre-defined by the NSF and a model is used to assess differences in patenting between the types of research.

Within the literature reviewed, disaggregation by administrative unit or program has not been done in the production function with intermediate outputs. This does not mean that it is not feasible, as it is clear from the reviewed literature that such disaggregation can be done with intermediate outputs. Examples of papers supporting this assertion are Jaffe et al. (1992) and Jaffe and Lerner (1999) that both obtain granular information on the inventor of patents, with information such as inventor location. If inventor information is obtained by NSF program area, a production function with intermediate outputs could produce estimates of the production of knowledge capital from NSF research.

Multi-stage and dynamic production functions

Multi-stage production functions that model disaggregation by type of research include Akcigit, Hanley, and Serrano-Velarde (2021), Fieldhouse and Mertens (2023), and Gersbach et al. (2018). The description of the methodology for Akcigit, Hanley, and Serrano-Velarde (2021) in Section 7.6 provides details on the use of multi-stage production functions for type of research.

Multi-stage production functions that model disaggregations of performer type include Dyevre (2024), Fieldhouse and Mertens (2023), Gersbach et al. (2018), Guellec and van Pottelsberghe de la Potterie (2001), Guellec and Van Pottelsberghe de la Potterie (2003),

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[91] Jaffe et al. (1992) does not thoroughly provide sources of patent or related information.

[92] Trajtenberg et al. (1992) does not thoroughly provide sources of patent or related information. It is noted that data for firms come from S&P Compustat.

Lanahan (2016), and Myers and Lanahan (2022). Fieldhouse and Mertens (2023) shows the power of multi-stage production function models, as it captures spillover effects between public and private R&D, and the spillovers of difference types of R&D including defense R&D, non-defense R&D and research infrastructure. The Fieldhouse and Mertens (2023) model is based off of changes in government R&D expenditure affecting the R&D investment decisions of firms, and the resultant shocks to TFP that result from government R&D spillover effects. Data required for this model include public capital data, gross investment, public R&D capital, R&D expenditure, and TFP.[93] Control variables include stock market returns and the presence of military news which are from the Kenneth French Data Library and Ramey and Zubairy (2018), respectively.

Multi-stage production functions that model disaggregations of geographic region include Guellec and van Pottelsberghe de la Potterie (2001; 2003) and Altomonte et al. (2016). Altomonte et al. (2016) uses the European Firms In a Global Economy (EFIGE) survey of European manufacturing firms to create a dynamic system of equations that assess how TFP, exports, firms funding constraints, and R&D interact. Data in this model include ownership, internal structure, investment, innovation, internationalization, financial structure, market and pricing strategies, R&D investment, and self-reported credit constraints from EFIGE and balance sheet data including labor, fixed assets and derived TFP are sourced from the Bureau Van Dijk Amadeus database. Control variables include exporting firms in the same region, R&D performing firms in the same region, tax incentives to export, tax incentives on R&D, and self-reported dependency on external financing all from the EFIGE survey.

Cost function

The cost function can be disaggregated by type of research and geographic region but cannot be disaggregated by administrative unit or program or performer type.[94] Besides use-inspired R&D, research infrastructure can be included in the cost function.

Mamuneas (1999) includes investment in R&D physical capital as a separate term to R&D labor, effectively measuring investment in research infrastructure. The full factors of production used in Mamuneas (1999) thus include intermediate outputs from R&D, R&D capital investment, R&D labor cost in addition to labor and capital for production.[95] This specification allowed for the possibility of R&D spillovers from other industries and the government since intermediate inputs in the model were adjusted for prior firm R&D expenditure. The goal of the model was to measure spillovers of government-funded R&D compared to private R&D, but this type of specification could be used for measuring spillovers between types of R&D.

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[93] Data on public capital come from the BEA Fixed Assets and National Income and Product accounts, which provides data that can be split between R&D and physical capital. R&D expenditures for all recipients of federal R&D dollars are from the NSF National Patterns of R&D Resources. Government R&D spending by agency is from annual editions of the Budget of the U.S. Government. TFP is from the Federal Reserve Bank San Francisco Total Factor Productivity series.

[94] The cost function cannot be performed for publicly performed R&D; however, it can include publicly-funded R&D performed by firms. This can be seen in (Levin and Reiss 1984; Mamuneas 1999; Nadiri and Mamuneas 1994).

[95] Output, labor, physical capital and intermediate inputs are from the BLS. Firm R&D expenditure is from the NSF Research and Development in Industry and Government R&D expenditure is from the NSF Federal Funds for Research and Development.

The only disaggregation of the cost function by geographic region that was reported is disaggregation by country. Nadiri and Kim (1996) performed the cost function across seven countries for the measurement of R&D spillovers. The output variable in this model is GDP, with factors of production including capital stock, labor, R&D capital stock, and R&D capital stock in other countries as a measure of spillovers.[96]

Below the country level, the cost function is most commonly performed to measure spillovers between industries within a country. This is seen in examples at the industry level including Bernstein (1988), Bernstein and Nadiri (1991), Mamuneas and Nadiri (1995), Mohnen et al. (1986), and Nadiri and Mamuneas (1994).

Disaggregation by more granular geographic region is possible using the approach taken in Nadiri and Kim (1996). This approach could be applied by using firm-level data for output and factors of production to create samples for regions of interest. The use of firm-level data and custom aggregation of the factors of production has been demonstrated in Bernstein (1988). Bernstein performed a cost function approach on a sample of Canadian manufacturing firms, using firm level data for the factors of production, which was aggregated to the industry level.[97]

Input-output

I-O estimates can be disaggregated at the program level, geographic region, and performer type. I-O however, has only been applied to use-inspired research and is not used for estimates of the benefits from discoveries of basic research, human capital or research infrastructure. No I-O studies were identified that provided estimates of impact from research discoveries besides for use-inspired research performed by private firms, making it difficult to assess whether such studies are generally feasible. This is because the use of sales data may be a limitation for types of research that are not immediately connected to downstream industrial applications and research performers outside of industrial R&D performers.

I-O methods require data on sales for products that arise from R&D awards and the corresponding tables of relevant sector economic activities based on the I-O software selected. For the disaggregation of I-O estimates by program level, geographic region, or institution type, product sales data must be associated with the program, institution or geographic region in which downstream sales took place.

The TechLink studies disaggregate their I-O analysis of SBIR funding by state (TechLink 2014; 2019b). For these studies, sales data that result from the Navy and Air Force SBIR/STTR programs were identified by connecting SBIR/STTR recipients to sales data provided by program participants. With sales data separated by state, a different form of I-O can be performed which can disaggregate by geographic region, known as Multi-Regional Input-Output (MRIO) analysis. MRIO analysis can also be used for more granular regions such as counties, if sufficient granular data are acquired.

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[96] GDP, wage rate and cost of capital data are from the OECD National Accounts series, labor statistics of manhours from the OECD Yearbook of Labor Statistics, gross capital stock from the OECD Flows and Stocks of Fixed Capital, and R&D stocks from the OECD, Main Science and Technology Indicators.
[97] Data on CANSIM databank of Statistics Canada. The source of data specific to corporations is the CALURA survey of Statistics Canada, and the R&D data are from the R&D survey of Statistics Canada.

Besides disaggregation by geographic region, no other disaggregations are performed in the reviewed literature. However, it seems possible that I-O could be flexible to include disaggregations by administrative unit or program or by performer type. For these disaggregations, a modification of the sales data that is inputted to the I-O model is required. If sales data is disaggregated by research performer or by the sector of research performance, separate analyses could be conducted to assess separate estimates by these disaggregations.

Despite the possibility of disaggregating by administrative unit or program or performer type this is severely limited by the requirement of acquiring downstream sales data. The Techlink series of studies is performed on SBIR/STTR research, which consists of use-inspired research that is directly connected to commercial outcomes. Attributing downstream sales data to prior R&D performance may be difficult for any type of research that is not use-inspired research or for research performed by academia or public research institutions that do not produce their own commercial outputs. Thus, from the reviewed literature, we consider I-O to be limited to estimating the economic impact from research discoveries of use-inspired research from private R&D performers.

Cost-benefit analysis

CBA can be used to assess impacts from any type of NSF research support. Many studies have explored basic research (David et al. 1992; Weisbrod 1971), programs funding use-inspired and applied research (Link, 2010; O'Connor et al. 2010; Pelsoci 2010) and in a few cases research infrastructure spending (e.g., Forster and Seeger 2014). CBA also offers many benefits for the exploration of research impacts. Whereas I-O methods produce fiscal impacts from innovated products, and econometric methods report productivity growth, CBA can incorporate non-market impacts such as environmental or social benefits.

CBA approaches can be performed for any level of regional aggregation but there may be data and method limitations to lower levels of disaggregation. Many forms of estimation can be incorporated into CBA including econometric analysis (Link 2010; Trajtenberg 1989), aggregation of sales figures (Forster and Seeger 2014; Tassey 2003), estimation of consumer and producer surplus (Allen et al 2012; Link and Scott 2019), performance of I-O models (Buxton and Hanney 1998; CONSAD Research Corporation 1996), and monetization of other benefits such as environmental or health benefits (Link 2010; O'Connor et al. 2010; Pelsoci 2010). Use of national-level market data is an example of a method that may restrict disaggregation, however other estimation methods such as sales figures and I-O models may allow for estimated benefits that can be disaggregated at a narrower geographic level.

It is not common to perform CBA to analyze benefits at a regional scale lower than national, but such estimates could be obtained if desired, depending on data availability. Methods using downstream sales data to estimate economic benefits are likely the best candidate for performance of state or local disaggregated CBA studies, as such benefits can easily be attributed to smaller geographical units.

Similarly, CBA case studies can be performed at the program level, as the case study approach can be used at levels as granular as the impacts of individual technologies. However, CBA has similar data requirements to the intermediate outcome production functions. To identify downstream impacts, a case study should identify technologies that result from R&D and their downstream industrial applications. The case study model allows for the selection of individual cases that are representative of program impacts, meaning that data may only need to be available for some cases within each NSF award area to achieve understanding of differential impacts by program. However, robust CBA case studies require a full accounting of externalities from project performance. As such, each CBA case study requires understanding of each of the markets and non-economic externalities impacted by a project, which can be a sizeable research undertaking.

7.8 Conclusion

Among the approaches reviewed in Section 7, CBA and the production function are likely the most applicable candidates for estimating the impacts from NSF discoveries, whereas the cost function and I-O methods face severe practical limitations.

The cost function and I-O approaches both have clear limitations regarding ability to disaggregate NSF support in different ways. The cost function seeks to optimize investment in factors of production from the perspective of firms performing R&D, making it not applicable for estimating returns for R&D performed by public research institutions or academia. I-O cannot perform estimates of research discoveries for research that does not have direct connections to downstream products with sales data. As such, I-O methods cannot be used for basic research or research infrastructure estimates.

I-O models also suffer the limitation of not directly modelling the productivity impacts that R&D has on the economy. I-O models do not have mechanisms to account for the productivity increases of R&D and thus require data inputs to account for these differences. The TechLink series of studies accomplish this through the use of downstream sales data from products that resulted from funded R&D. This approach does not measure the productivity increase that occurs in the economy but measures financial returns generated after R&D outputs have affected downstream industries.

Both the production function and CBA clearly measure the transformation that occurs in the economy through discoveries. Both methods are flexible for the inclusion of multiple outcome variables, and both methods allow for the disaggregation of benefits by type of research, geographic region, administrative unit or program, and performer type.

The production function model connects R&D expenditure with downstream productivity benefits. While regression analysis is correlational in nature, the use of productivity as an outcome variable ensures that measured benefits are from research discoveries and not mere funding effects, as the fiscal economic benefits of awards do not result in downstream productivity effects. Variants on the production function model use intermediate knowledge outputs from R&D to identify with greater confidence the causal pathway by which R&D affects productivity. Such models, such as those performed by Akcigit et al. (2021), Crepon et al. (1998), and Dyevre (2024) provide more clarity on the exact processes by which R&D processes result in knowledge outputs that feed into industrial production.

For the production function, the assessment goal is often to disentangle correlation and diagnose the mechanisms of technology transfer rather than to assess their value. The outputs from the reviewed econometric approaches consist of elasticities of final and intermediate outcomes to R&D expenditure. Common variables used as outcome measures in the production (and cost) functions include TFP, sales, value added, GDP, employment, output, and exports. Final economic output elasticities can also be used to calculate the full extent of social benefits from R&D as can be done with cost-benefit methods. Intermediate outcomes that are calculated include patents, innovative activity, citations, and the calculation of spillover effects. If multiple outcome measures are desired from the production function, multiple models need to be performed.

The production function can also be used across disaggregations desired by the NSF, including geographic region (Aiello and Cardamone 2008; Fieldhouse and Mertens 2023; Jaffe et al. 1992) type of research (Elnasri and Fox 2015; Gersbach et al. 2018; Link 1981; Mansfield 1980), NSF administrative unit or program (Fieldhouse and Mertens 2023), and sector of research performance (Acs et al. 1994; Anselin et al. 2000; Azoulay et al. 2019; Jaffe and Lerner 1999; Jaffe and Trajtenberg 1996).

Unlike econometric approaches, CBA approaches do not look at aggregate increases in firm or industry productivity. Instead, CBA approaches isolate NSF discoveries through impact case studies of downstream industrial products. These case studies look at all impacts of individual technologies, such as industrial productivity increases or cost savings, or revenues from new products that are derived from the technology. CBA case studies try to be complete in accounting for all downstream impacts, including externalities that products have for other markets.

CBA provides a flexible approach to model aspects of commercialization in different economic forms. This can include modeling the effects for each market of downstream technologies relevant to NSF research and can include additional spillovers and non-economic benefits such as from environmental and health applications of technologies. CBA is flexible for disaggregation of benefits due to the bottom-up case study approach, which has been used to aggregate benefits from individual technologies for understanding of impacts at the portfolio level. While more modular than multi-stage production functions, CBA with a complete accounting of each NSF-relevant market would similarly require detailed metadata on the intermediate outputs of NSF research, technology transfer data such as patents, licensing data, spin-out company information, and market data for the markets of resultant technologies.

An advantage of CBA over the production function is the flexibility and narrative potential inherent in the case study process. Since case studies are naturally granular in assessing the impacts of an individual product or administrative unit or program, a full understanding can be achieved of the social returns of research. These returns then can easily be aggregated with other case studies to provide understanding of average social returns by type of research, geographic region, administrative unit or program, and performer type. Another beneficial quality of this approach is the granular understanding of the complete research translation process. Due to the focus of case studies on impact pathways, the case study process can result in helpful narratives regarding the benefits of research, which is not a natural byproduct from analyses at higher levels of aggregation.

8 What methods from the empirical literature are most relevant to estimating the economic impacts of NSF R&D support?

To conclude, we discuss the application of several methods to estimate the economic impacts of NSF awards and the discoveries resulting from NSF funding. We first return to possible impact pathways for NSF's R&D activities. We then present potential applications for estimating the economic impact of NSF awards along with data requirements and measures. We conclude this section with a discussion of potential applications for estimate the economic impacts of NSF discoveries.

8.1 Impact pathways relevant to NSF's support for R&D

This literature review found evidence that NSF can measure and estimate its economic impacts through the select use of indicators or proxies of economic impact as well as through the application of estimation methods to both the measurement of the economic impacts of NSF awards as well as the discoveries that arise from NSF supported R&D.

Among the four R&D activities NSF funding supports as described in this report, the most developed impact pathways exist for both basic research and use-inspired research. The measurement of the economic impacts of human capital development and research infrastructure has been less well studied. However, there is evidence that NSF could conduct further analysis to assess the feasibility of measuring intermediate outcomes using these possible impact pathways.

This literature review also established that it is possible to apply several methods to estimate the economic impacts of NSF awards and the discoveries stemming from NSF funded R&D.

8.2 Estimating the economic impacts of NSF awards

Potential Uses of Input-Output Modeling

I-O modeling represents a practical and efficient method for estimating the immediate economic impacts of NSF funding awards. The foundation in existing industry relationships, employment footprint, and employee earnings data underlying I-O models can significantly reduce the effort required to trace linkages from awards to the broader economy. I-O models can estimate the impacts of NSF R&D in the following ways:

- **Basic research:** Purchase of R&D materials, services, and consumer expenditures supported by NSF awards.
- **Use-inspired research:** Purchase of R&D materials, services, and consumer expenditures supported by NSF awards.
- **Research infrastructure:** Construction of facilities, purchase of R&D equipment, and consumer expenditures supported by NSF awards.
- **Human capital development:** Consumer expenditures supported by NSF financial support for students and R&D staff.

Potential Uses for Econometric Methods

Given the efficiency of I-O models, econometric methods are unnecessarily time-intensive to be used in estimating the short-run economic impacts of NSF awards.

The primary use case for econometric methods is for estimating the complementarity of NSF awards with non-federal R&D expenditures. Because NSF research awards stimulate other funders including universities, states, and private companies to invest in R&D, the immediate economic impact is not limited to employment and sales directly paid for with NSF awards. Econometric methods could be used to estimate the research funding multiplier for NSF awards which would increase the immediate economic impacts of NSF awards.

Award expenditure multipliers generated using econometric methods can then be used as inputs for I-O modeling. Estimated non-federal research expenditures stimulated by NSF awards can be added to the underlying level of NSF funding and treated wholistically as inputs for I-O modeling.

Data Requirements

The primary data required to estimate economic impacts using I-O models would be the amount and type of funding provided. Administrative award data from NSF can be used as inputs and I-O models can then estimate demand for goods, services, and labor.

Additional granularity can be achieved by using administrative and expenditure data to detail the demand for specific goods, services, and labor associated with different NSF funding programs. One of the limitations of RIMS II and IMPLAN is lack of specificity about the economic inputs required to conduct different types of R&D activities and funding for research infrastructure. The types of goods, services, and labor intensity of basic research differs from use-inspired research and across different R&D fields. Based on detailed expenditure data, it is possible in IMPLAN to construct tailored industries that better reflect the types of demand supported by specific NSF funding programs or awards. The IRIS UMETRICS dataset which provides detailed expenditure and employment data for NSF-funded R&D teams could be used to create tailored industries to capture the different types of demand and employment supported by specific NSF funding programs and awards.

Measures

One of the strengths of I-O models reported in the literature, is the ability to estimate multiple types of economic impacts simultaneously in the same modeling setup. The following measures can be estimated based on a set of inputs:

- Economic Output (RIMS II and IMPLAN)
- Value Added (RIMS II and IMPLAN)
- Employment (RIMS II and IMPLAN)
- Employee Compensation (RIMS II and IMPLAN)
- Tax Revenue (IMPLAN).

These measures of economic impact can be produced at the national level and can be disaggregated in the following ways:

- Regional, state, and county
- Type of award (e.g., basic research, use-inspired research, research infrastructure, human capital development)
- Funding program
- R&D performing entity (e.g., research university, research institutes, private companies)
- Individual awards.

The primary limitation in disaggregating economic impacts is in the cost of purchasing models and the time required to subdivide analysis. Both IMPLAN and RIMS II require that each region, state, or locality be purchased individually, increasing the cost of conducting analysis at more granular sub-national levels. Disaggregating results by type of award, funding program, R&D performing entity, or individual awards, requires that I-O models be conducted for each set of inputs, increasing the time required to conduct the analysis.

8.3 Estimating the economic impacts of discoveries

Review of the economic literature has shown that the production function and CBA approaches are suitable for the estimation of economic impacts from NSF research discoveries. To determine their applicability the main consideration was the capture of impacts across NSF awards, including basic research, use-inspired research, human capital, and research infrastructure. Due to the complex impact pathway of investments in human capital, no approach was suitable for determining impact of human capital on downstream production. However, both the production function and CBA methods proved to be the most applicable methods to the NSF, with literature supporting their ability to assess impacts from basic research, use-inspired research, and research infrastructure.

In reviewing possible approaches for their applicability to NSF awards, additional disaggregations were considered that relate to the needs of NSF in estimating the impacts of research. These include disaggregations by geographic region, NSF administrative unit or program, performer type, and temporal frequency. Temporal frequency was not explored in detail in this literature review, as most literature sources use annualized data.

Use of the Production Function

The production function is flexible in its coverage of possible disaggregations of interest to the NSF. This includes coverage of the main feasible research areas of basic research (Gersbach et al. 2018; Leyden et al. 1989; Link 1981; Mansfield 1980), use-inspired research (Akcigit et al. 2021; Gersbach et al. 2018; Link 1981; Mansfield 1980) and research infrastructure (Elnasri and Fox 2014, 2015; Andrew J. Fieldhouse and Mertens 2023), as well as coverage of disaggregations by geographic region (Aiello and Cardamone 2008; Andrew J. Fieldhouse and Mertens 2023; Jaffe et al. 1992), NSF administrative unit or program (Andrew J. Fieldhouse and Mertens 2023), and sector of research performance (Acs et al. 1994; Anselin et al. 2000; Azoulay et al. 2019; Jaffe and Lerner 1999; AB Jaffe and Trajtenberg 1996).

In estimating the benefits of NSF discoveries, the production function provides estimates of the elasticities of R&D to productivity and estimates of the rates of return from R&D. In any case. Production function models, based off the level of aggregation, differ whether national level TFP, sales, or value added are used as the output to represent productivity increases. Knowledge production function models that use intermediate outcome data also provide statistics of knowledge outputs that result from R&D process such as publications, patents, citations, and innovations.

Among the production function methods, many different types of spillovers can be identified which may be important to the NSF, including spillovers by type of research, geographic region, administrative unit or program, performer type, and technology area. Models of the production function have tradeoffs in what spillover effects that they measure, based off of available data and units of observation. For example, due to available firm survey data Europe, Altomonte et al. 2016) was able to perform analysis of firm spillovers between countries based on R&D, export and financing behaviors. With much different data on the R&D funding of public agencies, Fieldhouse and Mertens (2023) performed analysis of public R&D spillovers based off Federal spending socks, with differential estimates for defense, non-defense, and research infrastructure shocks.

Use of Cost-Benefit Analysis

While the production function methods require different models based on the disaggregations of interest, the CBA case study approach is instead dependent on individualized performance of case studies by each disaggregation of interest.

CBA can be performed across the disaggregations of interest to the NSF because it is flexible for the inclusion of differently modelled impacts from research discoveries. This can include modeling the effects for each market of downstream technologies relevant to NSF research and can include additional spillover and non-economic benefits such as from environmental and health applications of technologies. CBA is flexible for disaggregation of benefits due to the bottom-up case study approach, which has been used to aggregate benefits from individual technologies for understanding of impacts at the portfolio level. While more modular than multi-stage production functions, CBA with a complete accounting of each NSF-relevant market would similarly require detailed metadata on the intermediate outputs of NSF research, technology transfer data such as patents, licensing data, spin-out company information, and market data for the markets of resultant technologies.

An advantage of CBA over the production function is the flexibility and narrative potential inherent in the case study process. Since case studies are naturally granular in assessing the impacts of an individual product or administrative unit or program, a full understanding can be achieved of the social returns of research. These returns then can easily be aggregated with other case studies to provide understanding of average social returns by type of research, geographic region, administrative unit or program, and performer type. Another beneficial quality of this approach is the granular understanding of the complete research translation process. Due to the focus of case studies on impact pathways, the case study process can result in helpful narratives regarding the benefits of research, which is not a natural byproduct from analyses at higher levels of aggregation.

APPENDIX A: KEY TO ACRONYMS

This section contains the definitions for acronyms used throughout the literature review document.

Exhibit A-1: Acronyms used in this report

Acronym	Definition
ARC	Australian Research Council
ATP	Advanced Technology Program (within NIST)
BCR	Benefit-cost ratio
BEA	Bureau of Economic Analysis
BIO	Biological Sciences (NSF directorate)
BLS	Bureau of Labor Statistics
CBA	Cost-benefit analysis
CERN	European Organization for Nuclear Research
CHIPS	Creating Helpful Incentives to Produce Semiconductors (CHIPS and Science Act)
CISE	Computer and Information Science and Engineering (NSF directorate)
CRS	Congressional Research Service
CSIRO	Commonwealth Scientific Industrial and Research Organisation
CT	Citation tracing
DOD	U.S. Department of Defense
DOE	U.S. Department of Energy
DOI	Digital object identifier
EAC	Evaluation and Assessment Capability
EDU	STEM Education (NSF directorate)
EFIGE	European Firms in a Global Economy survey
ENG	Engineering (NSF directorate)
EPSCoR	Established Program to Stimulate Competitive Research
ERC	Engineering Research Center
FFRDCs	Federally funded R&D centers
FWF	Austrian Science Fund
GDP	Gross domestic product
GEO	Geosciences (NSF directorate)
GERD	Gross expenditures on research and development
GNP	Gross national product
HE	Higher education
IDeA	Institutional Development Award
I-O	Input-output
IUCRC	Industry-University Cooperative Research Center
LHC	Large hadron collider
MPS	Mathematical and Physical Sciences (NSF directorate)

Acronym	Definition
MREFC	Major research equipment and facilities construction
NASA	U.S. National Aeronautics and Space Administration
NCI	U.S. National Cancer Institute
NCSES	U.S. National Center for Science and Engineering
NHS	U.S. National Health Service
NIH	U.S. National Institutes of Health
NIST	U.S. National Institute of Standards and Technology
NME	New molecular entities
NPV	Net present value
NSF	U.S. National Science Foundation
OECD	Organisation for Economic Cooperation and Development
OISE	Office of International Science and Engineering
OLS	Ordinary least squares
OMB	Office of Management and Budget
PPP	Purchasing power parity
QALY	Quality adjusted life year
R&D	Research and development
R&DSA	R&D Satellite Account
R&RA	Research and related activities
RDI	Research and development infrastructure
REF	Research Excellence Framework
RIMS	Regional Input-Output Modeling System
RR	ResearchRabbit
RTI	Research Triangle Institute (RTI International)
S&E	Science and engineering
SBA	Small Business Administration
SBE	Social, Behavioral, and Economic Sciences (NSF directorate)
SBIR	Small Business Innovation Research
STEM	Science, technology, engineering and mathematics
STTR	Small Business Technology Transfer
TFP	Total factor productivity
TIP	Technology, Innovation, and Partnerships (NSF directorate)
TWG	Technical working group
U.S.	United States
USD	United States dollar
USPTO	United States Patent and Trademark Office
WoS	Web of Science

Note: Acronym definitions are translated to English if originally in another language.

APPENDIX B: DETAILS OF LITERATURE REVIEW METHODS

This section contains the details of how the literature review was conducted.

To identify the academic and gray literature relevant to estimating the economic impacts of R&D, we applied two complementary search strategies—keyword search and citation tracing—aiming for redundancy to capture as many relevant documents as possible. Literature found through these processes was supplemented with suggestions from the project's Technical Working Group, an advisory panel of experts in the field.

Three independent sets of keyword search terms were developed, allowing for a greater diversity of results. Two of these sets were compiled within the project team and an additional set by an RTI librarian. The sets included synonyms for R&D and economic impacts, along with terms that represent the different stages of R&D, the names of key funding agencies and programs relevant to this study, and a variety of types of economic impacts and metrics.

The search sets were aggregated and implemented across a variety of platforms indexing academic and gray literature. These are listed in Exhibit B-1. The quality and practical utility of search results varied widely across these platforms. Additional documents found through citation tracing and sourced from the Technical Working Group complemented these keyword searches, further validating coverage of the topic area.

Exhibit B-1: Literature search repositories

Data repository	Repository type
Web of Science	Proprietary bibliographic database
Google Scholar	Open bibliographic database
National Bureau of Economic Research (NBER) working papers	Database of pre-review working papers in economics
EconLit	Proprietary database of working papers and journal articles in economics; documents are classified by Journal of Economic Literature (JEL) codes
Google	Open database for broad searches including gray literature
Overton	Proprietary bibliographic database of policy documents and white papers

Note: This list of data repositories is not exhaustive as we only describe the data repositories drawn on for our literature review.

The literature review task was broken into four iterative steps. As the team progressed through and learned from the literature review, we revisited and updated prior steps.

1. Literature review protocol. A literature review protocol was developed to act as a process guide.

2. Document search and collection. The team searched a variety of databases and literature repositories to identify potentially relevant works. The literature identified was catalogued in a centralized database.

3. Document screen. The team performed an initial screen of documents, selecting a set for detailed evaluation.

4. Information extraction, synthesis, and reporting. The team reviewed the literature selected through the screening process. High relevance information from these documents was extracted and synthesized. The team's findings are presented in this report.

The Technical Working Group (TWG), composed of four academic subject matter experts, supported the development of the literature review by providing technical expertise and feedback. The TWG provided guidance during multiple phases of the literature review task, suggesting important themes and literature as well as reviewing the draft report.

Literature review protocol

As the first step in conducting the literature review, the team developed a protocol for the literature review process. The protocol included:

- An initial set of definitions of key terms.
- Eligibility criteria for documents to be included in our literature review.
- A preliminary set of processes for all steps.

The initial set of definitions became the basis for Section 2.

The following are our eligibility criteria for documents to be included or excluded from the literature review:

Inclusion criteria

- Relevance: must have the economic impacts of research as a key focus, including both theoretical and empirical work
    - Papers that identify intermediate metrics strongly linked to economic impacts and economic growth will also be included, given that the opportunities to measure the economic impacts of discoveries may be limited. These intermediate outcomes would measure products of R&D spending that are upstream of economic impact. For example, if we find papers that make a strong case for a link between patent counts and economic impact, we will include these papers along with papers tying R&D funding to patents.
    - We will prioritize work most relevant to assessing the economic impacts of NSF's funding.
- Quality of work: the review will focus on high quality research, but all relevant research will be noted.

Exclusion criteria

- Language: Exclude non-English papers.

- Peripheral relevance: Exclude papers that mention the economic impacts of research but for which this is not a key theme. For example, cases where the economic impacts of research are part of the paper’s introduction, in service of other ends. We may examine the citations in these introductions.

- Papers of concern: Exclude papers where a post-publication erratum or expression of concern questions its relevant contributions.

Keyword search

The literature search strategy entailed developing a series of search terms and combinations of search terms and using these to conduct searches on multiple platforms indexing academic or gray literature. The team generated two types of searches: 1) project-wide searches that covered the overarching themes of the review, and 2) tailored search terms that focused on subcomponents of the work, such as the dimensions of interest highlighted by NSF’s Request for Quotes for this project.

Initial keywords were identified using exploratory searches and known seminal works, along with the text of NSF’s Request for Quotes. Two parallel teams worked independently to develop search terms, allowing for a greater diversity of results. The lists of search terms included synonyms for R&D and economic impacts, along with terms that represent the different stages of R&D, the names of key funding agencies and programs relevant to this study, and a variety of types of economic impacts and metrics.

The initial list of terms generated by these two teams was then aggregated into a preliminary list of search queries and supplemented by a search query generated by an RTI librarian. These queries were then tested in multiple databases to further refine terms, ensuring that results were reasonably comprehensive without including many irrelevant studies.

The search was implemented across a variety of platforms indexing academic and gray literature. These are listed in Exhibit B-1.

The quality and practical utility of search results varied widely across these platforms as described below.

After refinement on an initial set of search terms the following queries were used for Web of Science, EconLit, RePEc, Overton, and Google Scholar:

1 ("basic research" OR "applied research" OR "R&D" OR "research and development" OR "basic science" OR "university research" OR "pure research" OR “fundamental research”) AND ("equipment" OR "infrastructure" or "facility" OR "facilities" OR "procure*" OR "tool*" OR "apparatus" OR "instrument*" OR "machine*" OR "STEM education" OR "science education" OR "technology education" OR "engineering education" OR "mathematics education" OR "STEM" OR "workforce training" OR "laborator*" OR "lab*") AND ("public* fund*" OR "government fund*" OR "grants" OR "awards" OR "public* invest*" OR "public science*" or "public R&D" or "R&D policy*") AND (“economic impact*” OR “economic consequence*” or “cost-benefit” OR “benefit-cost” OR “multiplier effect*” OR “economic evaluation*” OR “return on invest*” OR “social return*” OR “financial implication*” or "technology-based economic development" OR “economic outcome*” OR “fiscal effect*” OR “revenue generation” OR “employment effect*” OR “market analysis” OR “income effect*” OR “wealth creation*” OR “economic growth” OR “productivity gains” OR “profitability analysis” OR

“expenditure patterns” OR “economic efficiency” OR “resource allocation” OR “input-output”)

2 (scientific research "human capital" "economic growth") OR (social return AND R&D physical capital) OR (spillovers AND "public R&D") OR (STEM education AND economic growth AND public)

3 ("basic research" OR "applied research" OR "R&D" OR "research and development" OR "basic science" OR "university research" OR "Pure Research") AND ("public* fund*" OR "government fund*" OR "grants" OR "awards" OR "public* invest*" OR "public science*" or "public R&D") AND ((“underinvestment” AND “Research”) OR “Market Failure*” OR “Spillover effect*” OR “Positive Externalit*” OR “Knowledge Production” OR "National Defense" OR "Technology frontier" OR "Industrial policy*" OR "Science Diplomacy")

4 ("basic research" AND "economic benefit*") OR ("federal laborator*" and "economic growth") OR ("national science foundation" AND "STEM" "economic growth") OR ("public R&D" AND "economic growth" AND spillover*) OR ("public research" AND "economic impact") OR ("applied research" AND "productivity" AND (government OR public OR federal)) OR (basic AND "public R&D investment") OR(basic AND "government R&D" AND social return) OR ("economic return*" AND patents AND productivity) OR (federal AND "research funding" AND economic competitiveness) OR ("federal laboratory" AND "commercial*" AND "united states") OR ("federal R&D" AND "return on investment") OR ("research funding" AND business growth) OR (federally funded R&D AND "economic impact") OR (nsf AND research funding AND economic impact) OR (nsf AND research funding AND economic impact) OR (public AND "applied research" AND "human capital") OR (public R&D AND "economic impact*") OR ("public R&D invest*" AND economic growth AND spillovers) OR ("public research" AND productivity AND "R&D") OR ("R&D" AND "productivity growth" AND "public research")

5 ("basic research" OR "applied research" OR "R&D" OR "research and development" OR "basic science" OR "university research" OR "pure research") AND ("public* fund*" OR "government fund*" OR "grants" OR "awards" OR "public* invest*" OR "public science*" or "public R&D" or "R&D policy*") AND ((("R&D spillover*" OR "Innovation ecosystem" OR “Growth Accounting” OR “Technology Residual” OR “Absorptive Capacity” OR “Innovation Network” OR “Network Formation” OR “Complementary Asset*” OR “Total Factor Productivity” OR “New Growth Model” OR "Early adopt*" or "related variety")) OR ((“Tracer Studies” OR “Trace Studies” OR “Citation Analysis” OR “Patent Renewal” OR “Backwards Analysis” OR “Forward Analysis”)))

6 ("basic research" AND "return on investment") OR ("basic research" AND "economic impact") OR ("basic research" AND "social return") OR ("research infrastructure" AND "economic benefit*") OR ("applied research" AND "cost-benefit" AND economic) OR ("academic research" AND "economic returns") OR ("applied research" AND "business growth") OR ("applied research" AND "return on investment") OR ("government" AND "research equipment") OR (R&D AND "applied research" AND economic impact) OR (R&D AND "research equipment") OR (SBIR STTR commercial*)

7 ("basic research" OR "applied research" OR "R&D" OR "research and development" OR "basic science" OR "university research" OR "pure research" OR “fundamental research”) AND ("public* fund*" OR "government fund*" OR "grants" OR "awards" OR "public* invest*" OR "public science*" or "public R&D" or "R&D policy*") AND (“economic impact*” OR “economic consequence*” OR “cost-benefit” OR “benefit-cost”

OR “multiplier effect*” OR “economic evaluation*” OR “return on invest*” OR “social return*” OR “financial implication*” or "technology-based economic development" OR “economic outcome*” OR “fiscal effect*” OR “revenue generation” OR “employment effect*” OR “market analysis” OR “income effect*” OR “wealth creation*” OR “economic growth” OR “productivity gains” OR “profitability analysis” OR “expenditure patterns” OR “economic efficiency” OR “resource allocation” OR “input-output”)

Web of Science (WoS) and EconLit

WoS and EconLit presented fewer practical challenges than several other platforms. The preliminary search queries were refined to produce a manageable number of search results and those results were bulk-exported to Zotero using RIS records for each search result.

Google and Google Scholar

Google and Google Scholar contained multiple limitations that induced changes in the literature search procedure. These were a limitation of 30 term maximum of search (including Boolean operators such as AND or OR), and limitations in Boolean logic that were available for searching. Whereas other databases allow for scaffolding of Boolean operators using parenthesis for complex searches, Google has a limit on one set of parentheses surrounding search terms. Accordingly, complex search terms that used multiple layers of parenthesis and Boolean operators had to be dissected into multiple searches to preserve the logic of desired search terms.

Google also faced the drawback of having no bulk download capability. Accordingly, searches were refined until they hit a threshold of roughly 200 applicable, non-duplicative, matches. This involved refinement of searches to include additional restrictive logic to reduce the number of matches for a search term. The search team qualitatively judged whether additional restrictions captured literature that was relevant to NSF’s objectives. Due to both restrictions of Google, the total searches used increased to 24 from the 7 base searches.

Google Scholar has similar limitations to using the Google search engine. Google does not have a feature to download multiple records at the same time. We attempted to circumvent this limitation by using packages in R and a program known as Publish or Perish. These programs allowed us to download multiple records at the same time but had their own limitations. These programs limit the number of characters in a search to 256 characters. Additionally, Google blocks attempts to query the Google Scholar database and will block user’s IP addresses if too many attempts are made in a short period of time. As such, these programs limit the speed with which searches are conducted. Given the size of our queries it was not feasible to use this approach.

National Bureau of Economic Research

NBER faced similar limitations to Google Scholar. NBER could not process more than 50 terms per search (including Boolean operators such as AND or OR) and could not process complex searches with multiple layers of parentheses. Also, like Google Scholar, NBER did not have bulk download capabilities. Accordingly, the threshold for inclusion was refinement of searches down to less than 500 matches per search. Results then had to be manually imported to Zotero. Due to the Boolean logic of the core searches, this required expansion of the search terms from the 7 desired searches to 27 total searches.

Overton

Overton also presented technical challenges, principally in the large number of search results generated and the inclusion of a large number of irrelevant results. Using the same search terms that had produced high quality results in WoS and EconLit, Overton returned a much larger number of results, most of which were not applicable to the current study. For example, the first search term which returned 97 documents in WoS and 114 for EconLit resulted in over 84,000 search results in Overton.

To overcome this lack of discernment in the Overton search results, the following search process was conducted:

1 The search was filtered to include only documents that cited other documents, documents that were published in the last ten years, and limited to document type "publications."

2 Each of the search queries outlined above were then conducted and the research team manually reviewed the first ten pages of results for each search and exported results that were applicable to this study.

EconPapers

EconPapers presented both search validity and practical challenges that ultimately resulted in it not being used for this study. First, multiple platforms provide functionality to search the RePEc service but were found to produce significantly different results based on the same search query. For example, search query #2 listed above produced over 860,000 results on the EconPapers search portal but only 240 results on Ideas. This lack of consistency over search platforms raised concerns about the validity of search results. The number of search results also presented practical barriers to implementing searches using EconPapers.

The research team was unable to identify a tool for bulk export of citation metadata. Individual records contained RIS files for each result, but a functional tool for bulk exporting all of the results from a given search does not appear to exist. An email inquiry was sent to the EconPapers administrators about whether such a tool exists but no reply was received.

Citation tracing, suggestions from the TWG, and other supplementary processes

The team used citation tracing as a separate, complementary process to keyword searches, further validating coverage of the topic area. The team compiled a list of 55 seminal, review, and/or key contemporary papers and conducted both forward and backward citation tracing. We queried the 55 papers on WoS, ResearchRabbit[98], and Overton, aiming for a variety of document types linked by citation, including the gray literature covered in the Overton database. We captured the backward citations (references) from WoS and ResearchRabbit and the forward citations from all three sources. Due to the large number of papers found through citation tracing, we used multiple criteria to prioritize certain

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[98] ResearchRabbit is a literature search tool built on publicly available literature data that allows easy tracing of papers via their reference citation networks. It is available at researchrabbit.ai

documents, reducing the number of papers included in the final citation tracing search results.

We compiled a list of 55 papers from multiple search results and conducted both forward and backward citation tracing (CT). After querying the 55 papers on Web of Science (WoS), ResearchRabbit (RR), and Overton, we imported the backward citations (references) from both WoS and RR and the forward citations from all 3 sources. We compiled all the forward and backward citation search results of each source separately and created a count of the number of times each publication appeared in the results. For backward citation results, the higher the count, the larger the number of the 55 papers that cite them. For forward citation results, higher counts indicate that they are citing multiple papers from the 55 citation tracing papers. Therefore, higher numbers indicate more "links" with the CT papers and suggest higher relevancy.

We sorted the papers in descending order by the number of links and determined cutoff points to reduce the total number of CT results. In addition to using the number of links, we also used publication year and the number of times cited (in the case of WoS) to reduce the total number of CT results. The criteria used were:

- *RR*
    - Forward: paper has more than 3 links to the CT library and published after the year 2000
    - Backward: a paper has more than 1 link to the CT library
- *WoS*
    - Forward: a paper has more than 1 link to the CT library in addition to meeting either of these 2 criteria:
        - Published after the year 2015
        - Published after 2000 and up to 2015 and is cited more than 100 times
    - Backward: a paper has more than 1 link to the CT library
- *Overton*
    - Forward: a paper has more than 1 link to the CT library

We aggregated the CT results from each database and deduplicated them. We also programmatically identified the papers' languages and removed non-English papers. After appending all results, we generated a final CT search result of 2,271 papers.

To complement the team's search, each member of the TWG independently provided a list of 10-30 articles they considered central to a review of this type. This helped ensure key references were not omitted.

The team also piloted a series of additional searches, including looking for publications produced by recent awardees of the Science of Science: Discovery, Communication, and Impact Program. Given the large volume of search results from other sources and that these pilots did not result in highly relevant additional work not otherwise captured, the team did not further engage with these supplementary processes.

Additional documents were found as the team read full documents and highly relevant citations were identified from those documents; these citations were also included in found document set.

Collection and organization of search results

Results from keyword, citation tracing, and the TWG were assembled into a master library of search results, catalogued in the reference software Zotero. In the process of adding documents to the library, each entry was marked with an identifier cataloging the search process and the search platform that produced it. For studies that appeared across multiple search terms or platforms, one search provenance was preserved for the purpose of reproducibility.

We performed verification processes after collecting the papers to minimize the occurrence of duplicates in the results. After completing all searches, we appended the results and removed duplicates by combining different identifying fields (titles, authors, publication years, DOIs) and removing papers with identical combinations of these fields; it is likely that a small number of duplicates remain. After deduplication, 5,966 papers were present in the document set, further supplemented by additional sources found during later stages of the process.

Document screen

Given the large number of documents collected in the search process, a screening process was necessary to identify the documents most likely to be relevant for more thorough review. Team members used a combination of document titles, abstracts, authors, year of publication, and number of citations to identify papers of highest relevance for the literature review. In cases where relevance was uncertain, screeners would briefly scan the full document.

The documents identified through the screen were then assigned a broad topic area to allow for all documents with similar content to be further reviewed together.

Information extraction, synthesis, and reporting

Team members took the documents identified through the screen and reviewed them more thoroughly to capture and summarize key approaches, data, and findings. The team then synthesized key themes across the literature, highlighting data and approaches most applicable for assessing the economic impacts of NSF's R&D. The team's findings are presented in this report. Supplementary materials such as the full database of found literature are provided under separate cover.

Limitations

This literature review is limited in two key ways: by its scope and by its approaches. There is a large body of literature directly or peripherally related to the relationship between R&D and economic impacts. The project team has carefully chosen scope and approaches to select a feasible set of literature to review.

The project scope was chosen to select the literature most relevant for understanding and generating key measures of the economic impacts of NSF. The key economic impact indicators were defined as changes to economic growth, productivity, and employment along with the creation of new firms. These are supplemented by intermediate indicators that may lead to economic impacts, such as publications, patents, and STEM workforce development. A much broader set of impacts could have been chosen. The review also focuses on work most relevant to estimating the economic impacts of federal funding agencies in the United States. While some literature on impacts of private sector R&D and R&D in other economies has been included, it is primarily included when useful for context setting or because it uses relevant approaches.

The review is also limited by the choice of approaches. The initial literature search focused on specific language and disciplines, particularly those of R&D and economics, and may have excluded work performed in other research communities. Citation tracing was used as a complementary approach, aiming to capture literature missed through key word searches. However, efforts in other communities may be effectively siloed and thus not findable through this approach. For example, efforts to estimate economic impacts for other, non-R&D, such as in finance, might provide relevant approaches. The team briefly searched for such efforts, but a more thorough investigation was deemed out of scope.

The team was also limited by the documents that are publicly available and searchable. Along with the academic literature, we aimed to capture research from non-academic sources such as reports from governmental and non-governmental organizations. However, the non-academic gray literature is often more difficult to find and may not be publicly available. The team relied on searches using Google and the Overton database as well as discussions with academic and government experts. Some of this gray literature may have high utility for our use case as it can represent an organization's concrete efforts to estimate its own impacts.

Finally, the team was limited by our inability to read every document we found in detail. Search processes generated 6,000 documents. Those documents went through a screening process, identifying those papers most likely to have relevance for estimating the economic impacts of NSF's R&D funding.

Additional literature identified during report review

During multiple rounds of review of drafts of this literature review, NSF staff, anonymous reviewers, and Technical Working Group members identified additional literature for review and consideration. The literature review team then incorporated these papers as appropriate into the relevant sections of this report.

APPENDIX C: ADDITIONAL DETAIL ON INDICATORS MEASURING ECONOMIC IMPACTS OF R&D

This appendix provides additional information on indicators used to measure the economic impacts of R&D as reported in Section 5. A supplemental data file Indicators Data Full Repository[99] contains detailed listings of key indicators used to estimate the economic impact of R&D, including definitions and source files. Included indicators cover:

- investment
- knowledge capital development
- human capital development
- commercialization
- economic impact

The file is a data repository of key datasets containing indicators commonly used in estimating economic impacts and intermediate outcomes of R&D awards and discoveries. The "Data Requirements" tab includes a table that lists the indicators, their definitions as described by the data sources from which they came, the names of the data sources, and the tab name of the corresponding dataset included in this supplemental file. Subsequent tabs in this file are the datasets containing the indicators of interest, collected as of April 2025.

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[99] Supplemental files available upon request. Email request to EAC@nsf.gov.

APPENDIX D: ADDITIONAL DETAIL ON METHODS FOR ESTIMATING THE ECONOMIC IMPACTS OF AWARDS

This appendix provides additional discussion of the background and logic of I-O models. This review discusses types of economic impacts that the leading I-O models can estimate, and provides details on two tools most commonly used in the United States and the indicators that I-O models can produce that are relevant to studying economic impacts of NSF awards.

Background on I-O models

I-O modeling is a framework for representing the interconnections between industries in a national or regional economy and was first developed by Wassily Leontief (1936). The purpose is to capture how a change in activity in an industry will change economic activity across the entire economy. For example, to understand the total economic footprint of a new automotive assembly plant, an I-O model will use existing industry purchasing and employment data[100] to determine the demand for parts and materials that will be required to produce a given value of final assembled vehicles. This will include the consumption of parts, raw materials, and labor at the assembly plant, as well as the supply chain industries that feed into it. I-O models will also estimate the increase in consumer demand in the broader economy that is generated by the additional employee compensation from this new economic activity.[101]

I-O practitioners in the United States typically distinguish among three types of economic impacts:

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[100] I-O models rely on data that capture inter-industry purchasing patterns, labor expenditures, and employment. A matrix of industry sectors forms the foundation of the analysis. Each cell reflects the share of final output value from the row industry that is allocated to purchases from the column industry along with the share of final output value that is allocated to labor costs. For example, for the motor vehicle industry row, cells would represent the value of goods or services purchased from other industries like automotive parts, iron and steel mills, software publishers, insurance carriers, and legal services respectively. I-O models also account for the share of inputs that are met by suppliers within a given region or country and the share that is met through imports. This permits calculations of how a change in output from a given industry ripples through the economy through changing output in other industries and consumer demand. I-O models can be used to estimate national or regional (e.g., state) effects depending on the context of the study.

[101] The Bureau of Economic Analysis (BEA) took responsibility for developing I-O tables in the late 1950s, added industry employment and employee compensation tables in the 1960s, and greatly expanded the number of industry sectors represented to provide more granular accounting in the 1970s (Horowitz and Planting 2009). The BEA continues to update I-O tables annually based on administrative data on industry purchases and sales and updates national benchmarking each five years based on the Economic Census conducted by the U.S. Census Bureau.

The national benchmark I-O accounts produced by BEA rely on the Economic Census conducted by the U.S. Census Bureau every five years. Conducted at the establishment level to disaggregate responses across larger companies with multiple business locations, the 2022 survey was sent to approximately 4.2 million business locations (U.S. Census Bureau 2022a). Survey responses are combined with administrative data on payrolls, receipts, employment, and industry classification. The combination of large datasets, both survey responses and administrative data generated by business activity, produces a robust picture of the real economy that provides a firm foundation for I-O modeling of changes in economic activity. For this current study, the BEA industry accounts underlying I-O models provide a robust time-series of industry linkages that can be used to track how NSF R&D funding likely flowed through the economy over time.

- **Direct:** The effects of changes in output for the industry being modeled. In the context of R&D funding, direct effects would include employment and employee earnings supported by NSF funding.

- **Indirect:** The effects of changes in demand for goods and services generated by the change in output for the industry being modeled. These effects are also known as backward linkages (Bureau of Economic Analysis 2018), reflecting how increases in output for a given industry creates new upstream demand across the industry's supply chain. For R&D funding, this would include the economic output, employment, and employee earnings driven by purchases as equipment, lab supplies, raw materials like chemicals used in experiments, and services like testing or engineering that would be procured from vendors and contractors outside of the primary R&D team. Indirect effects also would include effects further upstream in the supply chain such as goods and services required to produce the immediate purchases made by the R&D team. These would include everything from producing the component parts for an electron scanning microscope to the sand used to manufacture glass beakers.

- **Induced:** The change in consumer demand for goods and services created by the change in worker earnings. These induced effects come from the R&D employees and students or researchers that receive financial support outside of their employment as part of R&D teams, employees involved in the R&D supply chain, and the wages of employees who are employed to meet all three types of induced consumer demand (direct, indirect, and induced). Purchases can include necessities like food, housing, and transportation, as well as other purchases enabled by changes in income like travel, streaming services, and landscaping.[102]

The two commonly used I-O modeling tools in the United States are:

- **Regional Input-Output Modeling System RIMS II:** The RIMS II tool, maintained by the Bureau of Economic Analysis, provides industry multipliers to calculate the total impact of a given change in output for a chosen industry sector (Bureau of Economic Analysis 2024). Available at both the national and regional level, multipliers are available for changes in final output, earnings, employment, and value added.

- **IMPLAN:** IMPLAN is a private company that provides a platform for conducting I-O analysis. The tool simplifies the process of conducting I-O analysis by providing a user interface to automate the calculation of effects based on BEA multiplier tables and other federal data sources. IMPLAN also incorporates data beyond regional I-O accounts (IMPLAN 2024), including data that allow estimation of the impacts on federal and non-federal tax revenues.

I-O models are widely used to evaluate the economic impacts of investments, including federal R&D funding awards. By using the amount of R&D funding as an input, I-O models can estimate the output, value added, employment, employee compensation, and tax revenue.

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[102] I-O models use a basket of consumer purchases based on existing purchasing patterns and then apply the increased earnings driven by the direct, indirect, and induced effects to estimate the change in output, employment, and earnings driven by consumer consumption.

Estimates relevant to the economic impact from NSF awards

A supplemental data file contains estimates of economic impacts and outcomes from awards produced using input-output and econometric methods. For input-output models, the supplemental data file includes estimates of the impacts of awards on:

- economic output
- value added
- employment
- employee compensation
- tax revenue

For econometric models studying the impacts and outcomes of awards, the following types of estimates are included in the supplementary data file:

- economic output
- employment
- non-federal R&D funding stimulated by federal funding
- degree completion

APPENDIX E: ADDITIONAL DETAIL ON METHODS FOR ESTIMATING THE ECONOMIC IMPACTS OF R&D DISCOVERIES

Appendix E contains additional information pertaining to the estimating of economic impacts from R&D discoveries. This includes background literature review text on literature that was cited in Section 7, as well as descriptions of supplemental materials that contain additional tables that were created as part of literature review efforts.

Background on production function

The production function literature stems from the theoretical works of Harrod and Solow. Harrod's (1939) formulation of the production function used capital as the only factor of production. The earliest econometric literature on value of discoveries came from Griliches (1964), which incorporated Solow's changes to the production function (Solow 1957), which included the factors of labor and technological change to produce the now standard neoclassical production function equation.

Griliches (1963, 1964) developed the production function method that is used in much of the literature, connecting R&D investment to the flow of industrial outputs.[103] The 1963 paper focused on the influence of education of workers as a factor of production among other factors including livestock expenses, machinery, land, building, and labor years. The 1964 paper revised the model to include R&D expenditures as another factor of production.[104] Griliches found investment in research returned higher output, with greater returns than additional investment in other factors of production.[105]

Along with treating knowledge capital as a factor of production alongside labor and capital, R&D investment from prior periods generate R&D capital which is used to produce knowledge. Griliches (1979) further advanced the field through the development of the knowledge production function, which is explored at great length in the subsequent literature. Along with treating knowledge capital as a factor of production alongside labor and capital, R&D investment from prior periods generate "R&D capital," which is used to produce knowledge. Griliches (1979) also develops an early model of knowledge spillovers between industries, and discusses early issues with measuring spillovers from basic versus use-inspired R&D and public versus private R&D.[106]

Griliches (1979) did not estimate the economic value of research but was the precursor to many works that tackled private-sector productivity from various angles through the 1980s. Griliches (1980) applied the production function model using data from U.S manufacturing R&D across six industries.[107] Griliches (1985), Link (1981), and Mansfield (1980) performed

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[103] The model consisted of a Cobb-Douglas production function that tested for the influence of factors of production of agricultural goods.

[104] The study examined agriculture output using data from the U.S. Department of Agriculture on agricultural inputs, including expenditure on labor, machinery, land and buildings, education, and R&D.

[105] Overall return on R&D expenditure of 300-1300%.

[106] Griliches (1979) included disaggregation by the type of research categories of basic and applied research. In the main text, "applied research" has been replaced with "use-inspired research" to correspond with the types of research used by the NSF.

[107] Bureau of Labor Statistics growth sector output, labor hours, and capital stock data along with NSF data on applied R&D expenditure. Griliches calculates many estimates of the impact of R&D on TFP, finding elasticity of TFP from R&D investment of 0.07.

regressions on the impacts of basic and use-inspired research on TFP.[108] Griliches and Mairesse (1984) and Cuneo and Mairesse (1983) used data from American and French manufacturing industries, respectively, to measure the returns from private R&D.[109]

The early works of Griliches, Mansfield, and others consisted of simple econometric models that looked for correlation between R&D expenditure and productivity. In these early models, what differentiated the regression form from models that targeted benefits from research expenditure were the functional form and use of productivity as the outcome variable. The outcome variables in production function models thus consist of various measures of productivity, including TFP, value added, and firm sales.

Estimates of the private return on investment can be readily derived from the production function approach, such as in Cuneo and Mairesse (1983), Griliches (1985), and Griliches and Mairesse (1984). The private return on investment uses derived productivity statistics to determine the ratio of revenue to costs from investing in R&D. However, the private return on investment focuses on the returns experienced by the entity that invests in R&D. What is likely desired in measuring the impacts of R&D discoveries is the social return on investment, which is the full set of R&D benefits, regardless of who they accrue to, compared to the costs to the R&D performer.

Calculating the social rate of return is much more difficult than doing so for the private rate of return. Hall et al. (2010) describes the social rate of return from the production function model as the private rate of return added to the sum of the returns on outside R&D for all recipients of spillovers. Hall et al. (2010) identifies the issue of obtaining social rate of return estimates, as there are many possible entities that could receive spillovers of some type from the R&D operations of a given entity. However, many possible spillovers may be relevant to an R&D performer, complicating what spillovers need to be calculated to derive social rate of return from R&D.

Hall et al. (2010) identifies several papers that estimate the social return on investment from R&D discoveries. These include Griliches (1958), Mansfield et al. (1977), Trajtenberg (1989), and Weisbrod (1971) which all use econometric methods, but all do so within a cost-benefit case study framework. This highlights a principal difficulty of achieving an estimate of the social rate of return, in that any given R&D output may have several technology and knowledge spillovers. As such, the leading option to ensure that full social returns are captured is through case study approaches, which interrogate individual examples of R&D derived technologies for all resultant impacts.

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[108] Both Link (1981) and Mansfield (1980) used a sample of American manufacturing firms and found that industry-financed basic research is a significant determinant of TFP growth and that applied research is not a significant factor in predicting TFP growth. Link also found that government basic research is significant for industry TFP growth. Griliches (1985) examined R&D spending with a sample of large R&D performing corporations, finding that basic research had a 250-450% greater return than applied R&D and that privately financed R&D had a 50-180% greater return.

[109] Griliches and Mairesse (1984) used industry data from S&P Compustat, which provides estimates of labor and capital, and research capital (the role of R&D in improving production) is a variable constructed from lagged R&D investments. Cuneo and Mairesse (1983) used balance sheet and current account figures for estimates of labor, physical capital, and output, but also included lagged R&D expenditure as the estimate of research capital. Both studies used minimal regression specifications that considered the effects of labor and capital on output, with returns from research capital estimated at 35% and 90%, respectively.

When using the production function approach to understand social returns, the complexity arises due to the many different types of spillovers that may occur, and the difficulty in assessing aggregate spillovers. The primary spillover of importance for the NSF is spillovers that occur between public and private R&D efforts. Many studies have attempted to capture these spillovers, including at the firm and industry levels, yielding mixed results.

Levy and Terleckyj (1983) studied the short-term spillovers from public to private R&D, specifically studying the effects of contract R&D and reimbursed private R&D on other private R&D investment. They found that government-contracted R&D is positively associated with other R&D funding but that reimbursed R&D crowds out other private R&D spending. Several other studies consider whether public and private R&D are complements or substitutes with Link (1982), Leyden et al. (1989), Levy (1990), Robson (1993), and Moretti et al. (2019) finding complementarity in federal and private R&D funding; Lichtenberg (1984) finding substitutability; and Lichtenberg (1987), Lichtenberg and Siegel (1989) and David et al. (2000) showing mixed results based across many specifications (David et al. 2000a; Levy 1990; Leyden et al. 1989; Lichtenberg 1984, 1987; Link 1982; Robson 1993).

Additional relevant spillovers that have been explored include R&D across countries, industries and technology areas. Below are studies that explore additional relevant spillovers:

- Geographical spillovers from R&D capital expenditure: Coe and Helpman (1995) find that a country’s openness to trade positively impacts the knowledge spillovers that it receives from its neighbors. Frantzen (2002) finds that international R&D spillovers are impactful, and that foreign R&D spillovers within industries and across different industries. De Noni, Ganzaroli, and Orsi (2017) performed a knowledge production regression for the elasticities of innovation to intra- and inter-regional spillovers in Europe, finding that intra-regional collaboration is positively associated with spillovers and inter-regional collaboration is negatively associated with spillovers.
- Spillovers within industries: Cohen and Levinthal (1989) introduce the concept of absorbative capacity, which finds that firms’ ability to receive R&D spillovers is dependent on their own performance of R&D. Audretsch and Belitski (2020) explore the relationship between spillovers and firm decisions to invest in R&D, buy R&D outputs of other firms, and collaborate with other firms in R&D investment. Bloom et al. (2013) perform an analysis of spillovers within technology areas and between firms in the same product markets.
- Differential spillover effects of basic and use-inspired public search: Some studies in this direction include whether public use-inspired and basic research differentially affect private R&D (Leyden and Link 1991; Robson 1993). Other studied questions include concerns for funding of private entities such as through SBIR/STTR awards including whether government tax credits for R&D incentivize R&D (Bloom et al. 2002; David et al. 1999; Guellec and van Pottelsberghe de la Potterie 2001) and whether R&D subsidies change firm behavior (Altomonte et al. 2016; Cantner and Kösters 2012; Neicu, Teirlinck, and Kelchtermans 2016).

While not spillovers, another stream of literature has emerged considering the effects of artificial intelligence and internet communications infrastructure on R&D efficiency. Corrado et al. (2005) used a growth accounting model, which differs from prior production function regression models by assessing R&D as investment and including investment in “intangibles” as the source of R&D/innovation. Intangibles are classified as scientific R&D, non-scientific R&D, brand competencies, and computerized information. With the inclusion of intangibles in the production function framework, attribution of productivity increases may shift between labor, capital, R&D, and other referenced intangibles.

Several papers follow the Corrado et al. (2005) approach including Fraumeni and Okubu (2005), Haskel and Wallis (2010) and Elnasri and Fox (2014, 2015). Fraumeni and Okubu (2005) use the growth accounting model and analyze National Income and Product Accounts (NIPA) incorporating effects of intangible investments on GDP. Haskel and Wallis (2010) used the intangibles model focusing on computerized information, innovative property, and other firm-specific resources with the production function regression form. Elnasri and Fox (2014, 2015) reviewed the effects of R&D within the classification of other intangible capital assets in the growth accounting framework. They found that innovative property and public infrastructure both positively affected total factor productivity, including a 0.117 elasticity of innovation property to TFP and a 0.038 elasticity of public infrastructure to TFP.

Beyond the types of spillovers that are experienced, another consideration is whether data is mature enough to capture the full effects of knowledge spillovers. This is an especially pertinent issue in the study of impacts from basic research or research infrastructure, as fundamental breakthroughs in science or the usage of scientific infrastructure for discovery may have long tails in downstream innovations and inventions that may improve industrial productivity. Adams (1990) and Adams and Clemmons (2013) provide estimates of these technology diffusion timelines. tested the tails scientific innovation of uses a production form with outputs as a function of disembodied economic growth due to technological improvement, own stock of knowledge and borrowed knowledge, capital, and labor. Though the relationship with own industry knowledge production is positive contemporaneously, greater effects are found when 10-year and 20-year lags are introduced. Similarly, interindustry spillovers are not statistically significant in the short term but are positive and significant with 20- and 30-year lags. Adams and Clemmons (2013) explore citation rates between academic and industrial research papers, finding that lags in the diffusion of academic research to industrial research averages 6.6 years. These findings are complementary with those from Adams (1990), as benefits from the industry diffusion of research is the precursor to accruing any downstream economic benefit.

While some early papers such as Griliches (1958) and Mansfield et al. (1977) estimate social return on investment, other, more recent literature creates social return on investment estimates using extensions to the production function form.

One branch of literature traces the pathways of knowledge diffusion from R&D intermediate outcomes data, such as patents and publications, that are proxy indicators for knowledge or discoveries and are not economic impacts in themselves. The discoveries they represent can be commercialized and generate economic impact as they reach the market and are more widely consumed or adopted. While some intermediate output-based models are one stage and calculate the relationship between R&D investment and knowledge output, many perform a two-step approach to estimating economic outcomes by connecting (1) estimates of the relationship of R&D and intermediate outcomes and (2) estimates of the relationship between intermediate outcomes and economic outcomes.

From the knowledge production function established by Griliches (1979), a new branch of literature evolved exploring the connection between R&D performance and R&D outputs. Adam Jaffe used the knowledge production function outlined in Griliches (1979) as a starting point and conducted a series of studies investigating spillover effects, largely using patent data to proxy for knowledge production.

Jaffe (1986) explored whether the size of spillover effects differ by technology clusters, generating technology clusters using similarities in patent class data. According to this research, increases in individual firm R&D is associated with increased patenting and profitability of other firms within the same technology area, and more tightly concentrated technology areas experience greater returns from these spillovers. The analysis in Jaffe et al. (1992) followed up Jaffe (1986) and found that patents were often more cited by other patents in close geographical proximity, though this effect appears to wane over time.

Building from Jaffe (1986) several other authors have used patents as a way to measure spillovers. Jaffe (1989) examined the relationship between academic and private R&D, finding that academic research was positively associated with corporate patenting activity. Anselin et al. (2000) explored the effects of university R&D on employment and innovation output in technologically advanced industries, such as the drug and chemicals industry, machinery, and electronics industries. Jaffe and Lerner (1999) focused on the spillovers coming from DOE federally funded research and development centers (FFRDCs).

Bound et al. (1984) created a sample of U.S. manufacturing firms from the S&P Compustat Annual Industrial files. Bound et al. (1984) matched companies to patents, resulting in a final sample of sales, employment, book value in various forms, pre-tax income, market value, R&D expenditures, and patent applications in 1976 for approximately 2,600 firms in the manufacturing sector. They found that much of the variation in private R&D expenditures was explained by variation in sales among firms.

In its own analysis, Griliches et al. (1986) uses the Bound et al. (1984) data to examine the relationship of R&D and patenting. These included even returns from R&D across firm sizes, improved productivity, and sales growth of R&D performing firms. Hall et al. (1986) used the same dataset as Bound et al. (1984), including matched R&D data of manufacturing firms and corresponding patent data and uses multiple regression specifications to determine the effect of R&D spending on patents produced. Hall et al. (1986) found similar estimates of total patents produced to R&D spending (1% increase in spending to 0.66% increase in patents), with much of the effect being within the same year.

Beyond patents, several other variables have been used to measure innovation activity. Leyden and Link (1991), revisited direct public R&D expenditure by investigating the complementarity between public and private R&D, and basic and use-inspired research,[110] using estimates of knowledge outcomes from an NSF R&D survey question on the percentage of labor activities that led to published articles and books. Leyden and Link (1991) found a significant complementarity of government R&D with private R&D levels, increased sharing of R&D between laboratories and that basic research increases spillover effects from government R&D. Feldman and Florida (1994) used innovation citation data collected by SBA to estimate the effects of industry and university research on innovations. Acs et al. (1994) performed a production function analysis using innovations from the SBA's Innovation Database, finding that business R&D, university R&D, and geographically proximate university research are all associated with greater innovative activity. Audretsch and Feldman (1996) also used the SBA Innovation Database to measure innovative activity, considering the relationship between geographic proximity and R&D spillovers.

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[110] Leyden and Link (1991) included disaggregation by the type of research categories of basic and applied research. In the main text "applied research" has been replaced with "use-inspired research" to correspond with the types of research used by the NSF.

Myers and Lanahan (2022) also explored spillovers from DOE-funded R&D, in this case through SBIR awards. Their model found that the SBIR grant recipients internalized roughly 25% of the value of SBIR grants as measured by patents, with spillovers found by both technology area and geography. The large magnitude of spillovers suggests that the social benefits to research are about 100–300% of expenditure (Myers and Lanahan 2022).

Alongside patents in themselves, patent citations can also be used to track innovative activity and value, as well as the path of knowledge transfer. Early work by Trajtenberg (1990) and Jaffe et al. (1992) contributed to the development of these approaches. Trajtenberg (1990) used patent count and patent citations from the PATDATA database and devised a measure of patent count weighed by citations as a measure of the value of innovations. Applied to his topic of computed tomography scanners, he found that his weighted patent metric performed better than simple patent count metrics. Jaffe et al. (1992) tested for the geographic localization of patent citations, finding that knowledge spillovers from innovation could be seen in the form of localized citations of patents. This held true across university and corporate patents and slowly diminished over time (David et al. 1999; Jaffe et al. 1992; Trajtenberg 1990).

Additional efforts on patent citations come from Jaffe and Trajtenberg (1996) and Bacchiocchi and Montobbio (2009) with the former showing that federal R&D patents were more likely to be cited than corporate patents but the latter showing that university patents were more likely to be cited than corporate patents (Bacchiocchi and Montobbio 2009; Adam Jaffe and Trajtenberg 1996). These works also suggest heterogeneity by field and time period: university patents related to electronics, optics, and nuclear technology had a higher base citation rate than other fields but face rapid obsolescence whereas drug, chemical, and medical university patents had citation advantages that persist over time.

Patents and patent citations are commonly used in other fields as a proxy for innovative activity. Examples include environmental models (Popp 2005, 2010) and energy models (Noailly and Shestalova 2017; Popp 2002, 2019; Popp and Newell 2012; Sun et al. 2021). Popp (2019), who has used patents and patent citations in numerous papers, notes the inconsistency of patents as a measure of innovative activity. This is partly because patents measure invention, not innovation, and most patents are never put to use. Only a small percentage of inventions ever reach the market in the form of a commercialized product or service that is based on a patent. Patent volume by country is subject to odd variations—for example, Japanese firms tend to put fewer claims in each patent, so their patent numbers are somewhat inflated compared to other OECD countries.

Patents can also be linked to more direct measures of economic impacts. Sampat and Ziedonis (2005) sought to use patent citations as a relative measure of patent value and suggested four value channels that would align patent citations with economic benefits: citations as reflections of the value of spillovers, citations as a reflection of profitable inventions, citations due to notoriety of inventions, and citations due to commercial interest.

Toole (2012) performed a Poisson regression analysis to estimate the effect of NIH support for biomedical research on new molecular entities (NME) applications. Toole used a panel database that includes NME data from FDA, industry data from the Pharmaceutical Research and Manufacturers Association, public biomedical science R&D data from NIH, mortality and hospital discharge data from the U.S. National Center for Health Statistics, and population and income data from the U.S. Census Bureau. Toole (2012) found that a 1% increase in NIH biomedical research funding was associated with a 1.8% increase in NME applications. Toole then used a formula developed by Grabowski and Vernon (1994) that estimated increased production to generate an estimate that NIH-funded biomedical research results in a 43% return on investment.

Azoulay et al. (2019) used grant acknowledgment data from patent records to link them to NIH grants to isolate public R&D funding targeted to influencing industry within specific biomedical topics. Their empirical work found that a $10 million increase in NIH-funded academic biomedical research led to 2.7 additional patents filed by private firms.

R&D activity occurs in a dynamic environment, with many public and private actors supporting R&D and engaged in R&D to meet different objectives. Their efforts often interact, as illustrated by the spillover effects described in many of the papers discussed above. Econometric methods largely rely on statistical correlations and are not able to model the complex pathways that underly the R&D activity of many different actors and the resulting economic impacts of this activity.

In contrast, simultaneous equation model is a model in which two or more equations are used together to determine the value of multiple variables simultaneously. The increased complexity of these models provides the potential for more in-depth analysis of the role of R&D in technological change and the economy. It can also require additional assumptions.

In a seminal paper modeling endogenous technological change, Romer (1990) used a series of equations to construct a model of growth. Romer built on the production function approach of Solow (1956) and Griliches (1979) to create a dynamic equilibrium version where human capital is one of the factors of production in addition to labor, raw materials, and physical capital. Romer found that human capital, not labor, was responsible for growth and that human capital increased through the investment of labor in research sectors over final output sectors. Romer also found that there is an underinvestment in research at model equilibrium if multiple actors are involved, resulting in less growth than the social optimum (Romer 1990a).

Related to Romer (1990), Aghion and Howitt (1992) developed a model of endogenous growth that incorporates the theory of creative destruction from Schumpeter (1939). This model, while it is not used to create estimates, shows a new type of spillover effective of negative intertemporal spillovers within an industry/technology area. These creative destruction spillovers theorize that current R&D is stifled by future R&D, as future innovations may eat into the expected profits from innovations that result from current R&D. This theory is another justification for government intervention in R&D, as due to the creative destruction theory, firms will underinvest in R&D compared to what is socially optimal.

Caballero and Jaffe (1993) applied the model of creative destruction to the knowledge production function using data on patent citations. This model includes both a production sector and a research sector, with the model exploring factors that affect spillovers from R&D to goods production such as the absorbative capacity of firms and the rate of obsolescence of knowledge. The Caballero and Jaffe (1993) model finds that a slowdown in the rate of production of new knowledge correlate well with the slowdown of productivity increase over the sample reviewed.

Peri (2005) performed a knowledge production function using patent citations that tested for several types of spillovers including between regions, countries, and across language barriers, with controls for technology area, geographic distance, and trade relationships. The Peri (2005) model includes patent citations as a measure of knowledge spillovers, accounting for differences in spillovers by region, technology area, etc. Data comes from the

NBER patent and patent citations database, with 1.5 million patents across Europe and North America. Findings show the degradation of knowledge flows increasing by geographical and technological distance. Compared to a baseline of spillovers within regions, adjacent regions only received 21% of relative spillovers, regions that are two borders away receive only 15% of spillovers, and only 12% of spillovers crossing country borders. Technological differences also significantly affect spillovers with regions with the furthest technological separation contributing only 5% of the spillovers of regions with identical technological areas.

Los and Verspagen (2000) developed a model of the production function for manufacturing firms with refinements to reflect endogenous growth theory. This includes the separability of R&D outputs, with some R&D outputs being excludable and benefiting only the R&D performing firm, and others being non-excludable. Additionally, spillovers are separated out into two components described in Griliches (1979) of rent spillovers and technology spillovers. Technology spillovers from the R&D of other firms are modelled through technology spillovers, which is achieved through the mapping of each firm to International Patent Classification (IPC) codes. Results show that technology spillovers are much larger than rent spillovers, as the sum of total spillovers is nearly equal to the sum of all technology spillovers.

Several papers incorporate the knowledge production function with the production function, resulting in multi-stage models that follow the causal pathway between R&D performance, to R&D outputs, and finally to industrial output.

Guellec and van Pottelsberghe de la Potterie (2001, 2004) work from a production function model to measure the relationship between R&D performance by the business sector and productivity growth, looking across funding sources and countries. The authors used a production function model to assess cross-country spillovers, with separate terms for business sector, public sector, and foreign firms R&D. Guellec and van Pottelsberghe de la Potterie (2004) focuses on the source of funds for R&D, again discriminating between the domestic business sector, foreign business sectors, and public sector R&D across 16 countries. They find that increasing shares of government funding decrease the elasticity of TFP with respect to business R&D. Increased share of university R&D increases the returns of public R&D and increased defense spending lowers the returns of public R&D (Guellec and van Pottelsberghe de la Potterie 2004).

Fieldhouse and Mertens (2023) created an aggregate production function with public infrastructure and government R&D capital as separate arguments to structurally estimate the elasticity of government R&D capital. The model specifies differences between four types of government capital: defense R&D capital, defense non-R&D capital, public infrastructure, and non-defense R&D capital. R&D capital measures came from the NCSES data and federal R&D appropriations came from the U.S. federal budget. They found that federal R&D shocks were associated with increased business TFP, but that defense R&D shocks do not exhibit a positive TFP effect. Non-defense R&D shocks also were positively associated with increases in patent-based innovation indices, STEM PhD recipients, active researchers, and new technology book publications. They also found a positive association between federal R&D shocks and private R&D spending.

Dyevre (2024) performs a two-stage model that focuses on the non-excludability of public R&D versus private R&D. The model uses firm-level data from S&P Compustat, patent data from the USPTO PatentsView portal, and records of government funding from the historical federal government budget tables from OMB. Dyevre (2024) connected public R&D to patents using government interest reporting from PatentsView and connected private R&D

to patents via automated string matching of R&D performers to patent recipients. The analysis uses simple regressions to test for differences between public and private R&D for multiple aspects of R&D outcomes, including findings that patents originating from public R&D are more reliant on science, are more technologically "disruptive," and generate a wider breadth of spillovers than private R&D originated patents. For the main analysis of public and private R&D spillovers, Dyevre constructs a model of productivity growth that is dependent on own firm R&D effort and the influence of public and other firm R&D, with firms likely to benefit from spillovers in technology areas that are similar to theirs. The model uses lags of 5 years for funding to patenting, 5 years for patenting to downstream productivity growth effects. Due to risk of endogeneity bias stemming from economic shocks that could impact R&D spending and R&D outcome variables,[111] the author uses an SSIV procedure, in which shocks to agency budgets are the dependent variable. In the SSIV model, a 1% increase in federal R&D expenditure results in a 0.23% increase in private R&D expenditure, and a 0.20% increase on TFP.

Crepon et al. (1998) move from the standard production function model to a model that incorporates innovative output. This model, which contains separate equations for firm investment in R&D, R&D output, and industry production, calculated using an asymptotic least squares method, is known as the CDM model, and has become a common modern approach to measuring the economic impact of R&D. The CDM model is composed of an equation to model firm investment in research, an equation to estimate the resultant innovative output that results from research, and the Cobb-Douglas function, which uses the estimate of innovative output as the variable for how R&D impacts productivity. Firm R&D determinants in the CDM model include employment, market share, firm diversification industry segments, and various demand, technology and industry dummies.[112] Two versions of the model are used: one that uses patents as the innovative output and another that uses innovative sales.[113] The results of Crepon et al. (1998) show that the procedure used is of merit. The innovation output equations yield elasticities of 0.88 and 0.43 for patents and innovative sales to R&D investment.

Several authors have used the CDM model introducing several variants including the use of firm profitability rather than productivity as an outcome variable (Jefferson et al. 2006; Lööf and Heshmati 2006), distinction between innovation outputs (Griffith et al. 2006; Parisi, Schiantarelli, and Sembenelli 2006; Polder et al. 2009), multiple types of innovation (Leeuwen 2002; Parisi et al. 2006; Polder et al. 2009), firm innovation decisions (Audretsch and Belitski 2020; Giovannetti and Piga 2017).

Audretsch and Belitski (2020) performed a notable variant of the CDM model that accounted for firm collaboration. Like the original CDM model, this model includes three stages; the firm choice of innovation strategy, the production of innovation outputs, and the use of

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[111] Endogeneity bias in this case is thought to stem from economic shocks that could impact R&D spending and R&D outcome variables.

[112] Current accounts, balance sheet, and employment data come from the Systeme Unifie de Statistiques d'Entreprises. Market share and diversification indices come from the Enquete Annuelle d'Entreprises. The demand and technology dummies come from the 1990 Innovation Survey of the Service des Statistiques Industrielles (SESS).

[113] Innovative sales come from the SESS Innovation Survey and are defined as the share of 1990 sales that result from new products launched between 1986 and 1990. R&D investment data come from the Firm Annual Survey performed by the French Ministere de la Recherche. Data on patents come from the European patent database.

innovation outputs in downstream industrial production.[114] In the model, firms choose between creating innovations in-house, allying with other firms, or introducing innovations created by others through buying or imitation. The outcome variable in the model is labor productivity, with some specifications of the model using labor productivity relative to a firm's industry, or a binary variable of whether a firm is upper quintile for labor productivity. Controls in the model include firm age, employment of firms, R&D investment and the presence of knowledge spillovers.[115] R&D investment and the presence of knowledge spillovers are found to be significantly positively correlated with labor productivity in all models. The firm decisions to innovate in-house or co-create innovations with other firms achieve positive significance in some models, but significance disappears when knowledge spillovers are introduced into the model as a control.

Lanahan et al. (2016) considered how federal research funding at U.S. universities influences research funding from state and local governments, nonprofits, and industry. They used data from the NSF Higher Education Research and Development Survey, for public and private funding of universities across 26 fields of scientific research and considered federal funding, other types of funding, and prior private funding levels. An instrumental variables approach was used to account for the endogeneity of prior trends in the control (independent) variables. They found that additional federal funding increased funding of other types within the same scientific fields, with 1% increases in federal funding resulting in 0.2-0.8% increases in funding from state and local, nonprofit, and university sources. This result suggests that any observed spillover effects may also be capturing the effects of additional private research investment.

Gersbach et al. (2018) developed a model of a closed economy with government, households, and use-inspired and basic research.[116] At equilibrium, the model finds basic research is key to economic growth. The authors calibrated the model against the U.S. growth rate, using estimates of basic and use-inspired research labor, research subsidies, spillovers between basic and use-inspired research, and estimates of the rate of innovation from the literature. Results suggested that the U.S. equilibrium is a state where basic research is more advanced than use-inspired research, and thus both basic and use-inspired research contribute to economic growth (Gersbach et al. 2018).

Akcigit et al. (2021) modeled the interaction of basic and use-inspired research by creating a three-stage model of the economy with upstream, midstream, and downstream firms, allowing firms to play different roles in the economy.[117] Firms invest in basic and use-inspired research and the government serves as another firm-like entity that also produces

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[114] Data for the Audretsch and Belitski (2020) model included the UK Community Innovation Survey for R&D investment, organizational innovation, knowledge collaboration partners, impediments to innovation, process innovation and business strategy, the Business Enterprise Research and Development survey for knowledge spillovers, and the Business Structure Database for revenue, firm legal status, ownership, alliance information, sector of activity, turnover, employment and firm location.

[115] Knowledge spillovers in the Audretsch and Belitski (2020) model are constructed by multiplying the total value of sector's R&D by sector weirds from the ONS Input-Output matrix, normalized by a country's total R&D expenditure.

[116] Gersbach et al. (2018) included disaggregation by the type of research categories of basic and applied research. In the main text, "applied research" has been replaced with "use-inspired research" to correspond with the types of research used by the NSF.

[117] Akcigit et al. (2021) included disaggregation by the type of research categories of basic and applied research. In the main text "applied research" has been replaced with "use-inspired research" to correspond with the types of research used by the NSF.

basic research. Cross-industry spillovers and spillovers from basic to use-inspired R&D were modeled. Data for this model came from the annual firm R&D survey of the French Ministry of Research, along with patent citation data from the NBER patent dataset to estimate spillovers of basic and use-inspired research. Akcigit et al. (2021) found that public research patents are of higher quality than private patents, that basic research has spillovers 10% of the time, and that basic research makes use-inspired research 60% more productive. As a result, there is an underinvestment in basic research in practice, with 85% of total labor used for production, 15% for research, and basic research composing 7% of total research activities.

Altomonte et al. (2016) used both simple regression and simultaneous equation approaches. The OLS and probit regression analysis considered TFP, R&D, exports, and financing as dependent or outcome variables, in the models. These regression and simultaneous equation models suggest that additional financing does not result in increased R&D investment but is correlated with increased investment in exporting activity.

Scherer et al. (1984) traced the path of research expenditures to patenting through to economic impact measures by industry. For a sample of American patents, patent data were sorted by technology type, industry, complexity, industrial application, and relationship to federal contracts. This sorting was done via a labor-intensive manual process but allowed for a set of patent data that could be used within an I-O model of commodity use by industry. Along with the patent data, the paper used R&D data from the Federal Trade Commission line of business survey of basic and use-inspired R&D outlays and data on patent lags from U.S. and German surveys by Sanders (1962).

Background on cost function

The cost function approach contrasts with production function-based approaches in focusing on cost minimization rather than the productivity effects of R&D spending. Cost functions aim to reflect firms' decision-making as they allocate resources between the various factors of production. These models seek to measure the private return on investment in R&D relative to other factors of production. These models attempt to quantify the long-run benefits of R&D, which often include the reduction of future production costs. The cost of R&D is balanced against future cost savings, with the goal of maximizing the present value of future profits. Cost function approaches can also be used to estimate R&D spillovers, as one firm's R&D investments can reduce costs for others in the same industry.

The earliest cost function approach in the field comes from Levin et al. (1984), who sought to model R&D spillovers, including knowledge and advertising expenditures. Firms in this model are subject to industry-wide price and R&D competition, with R&D resulting in innovation that lowers unit costs. A competitive equilibrium was assumed where each firm earns zero profits. R&D competition in the model depends on the overall investment in R&D, technological opportunity, and potential spillover effects, which may cause a free-rider problem. In addition to industry competition, the paper modeled spillovers from government R&D expenditures, which can also decrease firm unit costs. R&D data for the model came from the McGraw-Hill and NSF R&D surveys, prices from BEA's I-O models, and industry input and output data from the Census of Manufactures. Government R&D spending was found to increase private R&D spending, although increases in the share of government R&D spending reduced total R&D spillovers.

A cost function approach was also taken by Mohnen et al. (1986) who used national-level manufacturing industry data from Germany, Japan, and the United States. Mohnen et al. (1986) created a dynamic model of cost minimization with labor and energy as variable inputs and capital and R&D as quasi-fixed inputs. It is a generalized model of the second order conditions for a restricted cost function reflecting constant returns to scale technology. From this functional form, demand functions are obtained for the variable and quasi-fixed factors of production. The data required to estimate this model included labor hours, net capital stock, energy consumption, R&D stock, wage rate, user cost of capital, user cost of R&D, energy prices, and gross output for all three countries. They found returns on industry R&D of 11-15% across Germany, Japan, and the United States.

The Mohnen et al. (1986) model serves as a baseline cost function model, assessing firm R&D as a factor of production influencing future output. Other cost function studies extend this approach to measure social returns from private R&D and assess how public R&D spillovers factor into industry production and private R&D decisions.

Bernstein and Nadiri (1988) measured the social return from spillovers from five high-tech industries. They used statistics on gross output, wages, total payroll costs, and capital obtained from BEA and R&D expenditures from NSF. They found that industries varied in how many other industries provided spillovers and in the degree to which spillovers reduced variable costs and influenced variable factor demand. Industries also differed in whether R&D spillovers incentivized increases or decreases in physical capital investment.

Bernstein (1988) built on the cost function approach of Bernstein and Nadiri (1988) but separated intra- and inter-industry spillovers. The work was performed using a sample of Canadian manufacturing firms, with production costs that were dependent on labor, materials, physical capital, and R&D capital. Bernstein (1988) found that intra-industry spillovers, in general, generate larger cost reductions relative to interindustry spillovers. Unit costs decreased more from spillovers in industries with high R&D shares. Spillovers were also found to decrease R&D capital inputs, serving as a substitute for R&D investment. Bernstein (1988) also calculated the social return to R&D capital, with estimates of 19-27% depending on the industry. The social return to R&D capital consists of a private rate of return of roughly 11.5%, intra-industry spillovers of 6-12%, and interindustry spillovers of 1-2%.

A number of studies use a cost function approach to explore the relationships between public and private investments and any spillovers. Nadiri and Mamuneas (1994)[118] include public infrastructure and R&D in their model. They used data from the BLS on quantities and price indices of output, labor, physical capital, and intermediate inputs for manufacturing industries. Additional data on government net capital stock at the federal, state, and local levels came from the BEA and data on government-funded R&D from the U.S. Statistical Abstracts. Estimates of marginal benefits to industries from federal R&D funding were 0.15-0.6% and estimates of marginal benefits from public infrastructure capital were 0.1-0.64%. The social rates of return are 6.8% and 9.6% for infrastructure capital and R&D capital, respectively.

Mamuneas and Nadiri (1995) and Mamuneas (1999) studied the short-term spillovers from public to private R&D. Mamuneas and Nadiri (1995) used data from manufacturing industries, with estimates of public R&D from NSF and outputs, labor, intermediate inputs, and physical capital data from BLS. This effort complements work by Levy and Terlecky

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[118] Nadiri & Mamuneas (1994) is adjacent to a related body of cost-function literature that has focused on public infrastructure for industrial productivity, without considering R&D or R&D infrastructure. Such studies include Cohen and Morrison Paul (2004), Conrad and Morrison (1985), Morrison and Schwartz (1996) and Shah (1992).

(1983) using a production function approach (see Section 7.2), by again finding that publicly financed R&D can crowd out private R&D and that R&D tax credits can induce private R&D. Mamuneas and Nadiri (1995) also found that publicly financed R&D has stronger spillovers within industries than across industries.

Mamuneas (1999) used the cost function approach to estimate the spillovers from federal R&D to the private sector, including effects on other factors of production, on output, and on final economic benefits. The paper used data on output, labor, physical capital, intermediate inputs from BLS, and federal government R&D expenditures from NSF. The system of equations used in the Mamuneas (1999) model included the variable costs of industry, labor share, modeling of equilibria for physical capital, R&D capital, and output supply. Mamuneas (1999) found that public R&D spending reduced the demand for labor and intermediate inputs in most industries while also increasing outputs in all industries, generating a marginal benefit of public R&D for industries of 0.5-5%, and an average social rate of return of 16%.

Aw et al. (2011) constructed a dynamic model of a firm's decisions to invest in R&D and engage in exporting. The framework is focused on investment decision-making, as exporting and R&D both require start-up costs to generate productivity benefits in future periods. Estimation of the model required firm-level data on export market participation, export revenue, domestic revenue, capital stocks, and R&D investment from the Taiwanese electronics industry. They found that exporting and R&D investment both increase future profits and that they are complementary.

Background on I-O models for the impact of discovery

The main macroeconomic approach to valuing research comes from the I-O approach. As discussed in Section 6.2, the I-O approach was introduced by Wassily Leontief in the 1930s and is currently performed via RIMS II and IMPLAN. There have been several studies conducted to value the outcomes of research using the I-O approach. These studies contain a methodological divide that separates those focused on the economic impacts of research spending from those interested in the impact of research discoveries.

Early efforts using the I-O approach to determine the value of research discoveries included an assessment of NASA R&D Programs by Michael Evans from Chase Econometrics (Evans 1976) and the CONSAD Research Corporation's (1998) review of a joint research program between the NIST Advanced Technology Program and automotive manufacturers. What distinguishes the Chase Econometrics and CONSAD methodologies (discussed below) from the methodologies reviewed in Section 6 is the isolation of the mechanisms of how the economy is impacted by the inventions and innovations that result from research.

The Chase Econometrics (Evans 1976) review of benefits from NASA research focused on the mechanism of R&D expenditure affecting the broader economy through the effect of innovation and invention on productivity. The authors performed a regression that associated NASA R&D spending with the resulting improvement of productivity growth from technological progress, with controls for non-NASA research spending and shifts in industry mix between study periods. The authors then used the estimates of increased productivity, in addition to the figures of NASA R&D expenditure, as inputs to the Chase Econometrics I-O model to measure total economic impact from NASA R&D expenditure. Based on a scenario of a one-time increase in NASA R&D spending of $1 billion, outcome measures from the analysis include an increase in Gross National Product (GNP) of $83.6 billion over 10 years, an employment increase of 0.4%, an industrial output increase of 3.2%, and a labor productivity increase of 2.0%. In addition to the total GNP figures provided, the authors provided estimates of GNP that resulted from spending effects and from downstream productivity effects. Of the projected $83.6 billion increase in GNP, $4.2 billion is associated with the productivity effects that come from R&D outputs, representing an estimate of the economic impact of research discoveries.

The CONSAD Research Corporation (1998) study on the NIST ATP program estimated the returns to an improvement in American car manufacturing. This improvement was to increase the precision by which American automotive assembly lines assembled finished cars, with intended benefits being reduced costs for manufacturers, increased car reliability, and increased market share over foreign competitors. The authors used expert estimates of production savings and reliability savings for those benefits streams. The Regional Economic Models, Inc. 53-sector input-output model was used to estimate the benefits from shifting market share as a result of change in consumer preferences from the project. These estimates were based on a crude expert estimate that American manufacturers would receive at least a 1% increase market share from the project's output, which resulted in an estimate of $8.7 billion in output from the $14 million ATP project. Despite the dubious nature of the estimates, the methodology employed did attempt to separate out the benefits from research discoveries, namely the innovations of product savings and reliability savings, and the resulting consumer demand for an improved downstream product.

Other, more modern efforts include the TechLink studies addressed above, such as the impact of DOD SBIR/STTR grants from 1995-2018 (TechLink 2019c), the cumulative impacts of NCI SBIR/STTR awards from 1998-2018 (TechLink 2019a), NASA SBIR/STTR awards in 2016 (NASA 2017), the Navy SBIR/STTR awards from 2000-2013 (TechLink 2016), and the Air Force SBIR/STTR awards from 2000-2013 (TechLink 2014a). These studies all rely on the same core methodology, in which the IMPLAN I-O model is used to assess the economic impact of initial SBIR/STTR funding, and the resultant economic impact of sales from downstream products resulting from SBIR/STTR research.

As an exemplar study, the TechLink study on DOD SBIR/STTR grants reviewed the historical impact of the SBIR and STTR programs from 1995 through 2018. This involved surveying recipients of SBIR/STTR awards across the 16,959 DOD SBIR/STTR awards during this period, including for information regarding products that were developed from the award, resultant sales, awarded contracts, spin-out companies, further venture capital investment, and licensing revenues. Awardees were assigned North American Industry Classification System (NAICS) codes based on industry to allow for input of award and sales figures into the IMPLAN I-O model. The macroeconomic figures from the IMPLAN model were divided by the initial economic impacts of funding and the downstream impacts that resulted from sales of SBIR/STTR innovated products. From survey efforts, the authors assessed a total of $121 billion in sales of products from DOD SBIR/STTR-funded projects, resulting in $304 billion in total economic impact, with a multiplier effect of 2.52. This compares to the original $16 billion in SBIR/STTR funding resulting in $42 billion in total economic impact, with a multiplier effect of 2.68.

The other TechLink studies yielded similar results:

- The study of NCI SBIR/STTR awards from 1998-2018 (TechLink 2019a) reviewed $787 million in total SBIR/STTR expenditure that resulted in $1.9 billion in total economic impact, for an economic multiplier effect of 2.52. In addition, $9.1 billion in sales of downstream products resulted in $24.2 billion in economic output, for an economic multiplier effect of 2.64.

- The study of NASA SBIR/STTR awards from 2016 (NASA 2017) reviewed $172 million in SBIR/STTR investment for a total economic impact of $474 million. No downstream sales were considered.
- The study of Navy SBIR/STTR awards from 2000-2013 (TechLink 2016) reviewed $2.3 billion in total SBIR/STTR expenditure that resulted in $6.1 billion in total economic impact, for an economic multiplier effect of 2.69. They also found that $14.17 billion in sales of downstream products resulted in $38.17 billion in economic output, for an economic multiplier effect of 2.69.
- The study of Air Force SBIR/STTR program from 2000-2013 (TechLink 2014a) reviewed $3.99 billion in total SBIR/STTR expenditure, which resulted in $10.51 billion in total economic impact, for an economic multiplier effect of 2.64. The study found $14.7 billion in sales of downstream products resulted in $37.36 billion in economic output, for an economic multiplier effect of 2.55.

The TechLink approach to assessing the value of research provides a clear split between the value from spending and from resultant research discoveries is to distinguish between the initial economic value from spending and the downstream economic impact of resultant product sales. However, input-output methods are not sufficient for accomplishing such an analysis. In these TechLink studies, the ability to assess any downstream benefit comes from the administrative SBIR/STTR data of research performers and the surveys that gathered information on historic downstream sales. Accordingly, such survey efforts were necessary for the applicability of I-O models for the assessment of the impact of research discoveries.

Background on CBA models

The original Griliches (1958) paper is notable for its similarity to modern cost-benefit methods since it traced the effects of research through to its economic impacts (growth of the American corn industry). However, the Griliches approach would not meet NSF's needs due to its simplicity in tracing technologies from research through to industrial applications. Whereas Griliches focused purely on one research output and the comprehensive measurement of its economic effects, NSF aims to trace the impacts of all research outputs of NSF work, greatly complicating the types of market data that would be required for a complete accounting of economic impacts from discovery.

The foremost pioneer of tracing multiple technologies through to their market impacts has been Edwin Mansfield. After collecting firm-level data using direct survey methods, Mansfield et al. (1977), estimated the social return of innovation (as measured by consumer surplus), using price elasticities and unit cost resulting from innovation. These are common CBA methods for determining the social benefit of innovation.

In addition to Mansfield et al. (1977), other studies have taken a CBA approach to evaluating the return to R&D from individual technological innovations. Many CBA case studies have been performed on individual technologies that have been the outputs of basic and use-inspired research. Within use-inspired research fields, common benefits that arise beyond economic benefits are health and environmental benefits. In CBA case studies, externalities for other industries are also commonly included in analysis, corresponding to spillover effects of econometric studies. Some notable CBA studies of basic and use-inspired research include the following:

- Weisbrod (1971) measured the return from abated mortality, morbidity, and treatment costs against basic research and vaccination costs for polio.
- Bresnahan (1986) measured the cost-benefit ratio of technological advancements in computing spill over benefits to the financial services sector.
- Trajtenberg (1989) computed the social rate of return to R&D from computed tomography scanners.
- Roessner et al. (2010), in another CBA of a research funding program, reviewed NSF-funded ERCs. Estimated values of impact came directly from values of NSF support, membership fees to the centers, employment benefits, human capital improvement, industry cost savings, and the value of hosted workshops. The report included non-calculated benefits such as decreased time of commercialization, development of new fields of science, entrepreneurship skills advancement, and non-academic human capital benefits.
- O'Connor et al. (2010) reviewed technology produced from the DOE investment in photovoltaic (PV) technologies. Reviewed projects include the flat-plate solar array project, the PV manufacturing technology project, the thin-film PV partnerships, and measurement characterization and reliability R&D. Benefits included in the cost-benefit statistics included the economic benefits of higher quality and lower cost PV modules, in addition to the environmental health benefits from reductions in adverse health incidences. Other quantified benefits include avoided CO_2 emissions, energy security benefits, and knowledge benefits from patents and publications, though these were not included in the cost-benefit calculations.
- Pelsoci (2010) reviewed the impacts of the DOE Wind Energy Program through their investments in wind turbulence models, Unsteady Aerodynamic Experiment results, advances in turbine blade material, advances in turbine analytical models, and turbine demonstration programs. Although many different benefits streams were mentioned and described, the calculated benefits for cost-benefit statistics only included the increased energy production from wind energy and health benefits of emissions reductions. Environmental, energy security, and knowledge benefits from research were also mentioned.
- Forster and Seeger (2014) used tax payments from Monsanto to assess the value derived from the innovations for their saccharin products.

Some notable case studies have been performed that use either econometric or survey methods to supplement other forms of benefit estimation.

In his analysis, Trajtenberg (1989) used econometric methods within a CBA framework. He used a multinomial logit model to estimate the cross-price elasticities between varieties of tomography scanners, finding that the different types of scanners do not compete in the same market. With these elasticities, Trajtenberg used a hedonic price function to calculate the total benefit from improved tomography scanners as a 2.5% increase in adoption for every $1 million invested in the scanners, with a 270% total return on investment.

Link (2010) reviewed impacts of the DOE Advanced Combustion research of laser diagnostic and optical engine technologies, combustion modeling, emission control technologies, and solid-state energy conversion. Benefits mentioned in the report include economic, environmental and health, energy security, and knowledge benefits. While all benefits were described, economic benefits and health benefits were the benefits monetized for cost-benefit statistics. To estimate the economic benefits from the engine technologies, a regression analysis was performed to estimate the relationship between brake thermal efficiency and fuel efficiency.

Also relevant to CBA studies are survey and interview methods for contingent valuation or expert estimates of benefits. Link and Scott (2004) provided an example of the utilization of such techniques on an ATP project for developing improved standard reference materials for the measurement of the wavelength of light in an optical fiber network. Both costs and benefits in this study were obtained via interviews with industry and other stakeholders. Benefits included production-related cost savings, calibration cost savings, increased production, savings from fewer costumer negotiations, and reduced marketing costs, resulting in a benefit-cost ratio of 267:1.

Florio et al. (2016) conducted a CBA on the CERN Large Hadron Collider. This is a notable CBA project as it was performed for a major research infrastructure that is largely dedicated to fundamental basic research. The study included techniques regarding the value of publishing, valuing startups and spinoff businesses, recreational and non-use benefits, human capital formation from basic research, and technological spillovers from basic research. However, the study did not provide summary statistics across benefit streams. This may be appropriate due to the uncertainty involved in many of the benefit streams for large research infrastructures.

Portfolio-level CBA studies

Beyond CBAs of individual projects, there have been portfolio-level approaches to CBA that better fit the objectives of NSF in pursing measures of economic performance across its portfolio. Several efforts to assess the impacts of entire research portfolios have been performed by compiling the results from individual CBA case studies.

Buxton and Hanney (1998) discussed an array of cost-benefit methods to assess the value of a UK National Health Service (NHS) R&D program. Methods for estimating these outputs include bibliometrics, patent analyses, estimates of human capital improvement from research, estimation of quality adjusted life years (QALYs) and the performance of I-O models. The authors examined outcome measures such as knowledge generated, cost savings from case studies of research impact, estimates of QALYs gained from research outputs, and aggregated monetary value estimates.

Ruegg and Feller (2003) reviewed studies commissioned by NIST's ATP to evaluate the results of their research and produced a toolkit of the evaluation methods used as well as how these tools can be used in practice. The authors discussed the importance of R&D and market spillovers and their relevance in assessing the value of ATP. Methods reviewed included cost-benefit methodologies as well as bibliometrics, sociometric analysis, expert panels, and survey methods. The study also referred to the Mansfield (1996) model, which attempts to capture social return on investment for the development of ATP projects. Social returns comprise both the increased profitability of private returns from the investment and additional consumer surplus from decreased cost and increased output.

For general approaches to CBA studies, Ruegg and Feller (2003) review a series of case studies performed for ATP and the methods performed within individual cases. These include:

- Expert assessments of the cost and quality impacts and likelihood of adoption of automotive technologies, feeding into REMI I-O modelling (CONSAD Research Corporation 1996).
- Expert assessments of the productivity improvements from collaboration and of increased production efficiencies from innovation (Link 1997).
- Assessments of the benefits of individual medical technologies compared to a counterfactual scenario, such as accelerated commercial benefits, increased likelihood of commercialization, and widened applications of technological application. Medical benefits were translated into economic terms using QLAYs (Martin et al. 1998).
- Use of industry adoption data and derived industry performance estimates for flow control machining for the automotive industry, feeding into the REMI I-O model (Ehlen 1999).
- Assessment of technical feasibility and risk assessment of commercial value of advanced refrigeration equipment; and market analysis, including benefits accruing from quality improvement, yield improvement, and higher production relative to other market competitors. Not all recorded benefits were monetized and included in final benefit statistics (Pelsoci 2001).

Tassey (2003) performed a CBA of the NIST ATP Program, including a discussion of how to perform CBA at a portfolio level and how to select case studies so that they are representative of total programmatic impact. The paper discusses general input and output data, such as records of contributions to science, technologies developed, and industry adoption of developed technologies. The impact measurements described include peer review, customer satisfaction surveys, net present value, cost-benefit ratio, and microeconomic models of productivity, sales, profits, employment, and value added. The study analyzed 30 case studies on the value of ATP's individual projects, allowing for summary return on investment figures for the R&D of the ATP.

Allen Consulting Group reviewed the impact value of the Australian Research Council (ARC) using CBA methods (2003). This is of particular relevance to NSF due to the ARC's focus on basic research, which is understudied in terms of its quantifiable impacts. The Allen Consulting Group (ACG) describes two approaches to valuing a large portfolio of work, such as those managed by the ARC. Approaches include a top-down method and a bottom-up one. The top-down approach involves gathering impact metrics across the portfolio of work to achieve understanding of total portfolio impacts, such as the use of microeconomic methodologies to understand the effects of R&D on TFP. ACG deployed the bottom-up approach, which involved the analysis of individual projects within different areas of the ARC portfolio. Aggregating the total benefits of individual projects across the portfolio provides an understanding of the total value and impact (Allen Consulting Group 2003).

The Australian Commonwealth Scientific and Industrial Research Organization (CSIRO) performs biannual reports to value the impacts of their programmatic work. In these reports, CSIRO aggregates case studies of project performance that have been conducted across scientific areas to provide an aggregate understanding of the worth of use-inspired scientific research across its practice areas (Walsh et al. 2022). This is a bottom-up approach similar to the ARC analysis performed by ACG and involves case studies across CSIRO's business units, including data and computing, energy, environment, health and biosecurity, space and astronomy, manufacturing, and mineral resources.

Link and Scott (2013) reviewed NIST economic impact analyses, including methodologies, key data sources, metrics, and impacts of interest. Methods for impact analysis included econometrics (such as productivity models), benchmarking analysis, innovation surveys, peer reviews, network analysis, and expert panels. Kanninen and Lemola (2006) discussed cost-benefit and qualitative methods for assessing the impact of basic research by major research institutions including the FWF, ARC, NIST, and the Wellcome Trust.

Allen et al. (2012) calculated producer and consumer surplus increases using sales and licensing revenue from SBIR-funded projects. Their findings suggested positive net economic value of SBIR grants, with significant differences between agencies.

The Research Excellence Framework (REF) is a system employed by the four UK higher education (HE) funding bodies to assess the performance of UK HE institutions. Thus far, there have been two assessments performed under the REF, one in 2014 and the other in 2021, with the next upcoming assessment planned for 2028. Data collected from institutions included the number of full-time staff, the number of doctoral degrees granted, and research income data (Research Excellence Framework 2023).

OECD (2014) is an example of a cost-benefit analysis framework that used qualitative methods to describe impact where monetization was not practical. This report was related specifically to research infrastructure, which is an area of NSF impact where attribution is difficult, and benefits are uncertain.

Link and Scott (2019) explained the benefits of publicly funded technology transfer projects, showing that public investment in technology transfer is justified if it can be done more efficiently than private technology transfer or in the case that the new technology moves firms above their hurdle rate for pursuing a socially beneficial project. On a case-by-case basis, benefits from either technology transfer scenario could come from the savings of private sector firms on R&D or the consumer surplus of new markets enabled by public technology transfer.

Ruegg and Jordan (2007), in their review of evaluation methods for R&D programs for the DOE, discuss case studies involving cost-benefit methods. The case study method that they described is wholistic, involving "a descriptive treatment of the project, cluster of projects, or program, and adds to it quantification of economic and other benefits and costs to the extent possible." For impacts that cannot be quantified, they can at least be described qualitatively.

Jones and Summers (2020) discussed economy-wide approaches to measuring benefits from innovation. They considered the productivity benefits to innovation in a similar way to the econometric literature, as a factor influencing economic growth. Returns to innovation were calculated as the ratio of GDP growth to the long-term discount rate, divided by the ratio of total public and private R&D investment to GDP. Returns were high, but diminished when capital investment costs are considered.

Florio and Sirtori (2016) completed a literature review discussing techniques to assess the value of research infrastructure. Their publication includes a thorough discussion of key cost-benefit methods, as well as in-depth discussion of tech spillovers, human capital formation, knowledge outputs, and other social impacts.

Data and estimates supplements

A supplementary data file[119] includes modeling approaches and data sources for estimating the impacts and outcomes of discovery. Modeling and data sources in the supplemental data file include:

- Employment
- Non-federal R&D funding stimulated by federal funding
- Exports
- Industry output and productivity
- Social returns and total spillovers
- Private revenue
- Supported trainees
- Publications
- Patents
- R&D investment
- Receipt of R&D subsidies
- Innovations
- Users of facilities
- R&D intensity
- Basic and use-inspired R&D spillovers
- Commercialization outcomes

Estimates relevant to the economic impact from NSF R&D discoveries

A supplemental data file[119] provides estimates of the economic impacts and intermediate outcomes of discovery from the literature. Estimated impacts and outcomes in the supplemental data file include:

- Productivity
- Economic output
- Value added

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[119] Supplemental files available upon request. Email request to EAC@nsf.gov.

- Exports
- Total returns
- Internal rate of return
- Social rate of return
- Supported trainees
- Publications
- Patents
- Private sales
- Innovations

This supplemental data file provides additional tables corresponding with Section 7 of the main text and Appendix E. Tables included in this supplement are the discovery impact possibilities table and extended estimates tables for the approaches reviewed in Section 7. A README tab in the file provides more information.

The discovery possibilities table categorizes studies that were reviewed in Section 7 across the reviewed approaches by the final impact measures that are provided in those studies. When applicable, studies in the discovery possibilities table also contain references to the main data sources from where key modelling data was obtained.

The estimates tables within this supplement contain key estimates from literature reviewed in Section 7 and Appendix E. These tables are separated by the four approaches covered in Section 7: 1) the production function, 2) cost function, 3) I-O, and 4) CBA. Estimates for the production function contain standard error estimates as an indicator of the significance of the stated statistics. Statistics in the production function table are in log-log form unless otherwise stated. Statistics for the cost function, CBA and I-O methods do not contain measures of statistical significance, as they all contain rate of return statistics for which there exist no relevant measures of statistical significance.

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Acknowledgements, Disclosures, and Citation

Acknowledgements

We would like to thank Taylor Rhodes, Erika Rissi, and three anonymous reviewers at NSF for their helpful guidance and feedback. We would also like to acknowledge the input and contributions of the Technical Working Group members including David Audretsch, Ina Ganguli, Bronwyn Hall, and Al Link for their thoughtful comments and feedback on iterative drafts of the work.

Disclosures

This report was prepared for the U.S. National Science Foundation's (NSF) Evaluation and Assessment Capability (EAC) under contract number 49100421D0013, order number 49100424F0028. The views expressed are those of the authors and should not be attributed to NSF, nor does mention of trade names, commercial products, or organizations imply endorsement of the same by U.S. Government.

Citation

Schnell, Joshua, Aviva Litovitz, Jeffrey Alexander, Adams Bailey, Carly Dotson, Joshua Fletcher, Lena Leonchuk, Jonathan Merker, Meaghan McGrath, Patrick McHugh, Jennifer Ozawa, Marwa Salem, and Amanda Walsh. 2026. *NSF Economic Impacts: Literature Review*. Alexandria, VA: U.S. National Science Foundation.

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