Accelerating Climate Innovation

A Mechanistic Approach and Lessons for Policymakers

Jessika E. Trancik
Micah S. Ziegler

Massachusetts Institute of Technology

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Correspondence to: trancik@mit.edu

About the Authors

Jessika E. Trancik is a Professor in the Institute for Data, Systems, and Society at the Massachusetts Institute of Technology. Her research examines the dynamic costs, performance, and environmental impacts of energy systems to inform climate policy and accelerate beneficial and equitable technology innovation. Her projects focus on all energy services including electricity, transportation, heating, and industrial processes. This work spans solar energy, wind energy, energy storage, low-carbon fuels, electric vehicles, and nuclear fission among other technologies. Prof. Trancik received her B.S. from Cornell University and her Ph.D. from the University of Oxford as a Rhodes Scholar. She is currently an external professor at the Santa Fe Institute, and was formerly at Columbia University's Earth Institute, and at WSP International/UNOPS (now Interpeace) in Geneva.

Micah S. Ziegler is a postdoctoral associate in the Institute for Data, Systems, and Society at the Massachusetts Institute of Technology. He evaluates sustainable energy and chemical technologies, their impacts, and their potential. His research shapes robust strategies to accelerate the improvement and deployment of technologies that can enable a global transition to sustainable and equitable energy systems. His work informs research and development, public policy, and financial investment. Dr. Ziegler earned a Ph.D. in Chemistry from the University of California, Berkeley and a B.S. in Chemistry, *summa cum laude*, from Yale University. He has researched international climate change negotiations and energy technology policy in the Climate and Energy Program at the World Resources Institute. He was also a Luce Scholar, advising companies on environmental sustainability at the Business Environment Council in Hong Kong.

About the Trancik Lab

The Trancik Lab builds data-informed models to evaluate the economic and environmental impacts of energy technologies over time and space. Our research aims to accelerate clean energy development by informing decisions made by engineers, policymakers, and private investors.

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Executive Summary

Significant improvement and deployment of sustainable technologies will likely be needed over coming decades for society to meet its global targets for climate change mitigation. Achieving these targets will require rapid rates of technological progress, including the rates at which we, as a society, invent, develop, and adopt climate solution technologies.

Government policy can play a crucial role in enabling technological progress. Public policies have the potential to influence decisions made by stakeholders across the landscape of technological innovation, from start-ups, established corporations, and investors to academic institutions, nonprofit organizations, and the government itself. Policy tools for supporting technological change can be divided into two categories: "technology-push" policies that enhance the supply of technologies (*e.g.*, government funding for research and development and demonstration projects) and "market-expansion" policies that can increase demand for new technologies (*e.g.*, regulations, subsidies, and government procurement). Enhancing the effectiveness of these policies will be critical for making the best use of limited public funds and limited time to mitigate the worst impacts of climate change.

To improve the efficacy of policies, we want to know: which strategies can accelerate the rate of innovation for climate solutions? Which government policy tools are the most effective in different scenarios? Recent research on the drivers of technological improvement helps address these questions. In this report, we describe an approach advanced in the Trancik Lab at MIT to identify promising mechanisms of technological change that can be targeted by efforts to accelerate innovation.

In the Trancik Lab, one focus area is on understanding and quantitatively modeling the drivers of underlying progress for a range of technologies—what we term the "mechanisms" of technological change. These mechanisms can refer to both specific, measurable changes in a technology, such as increased efficiency or lower input prices, or to more general improvement processes, including research and development and emergent phenomena such as economies of scale. Studying the mechanisms that drive technology improvements such as the exponential reductions in cost observed in recent decades for solar modules and lithium-ion batteries, helps provide insights into how policymakers, researchers, and the private sector can better target these mechanisms to accelerate future technological progress.

This mechanism-focused approach to studying innovation differs from previous efforts by relating each change to a feature of a technology or its manufacturing process to performance improvements, even when many changes occur simultaneously that interact with one another in determining costs. When this approach is used to study past changes in a technology, we can identify which mechanisms mattered, quantify their contributions, and answer important questions. For example, what percentage of a technology's cost decline was caused by a decrease in the price of raw materials as opposed to the building of larger manufacturing plants? Or, how much of its improvement can be attributed to research and development as opposed to economies of scale? These insights then allow decision-makers to identify public policies or business practices that could help drive further improvement, within physical limits.

In this report we review the concepts and methods underlying this mechanism-focused approach to understanding innovation, and then demonstrate the application of the approach and the types of insights that can be derived through case studies of three energy technologies: solar photovoltaics, lithium-ion batteries, and nuclear fission power plants.

Key takeaways for policymakers from the research include:

- **Research and development (R&D) and market-expansion policies each played essential and non-substitutable roles in spurring innovation in technologies.** Our examination of solar PV modules demonstrated that both "technology-push" policies (*i.e.*, public R&D funding) and market-expansion policies contributed significantly to the observed cost declines, and that the mechanisms they targeted differed considerably. Support for R&D led to cost reduction through improvements in conversion efficiency and reductions in the quantities of materials required per cell, among other low-level mechanisms. Meanwhile, market-expansion policies were essential for stimulating private R&D, as well as the growth in the sizes of manufacturing plants and bulk purchasing that reduced costs via economies of scale.

- **Government support was an important driver of cost decline.** Some of the initial research and development, including invention and early improvement of solar photovoltaic technology, relied on government funding, including substantial R&D support from the U.S. Government. This government funding was crucial as some of the early materials science and physics research leading to these improvements would have been considered too risky to pursue for a private company. Similarly, government passage of market-expansion policies, for example in Germany and Japan, was instrumental in incentivizing the growth of solar companies in the private sector, and in turn both the private R&D and economies of scale that lead to substantial cost reductions.

- **Many other technologies are also likely to need both R&D funding and market-expansion policies.** Policymakers involved in setting climate, energy, and industrial policies and those designing R&D budgets should coordinate to ensure that the potential benefits of both types of policies are captured, based on an assessment of innovation mechanisms. The balance of support for these different policy approaches might also need to be adjusted at different stages in the lifecycle of a technology, based on the most promising mechanisms for technological improvement given the features of the technology and its stage in development. Examples of technologies that could benefit from this approach, in addition to those described in this report, include other types of batteries (*e.g.*, stationary, fast-charging, those based on abundant materials), electrolyzers, wind turbine components, fuel cells, electric vehicles (*e.g.*, battery electric and hydrogen fuel cell vehicles), and even entire infrastructures such as those for producing hydrogen and charging electric vehicles.

- **R&D investment can be beneficial well past initial commercialization of a technology.** Our research suggests that sustained, and not just early-stage, R&D support can be an important driver of cost reduction for clean energy technologies. Conventional wisdom in technology policymaking is that ‘‘science and technology–push’’ processes should precede ‘‘demand-pull’’ processes. Our results are consistent with this model, but also show that technology-push policies, such as government funding for basic and applied research and development, may remain important for certain technologies even long after demand-pull processes also begin to contribute to cost reduction and other technology improvement.

- **Technologies with low levels of "design complexity", or high "modularity", may be particularly well positioned to advance rapidly.** In the case of lithium-ion batteries, R&D concurrently contributed to many low-level mechanisms of cost change, which highlights a feature of lithium-ion batteries that might help explain their rapid improvement: the diversity of materials and chemistry combinations that can be used in these devices. Our results are consistent with other research that suggests that technologies that allow some components to be improved without requiring changes elsewhere in a design can improve significantly more quickly than those with many dependencies between components.

- **For some energy technologies and infrastructures, carefully designed mechanistic cost change modeling and demonstration projects could contribute substantially to technological cost improvement.** Some technologies are constructed mostly in the field rather than in manufacturing plants. Examples of such technologies include nuclear power plants, electricity transmission systems, and some proposed infrastructures for producing hydrogen gas. For those technologies, cost reducing innovations might be identified through a combination of 1) cost change modeling that connects technological features to resulting costs, as described in this report, and 2) building demonstration projects that can provide empirical data to refine modeling assumptions. Neglecting this approach can lead to unanticipated cost overruns, as has been observed in U.S. nuclear power plant construction.

- **Analysis of prospective public policies that aim to drive technological improvement should consider physical features of technologies and relevant infrastructures.** The methodology advanced here shows how valuable it can be to begin with a model of the features of a technology or infrastructure that affect cost or another performance metric of interest. Even policies seemingly far removed from traditional R&D policies can potentially jumpstart significant innovation. However, it will be important to target the innovation mechanisms with the greatest potential impact, and we only know to target those mechanisms through first identifying them. This identification will require studies that clearly delineate how changes in technologies have, and could in the future, influence performance and cost. When researchers and technology developers seek funding to support their efforts, their proposals can be strengthened by analyses that consider the mechanisms of technological change and clearly, and where possible quantitatively, delineate how their technical proposals relate to the performance improvements or cost reductions they project. Similarly, government agencies could perform, or fund, independent analyses and expert elicitations, to both provide additional understanding and identify research directions that could effectively accelerate the development of clean energy technologies.

- **Policymakers and regulators should emphasize the need to collect and share empirical data on technology variables affecting costs and other aspects of technology performance, and how these variables change over time.** The studies of technological change we describe and the insights this research provides require extensive collection of data that is often difficult to obtain. Policymakers could require firms and researchers receiving funding from various governmental initiatives to collect and share such data, and also specifically allocate funding for collecting data on technologies and how they change. These data include details on technologies' components and other features, as well as on their manufacturing processes, and on technologies' performance and cost, and how these change over time. These data enable investigation of the possible mechanisms of technological change. Relevant data can be collected from academic institutions, businesses, and government agencies, and then be made available to researchers. In addition to implementing data collection and sharing requirements for projects receiving government support, another promising opportunity to collect data on the deployment of energy technologies in the earlier stages of market maturity would be through the funding and design of demonstration projects and hubs. Data on component costs and specifications, and importantly how they change over time, could be collected through these projects and be made available to researchers.

Introduction

The Climate Innovation Challenge

To limit the impacts of climate change, society must swiftly reduce its emissions of greenhouse gases (GHGs). This emissions reduction will require that economies transition to sustainable technologies across all sectors, including electricity, industry, transportation, and agriculture, in order to provide goods and services without emitting GHGs.[1,2] Many of the technologies needed to support this transition are already affordable and ready to scale. However, the further improvement of these technologies, and the development of new ones, can play an essential role in supporting a rapid, equitable, and complete decarbonization transition.[3]

Technological innovation can support society's adoption of climate solutions while simultaneously enhancing human wellbeing.[1,3] This innovation includes the large-scale deployment and continuous improvement of mature technologies like wind turbines, solar panels, and batteries.[3,4] This innovation also entails the research, development, and commercialization of technologies not yet widely established in the marketplace, such as those that can provide carbon-neutral fuels or capture and store carbon dioxide from the air.[3,5]

"Technology" as used in the context of this report encompasses individual devices and larger infrastructures and spans both hardware and non-hardware forms of codified knowledge. Innovation is important across this spectrum of technologies.

Accelerating Innovation: Role of Research

Scientific and engineering research plays a central and well-recognized role in developing new technology.[6,7] However, research into understanding processes of technological innovation can also inform the direction and pace of society's transition to sustainable technologies. Such research can generate important insight to help decision-makers make good use of finite resources and limited time to address climate change. This research can help answer key questions, such as: What technological functionality can help society reach its climate goals? How can public policies, as well as business and engineering decisions, effectively leverage resources to support the improvement and deployment of critical technologies? The first question has been the focus of much research, which has advanced knowledge on the roles that different technologies can potentially play in supporting a decarbonized and integrated energy system.[1,8–13] This report focuses primarily on addressing the second question, and complements previous research,[14–31] by outlining a modeling approach to data-informed, quantitative study.

In this report, we describe an approach to identifying the drivers of technological change and informing efforts to further technological innovation. In this approach, we focus on understanding the factors that influence the rate of technological progress for a range of technologies. We study technologies that have improved rapidly and substantially, such as solar panels and lithium-ion batteries, as well as those whose improvement and adoption has been hampered along one or more dimensions, as is the case for nuclear fission power plant construction costs and adoption rates. We elucidate the drivers, or "mechanisms", of technological change. These mechanisms include specific, measurable changes in a technology, such as increased efficiency or lower input prices. These mechanisms also entail broader efforts, including research and development and learning-by-doing, and emergent phenomena such as economies of scale. By studying the mechanisms that drove past technology improvements, we provide insights into how policymakers, researchers, and the private sector can better target these mechanisms to help drive technological progress going forward.

The method outlined could be used to inform forecasts contingent on different policy or other investment decisions as well as engineering design strategies. Primarily, this research aims to inform policy and business decisions so that they can be more successful than if decision-makers rely solely on intuition to direct the investment of time and monetary resources. The future is always uncertain, and the objective of the research outlined here is to inform decisions despite that uncertainty, by making use of information available in data and engineering knowledge on the processes and constraints influencing technology improvement.

The Role of Government and Public Policy

Public policies can significantly influence the process of technological innovation.[24,25,32] Many stakeholders contribute to technological innovation—the invention, development, and deployment of new technologies. These stakeholders include academic institutions, start-up companies, established corporations, investors, nonprofit organizations, and governments themselves. Public policies can affect the myriad decisions, big and small, that these stakeholders make about technologies, from which research directions to pursue to which technologies or resulting services to purchase. Some policies can influence decisions by providing support for certain options, for example by providing subsidies for technologies that meet environmental targets, or disincentivizing other options, for example via limiting greenhouse gas emissions. Policies that incentivize or disincentivize market growth for different technologies can have a large impact on private sector investments into innovation in those technologies. Policies can also fund efforts to research and develop new technologies. In addition, policies can reduce uncertainty surrounding decisions, for example by providing clear regulations and setting expectations.

Through its capacity to impact a wide range of decisions, effective government policy can be a critical lever for accelerating technological innovation and a transition to sustainable technologies. Accordingly, in this report we highlight insights arising from our research that are particularly relevant to the design of public policies.

The research we describe can help inform policymaking, and specifically how governments use limited public funds and limited time to help society accelerate the transition to sustainable technologies and meet its climate targets.[33] In particular, our research helps elucidate the relationships between the different tools available to policymakers and the various mechanisms underlying technological change, and thus provides insights into the conditions under which these different policy tools can most impactfully be applied to support innovation.

While in this report we focus on the role of government policy, the approaches and insights described can also inform the decisions made by other stakeholders about how to allocate financial resources and time, ranging from scientists and engineers to businesses and a range of private investors.

A Mechanism-Focused Approach to Studying Innovation: Concepts and Methods

When designing policies to promote technological innovation, it is useful to consider the various mechanisms that contribute to the change in the cost and performance of technologies, in order to identify those that might have the greatest impact on technological improvement. These mechanisms can be thought of as the drivers of technological change. Once identified, these mechanisms can then be targeted by public policies, increasing the likelihood that policymakers will achieve greater technological improvement given their investment of financial resources.

In the Trancik Lab, we have developed an approach to identifying mechanisms of technological change that can serve as leverage points for innovation. This approach comprises both a general conceptual framework and more detailed technical methodology for investigating the mechanisms that drove past technology change and for exploring how researchers, policymakers, and businesses can target these mechanisms to better direct or accelerate future technological progress.

Our approach fills an important gap in research on technological innovation. Many efforts to understand technological change use trends from historical data[28,29,34–36] or data from expert surveys.[30,37–39] Using these results, some studies then forecast different performance levels and rates of change for a given set of technologies, where the forecasts are based on time or an aggregate measure of effort such as the cumulative production volume of the technology. Missing from these studies is a method of elucidating how changes to features of the technology, such as changes to prices of its raw materials or manufacturing process, contribute to cost reductions, and how these relate to human efforts and policies.

The approach we present here focuses in on how specific investments, engineering designs, or manufacturing approaches can advance technology. By arriving at explanatory results about these mechanisms of technological change, these insights can inform a wide set of interventions to advance a technology, beyond the time-based and production-based forecasts that can be derived from trends in data. Our approach differs from many previous efforts in that it builds a model that connects changes to the physical functioning of the technology to changes in an aspect, or aspects, of its performance, such as its cost. Physical characteristics of the technology and its production are represented as variables. Each variable included in the model connects to an outcome in technology performance, and changes in these variables relate to changes in technology performance. In this way, the model allows us to investigate the underlying mechanisms of technological change. Through a focus on mechanisms, rather than correlations, we can explain why technologies changed; and we can estimate quantitatively the degree to which various underlying drivers led to an observed change in a technology. The explanation of technological change provided by this approach is of the underlying mechanisms that lead to the observed outcome.

When decision-makers understand how different mechanisms influence technological change, they can direct public policies, business decisions, and research efforts toward the mechanisms more likely to lead to success, in terms of the accelerated improvement and deployment of sustainable technologies. For instance, it is known that the soft costs of installation (*e.g.*, labor costs, permitting, project management, design, etc.) constitute a major contributor to the costs of nuclear fission reactors. Direct investments that target those mechanisms that affect soft costs (*e.g.*, investing in efforts to adopt design processes that are made to be flexible in response to construction site characteristics) might have an outsized impact on driving down the costs for that technology.

The methodology and case studies described below provide a roadmap for identifying and understanding key mechanisms of technological change. The application of this approach can be done more or less quantitatively depending on the context and the level of insight required. For instance, a technical expert overseeing research and development (R&D) funding awards at the Department of Energy may be interested in conducting a detailed quantitative study of the low-level mechanisms that contribute to the cost and performance of an emerging technology, such as hydrogen fuel cells or direct air capture plants. Such a study could help them better direct funding towards those mechanisms that present the most impactful leverage points for these technologies. However, this level of detail may be unnecessary for a Congressional policymaker who seeks to understand how to sequence the implementation of broader technology-push and market-expansion policies for a portfolio of technologies. In this case, a higher-level application of the conceptual framework may be sufficient.

While detailed studies of technologies may be overly time-consuming in some policy contexts, there are helpful and revealing lessons that can be derived from this way of thinking about how a technology's costs (or other aspects of performance) change over time, even without a detailed study. We therefore outline those generalizable lessons throughout this discussion, alongside the more detailed description of the approach. These lessons form the basis of a conceptual model that we can use to understand processes of technological change. Even if one does not have the resources to conduct a detailed study, we expect that thinking through or using only a few of the steps outlined below can help inform decision-making and improve policymaking.

Here we introduce and then apply the mechanism-focused approach to studying technology innovation. We highlight how this approach helps us understand technological change and provides insights that can inform decisions moving forward, with a focus on insights for government policymakers. We outline the approach and specifically demonstrate its application through case studies focused on three energy technologies: solar photovoltaic modules, lithium-ion batteries, and nuclear fission power plants.

Concepts: What Are Mechanisms of Technology Change?

Mechanisms of technology change can be understood as the drivers of changes in a technology, *e.g.*, the causes of reductions in cost or improvements in performance of a technology. In our work, we differentiate between two types of mechanisms: low-level and high-level mechanisms of technological change. Public policies and business decisions can influence high-level mechanisms of technological change, which in turn influence low-level mechanisms. Figure 1, below, illustrates the relationships between the different mechanisms and public policies for the example of solar panels, specifically silicon photovoltaic (PV) modules.

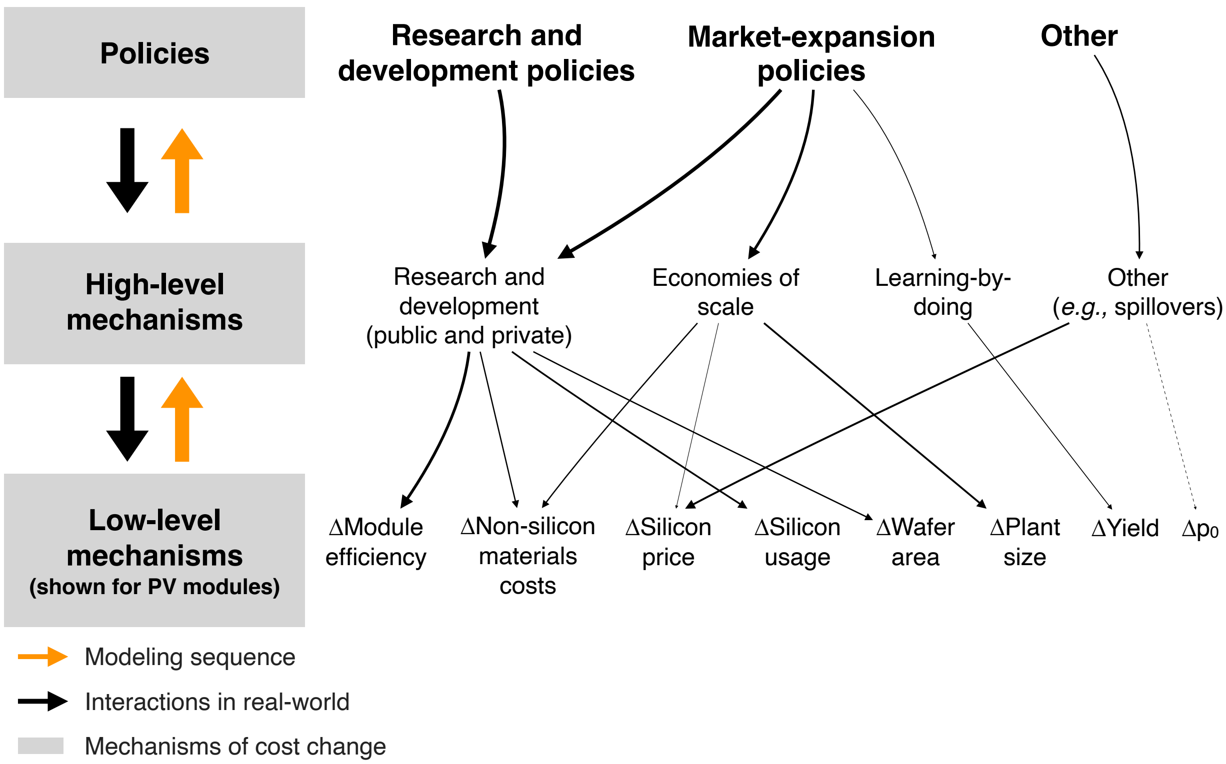

Figure 1. Identification of how public policies influence high-level mechanisms and how high-level mechanisms influence low-level mechanisms for solar (i.e., silicon PV) modules. The 'Other' policies category includes policies that aim to impact an industry unrelated to the technology being studied. For example, subsidies for manufacturers of computer chips could lead to spillovers that reduce the price of silicon used in the production of solar panels.

Low-Level Mechanisms

Low-level mechanisms are measurable, often tangible, changes in the characteristics of a technology or its manufacturing process that influence overall technology performance or cost. Examples of low-level mechanisms include prices of input materials, physical or chemical properties of components, manufacturing rates, and labor costs. These variables are often the focus of science and engineering efforts to improve technologies. For instance, if replacing an expensive input material with a less expensive version led to a reduction in the overall cost of a technology, we would consider the change in the price paid for the input material to be a low-level mechanism of cost change.

Low-level mechanisms reflect the specific characteristics of the technology being studied. The low-level mechanisms of cost reduction of solar PV modules differ from the low-level mechanisms of cost reduction of lithium-ion batteries. This difference results from the two technologies using different materials with different characteristics and being produced in different manufacturing processes. (Limited overlaps can occur, for example when technologies both incorporate the same materials, components, or processes.)

High-Level Mechanisms

High-level mechanisms refer to broader processes that lead to changes in the low-level mechanisms, and are themselves often the targets of public policies and business decisions. Examples of high-level mechanisms include research and development, learning-by-doing, and economies of scale. While other high-level mechanisms do sometimes play a role, as can be seen in the case study on nuclear fission power plants, these three mechanisms broadly apply across diverse technologies. These three mechanisms can impact a broad variety of low-level mechanisms, and have been discussed widely in studies of technological innovation. These mechanisms also reflect distinct processes that can be impacted by a range of decisions, including government funding for basic science and engineering research, investments made by private companies, policies that favor deployment of technologies that meet certain targets, and increases in the purchase of certain goods or services.

- Research and development includes changes that require experimental settings, from laboratory research through pilot-scale production, including work in both the public and private sectors.
- Learning-by-doing, as defined here, involves changes informed by routine manufacturing activity at commercial scale, *e.g.*, incremental process refinements. This definition is informed by the traditional use of the term and the economics literature.
- Economies of scale encompasses changes resulting from increasing scales of manufacturing plant production and production capacity, including price reductions from volume purchases.

Not all people who research or influence technological change define these mechanisms similarly. When studying technological change, it is important to provide clear definitions of these mechanisms so that the results can be interpreted and compared appropriately. Delineating specific definitions is important in applying the approach outlined here, so that different low-level mechanisms can be related to different high-level mechanisms.

Policies

Just as high-level mechanisms drive changes in low-level mechanisms, high-level mechanisms are, in turn, influenced by public policies, business strategies, and financial investments. In this report we focus primarily on the role of public policies.

Government policymakers have a collection of tools that can influence these many decisions and support technology innovation. Broadly, these tools can be divided into two categories: “technology-push” and “market-expansion” policies.

- **Technology-push policies** include research and development (R&D) funding, demonstration project funding, and other policies which help to stimulate the invention and development of new technologies by focusing on the conditions required to increase the supply of new technologies. R&D funding and demonstration projects have long been considered essential tools for policymakers to incentivize technological innovation.[6,40]

- **Market-expansion policies** include policies that stimulate demand and create markets for certain technologies. (An alternative label for this category of policies is "demand-pull".) This category includes a wide range of policies, including market-based instruments (*e.g.*, taxes or caps on emissions), regulations (*e.g.*, performance standards), subsidies (*e.g.*, tax credits or rebates on low-emitting technologies) and procurement policies (*e.g.*, government purchases of renewable energy or electric vehicles). While market-expansion policies have often not traditionally been considered a part of the toolkit for innovation policy, our research shows why they play an essential role in accelerating innovation. Relatedly, our research also provides strong evidence for considering both the transformation of markets (*i.e.*, the diffusion of technology) and the improvement in technologies as interconnected parts of the innovation process.

Both types of policies can drive changes in high-level mechanisms and their underlying low-level mechanisms. Often, technology-push policies support public research and development (R&D), and sometimes fund demonstration projects leading to a greater emphasis on 'development' in the broader category of R&D. Meanwhile, market-expansion policies can drive private research and development, learning-by-doing, and economies of scale. Moreover, the influence of public policies is not limited to the high-level mechanisms described here. For example, some public policies can also reduce uncertainty, aiding public and private sector decision-making.

As Figure 1 illustrates, low-level mechanisms, high-level mechanisms, and policies can all simultaneously change a technology's cost or performance. For example, suppose a worker who cuts materials on the factory floor identifies a way to minimize material loss during this cutting. This innovation could result in an increased "yield" of the material and lower the overall cost of the final technology. The resulting cost reduction can be explained in multiple ways. One way is to say that yield of the material increased (a low-level mechanism). Another way is to say that learning-by-doing (a high-level mechanism) drove down costs because the worker "learned" how to minimize material loss in the process of making the technology, *i.e.*, doing. Both explanations are correct and emphasize different parts of the process of technological improvement. Furthermore, the opportunity the worker had to develop an improved cutting approach might itself have been influenced by a public policy that spurred demand for the technology, like a subsidy that lowered its cost. The increased demand could have led to increased production, during which the worker learned how to increase yield. The approach we describe below allows us to better understand the connections between policies, high-level mechanisms, and low-level mechanisms, and quantify their contributions to technological change.

Methods: A Five-Step Approach to Identifying Key Levers of Technology Change

The approach we use to identify key drivers of innovation can be summarized in five steps:

1) Define performance metrics of interest, and estimate performance targets.
2) Develop a performance or cost equation.
3) Examine low-level mechanisms of technological change.
4) Examine high-level mechanisms of technological change.
5) Identify and evaluate policy drivers of technological change.

Each of these five steps is described in greater detail below. We have published detailed technical papers on this approach elsewhere[41–44] and focus here on describing the approach and highlighting the relevant policy insights we can arrive at through this approach.

The approach described below can be applied both retrospectively and prospectively, and both types of studies can inform the development of public policies, business strategies, and research directions. **Retrospective studies** help us understand what contributed to technological change in the past. For example, were research and development efforts the primary cause of the cost decline observed for silicon photovoltaic modules? Or did most of the cost decline come from the building of larger factories that allowed manufacturers to benefit from economies of scale? (The answer is discussed in one of the case studies detailed below.) We can also compare the mechanisms identified for technologies that improved rapidly to mechanisms identified for technologies that have improved slowly, or not at all. These results can provide policymakers evidence as to which strategies have successfully enabled significant technological change and why, and which aspects of these strategies might be successful going forward. **Prospective studies**, on the other hand, focus on revealing technology features and mechanisms that hold significant potential for improving overall performance moving forward. In this case, variables in the cost or performance equation are changed based on hypothetical future scenarios and the scenario outcomes are compared. For instance, prospective analyses can help identify the low-level mechanisms that might most substantially influence overall cost and would thus benefit from focused R&D. Prospective analyses can also help estimate the limits that both low-level and high-level mechanisms, and the policies that drive them, might encounter when trying to accelerate or redirect technological change.

1) Define performance metrics of interest, and estimate performance targets

Questions to ask: What are you looking for in a technology? In what ways do you want that technology to improve?

The first step is to identify what performance is valued in the technology, now and in the future, and how that performance can be quantified. When technologies compete in a market, cost is often a primary consideration; and the cost of a technology is typically scaled by the service it provides to allow for fair comparisons between options. Common energy metrics for electricity generating technologies, such as solar panels, wind turbines, and conventional fossil fuel combustion power plants, in which cost is scaled by service include cost per power (*i.e.*, USD/kW) or cost per energy generated in a given time period (*i.e.*, USD/kWh). These metrics are especially useful as they combine estimates of cost with those of service. For example, a given power generating technology might be improved by reducing its cost for a given power capacity or increasing its power capacity for the same cost; both changes are reflected in a cost per power output metric.

Other metrics can represent environmental impacts. A common impact metric is greenhouse gas emissions, sometimes summarized as CO_2-equivalent emissions, from a given service provided, such as electric energy (measured in kWh); the final metric would be CO_2-equiv/kWh. These performance metrics are also often used to inform decisions made when choosing between technologies.

It is important to clarify additional assumptions and conditions that are implied, but not always explicitly included, in certain performance metrics. For example, levelized cost of electricity (LCOE), which represents the cost of producing electricity with a given technology scaled by the amount of electricity generated, has units of USD/kWh. Meanwhile, energy storage systems are often characterized by their capital costs scaled by the amount of energy they can store at once, which also has units of USD/kWh. When choosing performance metrics, the characteristics represented, and the methods used to calculate the metrics, should be clearly described to avoid potential confusion.

In the examples discussed in the case studies below, cost per unit service is the performance metric of interest because of its central role in determining the competitiveness and adoption of a climate-mitigating technology. However, these methods can also be used to investigate past and potential future mechanisms that influence improvement in other measures of technology performance.

Related research seeks to estimate performance targets for these metrics of interest. This research contributes to addressing the first question highlighted in the Introduction section above: What technological functionality can help society reach its climate goals? The Trancik Lab has studied how to prioritize performance metrics and estimate performance targets based on how the technology will need to perform in context of a sustainable energy system.[45–49] In the case of some technologies, several different performance metrics are important to consider simultaneously. For example, in the case of energy storage, depending on the intended use of a storage system (*e.g.*, for price arbitrage or to reliably meet energy demand with variable renewable energy) the desired balance of power capacity costs (*e.g.*, in units of $/kW) and energy capacity costs (*e.g.*, in units of $/kWh) will shift. The different prioritization of these performance metrics can then influence which types of storage technologies should be the focus of research and development for various applications.

2) Develop a performance or cost equation

Questions to ask: What components or processes significantly contribute to the technology's performance or cost? How do these components and processes relate? What data are available? How uncertain are these data?

Once a performance metric is chosen, then a "performance equation" or "performance model" can be developed. When the performance metric summarizes a technology's cost, as is often the case, this equation can be referred to as a "cost equation" or "cost model". This equation relates the performance of the technology, as summarized in the selected metric, to components of the technology and a set of variables describing the characteristics of these components. These components include hardware components and soft components. Hardware components, sometimes referred to as tangible components, include the raw materials used to make the technology (*e.g.,* minerals, metals, plastics) as well as purchased, manufactured components (*e.g.,* wires, solvents, computer chips). "Soft" components, as in "software", are varied and are sometimes referred to as intangible components. "Soft" components can include the algorithms that control a technology's operation. "Soft" cost components can also include the labor of the workers who construct the technology, the financing of capital to build a manufacturing plant, and the administration required to oversee manufacturing processes.

In the performance or cost equations, components are represented by combinations of variables. For example, in a cost equation, components are often separated into the quantity of a material required (*i.e.*, a quantity variable) and the price of the material (*i.e.*, a price variable), with the product of the two (quantity times price) giving the cost component. Improvements to the technology (*e.g.*, a cost-reducing innovation) can come from using less of the material while achieving the same level of service, or replacing the material with a new option that has a lower price.

The performance equation is a representation of the technology that connects the physical, chemical, and other characteristics of its components to the technology's overall performance. We determine which components and variables to include in the equation by studying a technology's design, construction or manufacturing process, and operation. We investigate which materials are purchased by a manufacturer or installer, which components are produced and constructed and how, and what other factors might influence the performance metric we have focused on. We seek to include all significant contributors to the performance metric being examined, and to validate our model, can compare the results of our analysis to independent measures of how the performance metric changed over time. For example, to develop a cost equation, we can determine how variables in the equation contribute to the costs of every physical component found in a technology (*e.g.*, the materials); the costs of the equipment, electricity, and other resources required to make the technology; and the soft costs of manufacturing the technology (*e.g.*, labor, oversight, permitting, etc.). We can also account for the amount of material that is lost during manufacturing. If the sum of all cost components equals the overall cost, or in some cases price, of the technology as reported by other sources, we can have confidence that the cost equation accounts for the major cost components.

Performance equations can also be rewritten in terms of variables that highlight technology features or component characteristics that are considered important, because a decision-maker has agency over them (*i.e.*, a decision-maker can alter them through research-driven or manufacturing-driven improvements or redesign). For climate-relevant technologies, a variety of potentially important features and characteristics can be investigated using a performance equation, including energy efficiency, charge stored in a given mass of material, the ratio of materials that participate directly in electricity conversion (*i.e.*, active materials) to those materials that do not participate directly (*i.e.*, non-active materials), and the proportion of cost that results from labor. These features are often influenced by the underlying physics and chemistry of the technologies but can be altered within physical limits.

An example of a cost equation developed for photovoltaic modules is:

$$C\left(\frac{\$}{W}\right) = \frac{\alpha}{\sigma A \eta y}\left[\underbrace{A\nu\rho p_S}_{\text{Si}} + \underbrace{cA}_{\text{non-Si}} + \underbrace{p_0\left(\frac{K}{K_0}\right)^{-b}}_{\text{plant size–dependent}}\right]$$

Here, the cost of the module (in \$) is scaled by the power the module provides when exposed to sunlight (W). This scaled cost (in \$/W) is given as the sum of cost components that include the silicon-related costs, non-silicon related costs, and costs that depend on plant size. These components are defined as functions of a variety of variables relevant to the physics, design, and manufacturing of solar modules, including the energy efficiency of the module (η), price of silicon (p_S), the area of the wafers (A), the size of the manufacturing plant (K). (More details on the development of this cost equation, and the variables contained within it, can be found in the journal article describing the analysis.[41])

Developing a performance equation requires balancing the need to reflect important technology features and component characteristics in the equation with the ability to obtain high-quality data that describe these features and components. For example, the cost equation for PV modules, shown above, could be expanded to include many more details describing how the panels were manufactured, including the rate of manufacturing, the number of workers per shift, the wages paid to the workers, the electricity used by the factory, etc. A lack of reliable historical data precluded incorporating this level of detail. Regardless, even without this detail, the contributions of many important low-level mechanisms of cost change, and the three major high-level mechanisms highlighted above, could still be elucidated and quantified.

Constructing a performance equation can highlight important relationships between different technology characteristics and the overall performance metric. For example, if a given variable appears in multiple cost components, changes to that one variable might significantly impact overall performance. Delineating a performance equation also limits the chance of double-counting the effects of technology characteristics when examining how modifying these characteristics affects performance change (*i.e.*, when studying low-level and high-level mechanisms as discussed below).

3) Examine low-level mechanisms of technological change

Questions to ask: How have individual technology features changed? How have these changes impacted overall technology performance? How might changes in technology features influence future performance?

Once a performance (or cost) equation is developed, the impact of changes to the technology can be examined quantitatively. Changes in the variables that compose the performance equation are designated as "low-level mechanisms" of technological change. These low-level mechanisms are measurable changes in characteristics of a technology or its manufacturing that can influence overall technology performance or cost. Examples include an increase in energy efficiency, a decrease in input material prices, or an increase in labor costs. They can be thought of as the causes of technological change that reflect changes to variables in the performance (or cost) equation.

Using the methodology detailed in our recent papers,[41–43] the impact that changes in individual variables have on overall performance or cost can be estimated, even when multiple variables change simultaneously and have non-additive impacts on performance or costs. From the performance equation, performance change equations can be developed. These equations relate changes in the variables to changes in the overall performance metric. The performance change equations in this step are a key methodological advancement beyond previous work, which would define a performance equation but only examine the additive contributions of changes in cost components (for which a performance change equation is not required), rather than examine the impacts on performance of changing variables within those cost components.

Performance change equations allow us to disentangle the impacts of multiple low-level mechanisms (changes to variables), which is useful because it is often the case that changes in many technology features contribute simultaneously to technological change and important features can influence multiple cost components. Characterizing the impacts of these simultaneous changes is key to understanding past technology evolution and prioritizing investments going forward, including investments in stimulating different high-level mechanisms as discussed further below.

4) Examine high-level mechanisms of technological change

Questions to ask: What broader efforts or phenomena led to the low-level mechanisms of technological change? Can these broader efforts be distinguished?

Low-level mechanisms of technological change are themselves often the result of broader efforts and emergent phenomena that are influenced by public policies and business strategies. In our research, these are termed "high-level mechanisms" of technological change. In the context of energy-relevant and many other technologies, important high-level mechanisms include: research and development, learning-by-doing, and economies of scale. Other high-level mechanisms can also be identified and studied, but these three high-level mechanisms are commonly investigated in research on technological change and can influence a wide variety of low-level mechanisms. The analytical approach detailed here allows us to estimate the influence of these high-level mechanisms of technological change.

To estimate the contributions of high-level mechanisms, low-level mechanisms of technological change are assigned to the high-level mechanisms. In retrospective studies, assignments require knowledge of what drove the low-level mechanisms. For example, were decreases in the price of a raw material the result of bulk purchasing? If so, then the cost change contribution from the reduction in price could be assigned to economies of scale. Or was the decrease in the price due to the introduction of a new material that is less expensive that the material it replaced? In that case, the change in price could be assigned to research and development. Sometimes, changes in individual variables result from multiple high-level mechanisms, and the methodology allows for this by assigning portions of the change in variables to different high-level mechanisms.

After the mechanism assignment is complete, the contributions of the individual high-level mechanisms to technological change are estimated by summing the contributions of the low-level mechanisms assigned to each high-level mechanism. The results are estimates of the percentage of technological change that result from each high-level mechanism. Of course, there is some uncertainty in this assignment and estimation process. Often, we include an 'other' category for low-level mechanisms that do not have a clear assignment. Sensitivity analyses can also be employed to estimate the uncertainty in the contributions of the high-level mechanisms. For example, assigning the entirety of a low-level mechanism to one or another high-level mechanism can provide upper and lower bounds on the uncertainty that results from the assignment.

5) Identify and evaluate policy drivers of technological change

Questions to ask: What policies drive high-level mechanisms? How have these policies performed in the past? How can future policies be improved?

Public policies can directly and indirectly influence high-level mechanisms of technological change. A common direct policy approach is to promote public research and development. For example, allocating funding for research via the National Science Foundation or Department of Energy's Office of Science can encourage public research and development in universities and national laboratories. Similarly, funding demonstration projects can promote research and development as well as learning-by-doing. Other policies work indirectly. For example, subsidizing the purchase of a technology is considered a "market-expansion" policy. By encouraging companies to produce and improve a technology, market-expansion policies can support increased private research and development, learning-by-doing, and economies of scale. Take, for example, subsidies for battery electric vehicles. These subsidies drive consumer demand, which in turn encourages private companies to produce more vehicles. As production increases, the companies can learn in the process (learning-by-doing) and benefit from economies of scale. These companies can also invest in their own, often private, research and development to improve their vehicles. These effects can also pass through to the suppliers of electric vehicle manufacturers, such as those producing lithium-ion battery cells, and drive high-level mechanisms that help improve their component technologies.

Policymakers can improve their design of policies to encourage technological change using estimates of how high-level mechanisms contribute to technological change. Retrospective studies can provide evidence of what policies have worked and show whether the high-level mechanisms that drive a particular technology's change have shifted over time. For example, a common theory suggests that research and development become less important as a technology advances and economies of scale become more important, which would suggest that policymakers should adjust their funding priorities based on technological maturity.[16] Studies of technologies that have advanced rapidly can provide support for, or against, such theories and help policymakers decide how to balance their funding options. Using this evidence, policymakers can focus efforts on those mechanisms most likely to accelerate technological change. Prospective studies can help policymakers evaluate whether their proposals will have their desired impacts. For example, if a proposed technology remains costly but a cost change analysis suggests that it will benefit little from additional public research and development, policymakers could instead focus their efforts on developing market-expansion policies that promote economies of scale and learning-by-doing. Similarly, prospective studies that examine limits to technological change could improve projections of the pace of adoption of climate-friendly technologies.

Case Studies: Lessons from Three Technology Examples

In the case studies described below, we present the findings of analyses the Trancik Lab conducted to investigate the mechanisms that drove changes in the costs of three technologies that could help mitigate climate change: solar photovoltaic (PV) modules, lithium-ion batteries, and nuclear fission power plants. Two of these technologies—solar modules and lithium-ion batteries—are quintessential examples of rapidly improving clean energy technologies (see Figure 2). In contrast, in our third example, nuclear fission power plants in the U.S. have experienced construction cost increases over time.

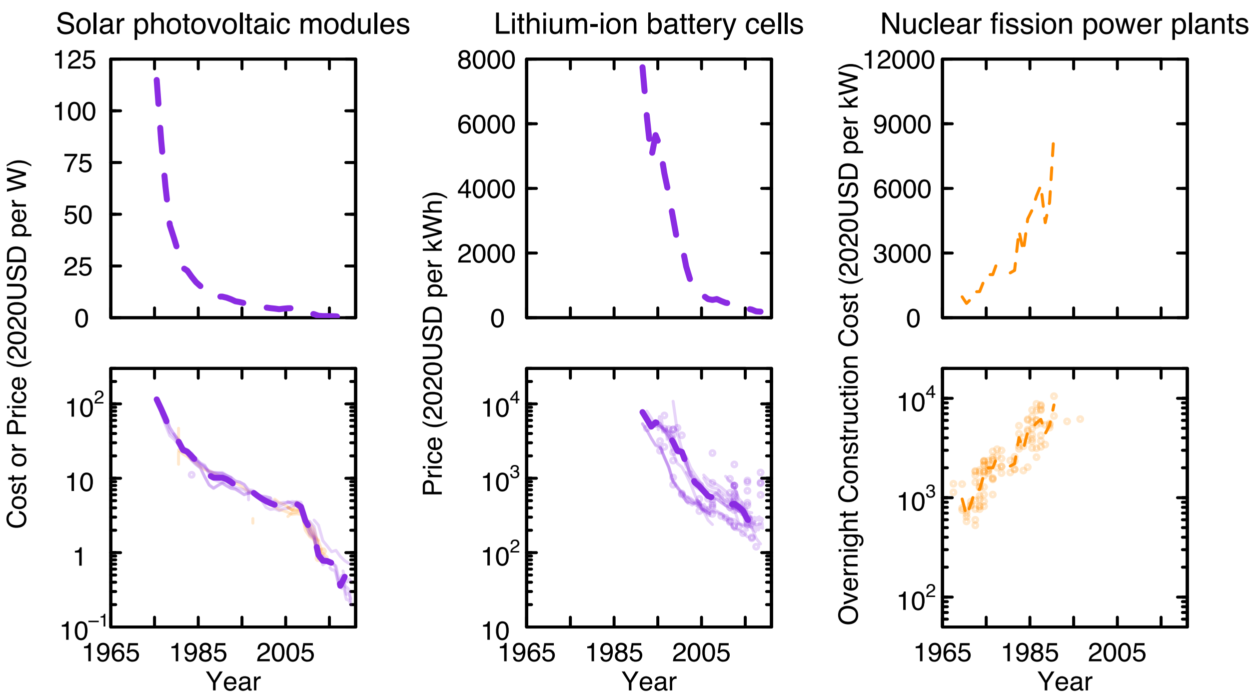

Figure 2. Costs (orange) and prices (purple) of solar modules, lithium-ion battery cells, and nuclear fission power plants from 1965 through 2020. Representative cost or price series are plotted as bolded, dashed lines. Additional detail on the data plotted is available in work published previously.[41,42,50]

Case Study #1: Solar Photovoltaic Modules

Why study solar photovoltaics? The substantial and rapid declines in the costs of solar photovoltaic (PV) modules over the past 40 years are considered a paragon of rapid technological change for energy technologies. By studying the drivers of their cost decline, we can identify factors that might be able to enable further improvements in solar PV technology, and arrive at insights that may help stimulate similar success with new and emerging technologies.[41]

How we applied the approach: We applied the mechanism-focused approach retrospectively, following the steps outlined above, to examine what led to the reduction in the cost of PV modules.[41] First, we defined our performance metric of interest: the cost of manufacturing modules scaled by the power they produce when exposed to sunlight, *i.e.*, cost per power output, given in units of USD/Watt (Step 1). We developed a cost equation whose variables reflect important characteristics of solar modules and their manufacturing, including their energy efficiency, the price of silicon, silicon usage, wafer size, non-silicon material costs, manufacturing plant size, and manufacturing yield (Step 2). We collected data to populate this cost equation at different points in time, and quantified how changes in these technology features, *i.e.,* the low-level mechanisms, contributed to the cost reduction of PV modules between 1980 and 2001, between 2001 and 2012, and overall, between 1980 and 2012 (Step 3). The results are shown in Figure 3.

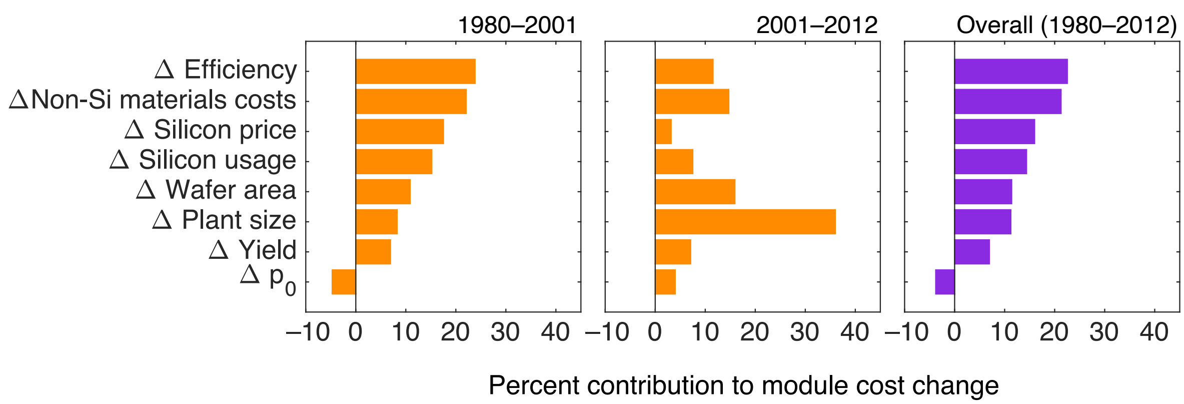

Figure 3. Contributions of the low-level mechanisms to the cost decline of PV modules, in the period 1980–2001 (left), 2001–2012 (middle), and 1980–2012 (right).

<u>Contributions from low-level mechanisms:</u> Our results show that between 1980 and 2001, most of the cost reduction came from improvements in module efficiency, followed closely by decreases in non-silicon material costs. Later, between 2001 and 2012, plant size was the major contributor to cost reduction.

Next, we assigned these low-level mechanisms of cost change to high-level mechanisms (Step 4). Some assignments were straightforward. For example, efficiency, silicon usage, and wafer size were attributed to a combination of public and private research and development, while plant size was assigned to economies of scale and manufacturing yield was assigned to learning-by-doing. Other assignments, such as the price of silicon, were less clear-cut. The drivers of silicon prices changed over time. During the first period (1980–2001), silicon for modules often came from the semiconductor industry, and thus the price of silicon was assigned to the 'other' category. During the second period (2001–2012), PV industry demand for silicon surpassed that of the semiconductor industry and polysilicon producers scaled to meet this demand, so the price of silicon was assigned to economies of scale. Still other low-level mechanisms, like non-silicon materials costs, were split between high-level mechanisms within the same period because they were likely influenced by both R&D and economies of scale. The resulting estimates of the contributions of the high-level mechanisms are presented in Figure 4.

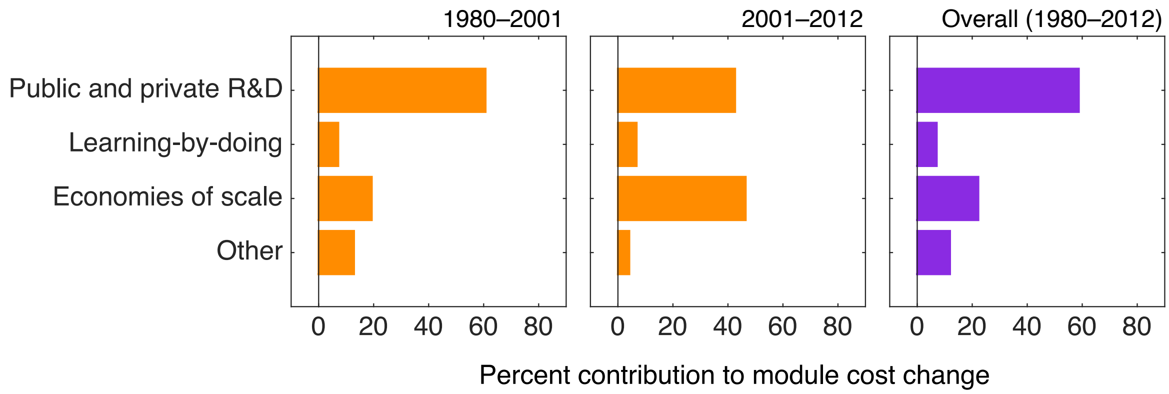

Figure 4. Contributions of the high-level mechanisms to the cost decline of PV modules, in the period 1980–2001 (left), 2001–2012 (middle), and 1980–2012 (right).

Contributions from high-level mechanisms: We found that early in the adoption of terrestrial solar panels, between 1980 and 2001, R&D was the dominant contributor to cost reductions. This R&D is a combination of both public and private efforts. As time went on, the role of R&D lessened, and economies of scale grew in importance. In the second time period, between 2001 and 2012, R&D and economies of scale were nearly equal contributors to cost reduction. When looking across the full time period studied, from 1980 through 2012, R&D still provided the bulk of the cost reductions. Economies of scale had a smaller, but still significant impact. Meanwhile, learning-by-doing was a relatively minor contributor.

Contributions from policies: We then sought to identify those policies that drove the high-level mechanisms and disentangle how much of the cost change could be attributed to efforts to support *public* research and development versus efforts to stimulate the market for PV modules, which drove economies of scale and investments in *private* R&D (Step 5). Our results show that market-expansion, or market-stimulating, policies contributed to about 55% of cost reductions between 1980 and 2001, and their contribution grew to approximately 75% between 2001 and 2012. Across the full period, market-stimulating policies contributed nearly 60% of all observed cost reductions, suggesting that market-stimulating policies were very important in driving the cost reduction of silicon PV modules.

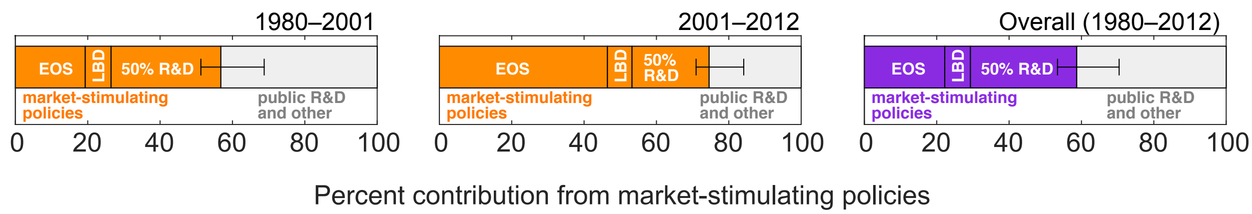

Figure 5. Contributions of the combination of market-stimulating policies (orange and purple bars) to the cost decline of PV modules, in the period 1980–2001 (left), 2001–2012 (middle), and 1980–2012 (right).

This step required that we differentiate the contributions of public and private R&D, for which we relied on estimates of roughly equal public R&D and private R&D expenditures. Based on these expenditures, we estimated that public and private R&D were similarly effective in driving the low-level mechanisms that acted to reduce costs. As a result, the contributions of public and private R&D were split evenly, and the results are presented in Figure 5.

While this assumption contributes to uncertainty in the estimates of the contribution of market-stimulating policies and public R&D funding, the overall conclusion that both policies contributed significantly to the overall observed cost decline is robust. It is clear from examining the low-level mechanisms of cost change that important changes occurred in both publicly funded labs and in companies.

Moreover, these mechanisms worked in concert to support cost change and were driven by very different types of efforts in these two distinct settings, where efforts in each setting were likely necessary but not alone sufficient for driving the observed cost change. In other words, it is unlikely that the two types of policies could have been substituted for one another with the same success as that which was observed in the historical data. Beginning our analysis with the engineering and manufacturing features of the technology, *i.e.*, building the cost equation, and developing a mechanistic model of performance change, *i.e.*, elucidating the low- and high-level mechanisms, were essential for arriving at a strong conclusion about the importance of these two types of public policy.

<u>Examining strategies moving forward:</u> In addition to the retrospective analysis, we also used the cost and cost change equations to outline an approach to conducting prospective analyses for informing strategies for future technological development. We sought to describe an approach for estimating how efforts to target certain mechanisms might influence cost reduction.

These types of prospective analyses can allow us to estimate the impacts of potential low-level mechanisms going forward, and can help prioritize future policy design and investments to target specific high-level mechanisms. In this analysis, we retain the same cost and cost change equations and change the values of the variables in them. For example, for solar modules, we can examine the cost reduction obtained by increasing energy efficiency or reducing the price of silicon or doing both simultaneously.

We assessed how influential each low-level mechanism is for reducing costs under our model, when they contribute individually. In the first analysis, presented in Figure 6, we investigated what would happen if each technology feature, except for yield and plant size, were changed by 25% in the cost reducing direction. The goal here was simply to better understand the influence of variables and not to model a likely future scenario. We examined these changes under two conditions: plant sizes increasing 3-fold (dark blue) and 10-fold (light blue). We find that increases in efficiency and plant size are the two largest possible drivers of cost reduction when these features are changed individually.

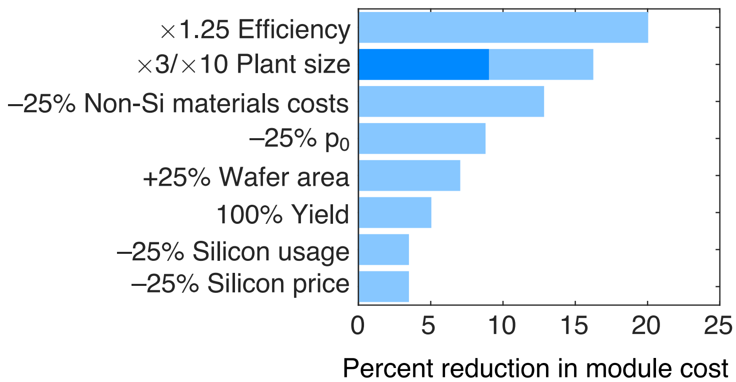

Figure 6. Prospective reductions in the cost of PV modules for one-at-a-time changes to various factors that influence overall module cost.

However, typically multiple mechanisms contribute to technological change over time. Thus, we also examined the contributions of the low-level mechanisms when all are changed simultaneously and grouped their contributions to estimate the prospective contribution of the three high-level mechanisms. We again examine the potential contributions when plant sizes increase either 3- or 10-fold. The results are presented in Figure 7.

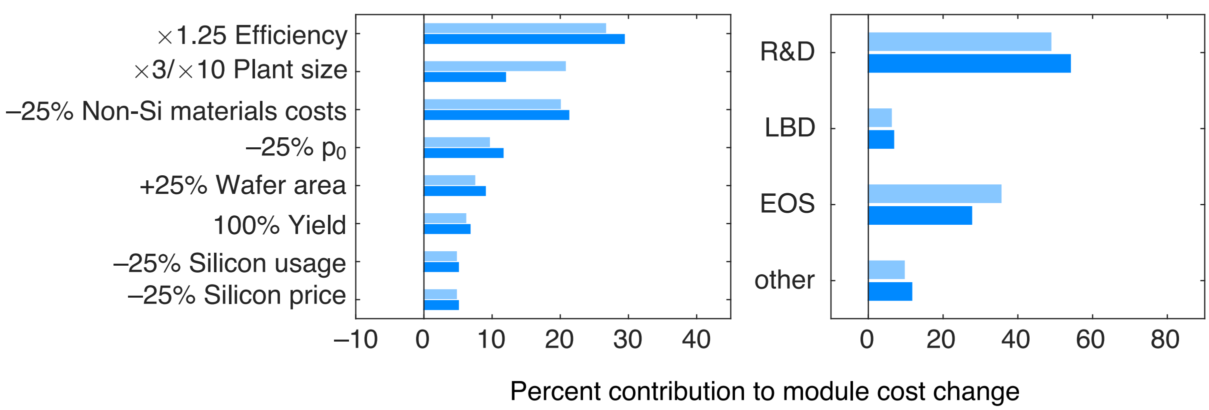

Figure 7. Prospective reductions in the cost of PV modules in a scenario in which cost equation variables are changed simultaneously by the amounts shown.

In both scenarios, a combination of public and private R&D contributes the most to the prospective cost reduction, while economies of scale contribute less but still significantly. The results highlight those technology characteristics that might be good targets for additional research and development. In the case of PV modules, increases in efficiency, larger plant sizes, and decreases in non-Si material costs are consistently the three largest potential contributors to further cost reduction. While results from prospective analyses must also be considered in conjunction with physical limits, they can help those who are directing both public and private research and development funding to identify potentially promising avenues for technological improvement.

These results can also estimate the impacts of broader public policies, and in this case, suggest balancing increased production and larger plants with support for additional R&D. For example, we find that, if plant sizes increase 10-fold, economies of scale and learning-by-doing would together contribute only 40% of the potential cost decline observed. Additional R&D, both public and private, would lead to considerably more cost reduction.

The hypothetical scenarios outlined here can be further developed into a set of more or less likely scenarios, and the modeled changes can be constrained based on physical limits. To implement such an approach, targeted expert elicitations can be informed by performance equations to solicit inputs on potential improvements to key variables. By focusing on a detailed set of variables as opposed to aggregate metrics such as device or project costs, which have often been the focus in the past, elicitations can be designed around specific knowledge sets. Experts can then be recruited who have direct insight into the technical feasibility of improving relevant design and manufacturing variables or the policy levers that could stimulate high-level mechanisms.

Key insights for policymakers

- **R&D and market-expansion policies each played essential and non-substitutable roles in spurring innovation in solar PV.** Public R&D funding is often considered an essential tool for policymakers to incentivize the improvement of technology while market-expansion policies are not always considered a key lever for innovation policy. Our examination of solar PV modules demonstrated that both public R&D funding and market-expansion policies contributed significantly to the observed cost declines, and that the mechanisms they targeted differed considerably. Support for R&D led to cost reduction through design improvements that affected conversion efficiency and the materials required per cell, among other low-level mechanisms. Meanwhile, market-expansion policies were essential for stimulating privately funded, applied R&D, as well as the growth in the sizes of manufacturing plants and bulk purchasing that reduced costs via economies of scale.

- **Government support was an important driver of cost decline.** Some of the initial research and development, including invention and early improvement of solar photovoltaic technology, relied on government funding, including substantial R&D support from the U.S. Government. This government funding was crucial as some of the early materials science and physics research leading to these improvements would have been considered too risky to pursue for a private company. Similarly, government passage of market-expansion policies, for example in Germany and Japan, was instrumental in incentivizing the growth of solar companies in the private sector, and in turn both the private R&D and economies of scale that lead to substantial cost reductions. Prior to these cost reductions, the cost of electricity provided by solar modules was higher than that of many other competitor technologies. Now solar PV modules are among the least expensive options for generating electricity.

- **Many other technologies are also likely to need both R&D funding and market-expansion policies.** Policymakers involved in setting climate, energy, and industrial policies and those designing R&D budgets should coordinate to ensure that the potential benefits of both types of policies are captured, based on an assessment of innovation mechanisms. Any technology that is manufactured and has the potential for substantial improvements will likely benefit from both types of policies working in concert to accelerate innovation. In addition, the balance of support for these different policy approaches might also need to be adjusted at different stages in the lifecycle of a technology, and based on the features of the technology. Mechanistic modeling can help policymakers improve how these policies are balanced, and aid in the direction of efforts toward the most promising mechanisms for technological improvement. Examples of technologies that could benefit from this approach, in addition to those described in this report, include other types of batteries (*e.g.*, stationary, fast-charging, those based on abundant materials), electrolyzers, wind turbine components, fuel cells, electric vehicles (*e.g.*, battery electric and hydrogen fuel cell vehicles), and even infrastructures such as those for producing hydrogen and charging electric vehicles.

Case Study #2: Lithium-Ion Battery Technologies

Why study lithium-ion batteries? We studied lithium-ion batteries to inform efforts to continue improving battery technologies, as well as to identify strategies that can effectively support rapid improvement for a wide range of technologies.[43]

The prices of lithium-ion batteries have fallen rapidly and substantially since their commercial introduction in the early 1990s, at rates comparable to those observed for solar PV modules.[50] Originally used in portable electronics, lithium-ion batteries are now powering electric vehicles and e-bikes, and increasingly helping to support the electric grid. Energy storage technologies will need to continue to improve in cost and performance in the coming years to meet climate policy goals, and studying lithium-ion batteries can help provide insight into strategies to continue to reduce the costs of both lithium-ion and nascent battery technologies. Moreover, comparing the insights derived from this example with those from the solar PV example can help policymakers, engineers, and private investors start to identify trends that carry across multiple technologies.

How we applied the approach: As with PV modules, we applied the mechanism-focused approach to elucidate the drivers of the observed cost decline in lithium-ion batteries.[43] In this case, the performance metric we studied was the cost of battery cells scaled by their energy capacity (in units of USD/Wh). Substantial efforts have focused on reducing the energy capacity costs of batteries to bring down costs of electric vehicles as well as stationary storage systems, which can help integrate solar and wind energy resources into the electric power system.

We developed a cost equation featuring a few dozen technology characteristics and examined how they changed between the late 1990s (1995–2000) and early 2010s (2010–2015). We aggregated the contributions of these changes to cost reduction to reveal the impacts of broader technology characteristics, such as cell charge density, voltage, cathode and anode materials prices, and costs that depend on plant size (*i.e.*, plant size–dependent costs). The results are shown in Figure 8.

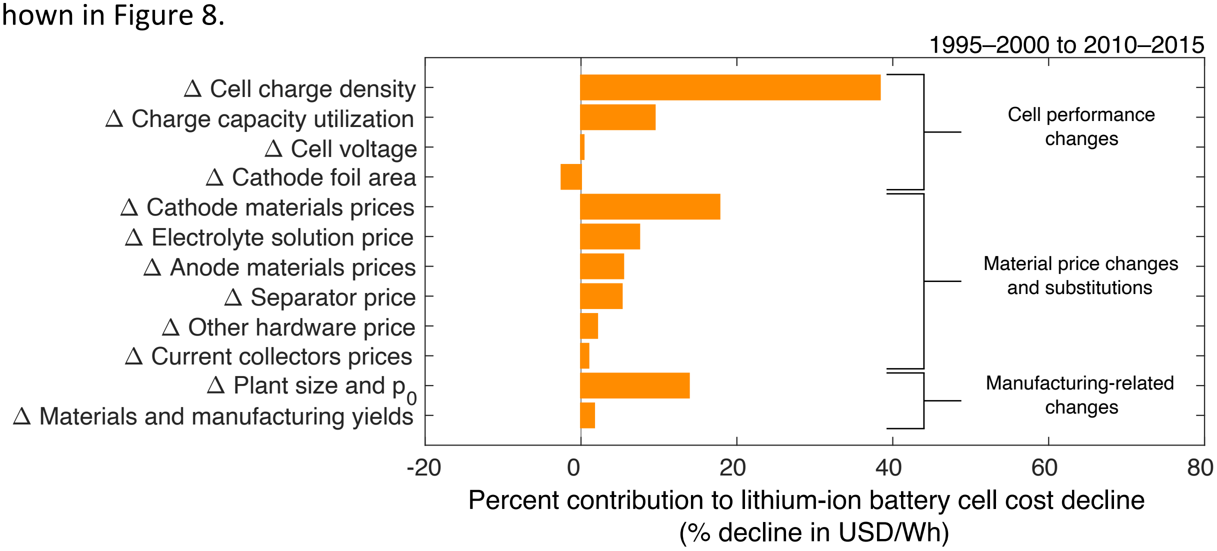

Figure 8. Contributions of aggregated low-level mechanisms to the cost decline of 18650-sized lithium-ion battery cells between the late 1990s and early 2010s.

Contributions from low-level mechanisms: Our results indicate that between the late 1990s and the early 2010s, the increase in cell charge density was the largest contributor to cost decline, followed by decreases in cathode materials prices and non-material, plant size–dependent costs.

We also examined the impacts of high-level mechanisms: public and private research and development, learning-by-doing, and economies of scale. We assigned the low-level mechanisms to these categories, or to an 'other' category, and summed the contributions to cost change within each. Assignments to research and development included changes that required experimental settings, from laboratories to pilot-scale production lines. For example, the increases in the specific capacities of the cathode and anode materials and changes in the dimensions of cell components are assigned to research and development. Leaning-by-doing, as defined here, is more limited, encompassing changes informed by routine production of lithium-ion batteries at the commercial scale; and in this analysis, it comprised the changes in yields of materials and the final cells. Meanwhile, the increases in the sizes of manufacturing plants and decreases in prices of some input materials that were attributable to increased volumes of production, were assigned to economies of scale. The results are presented in Figure 9.

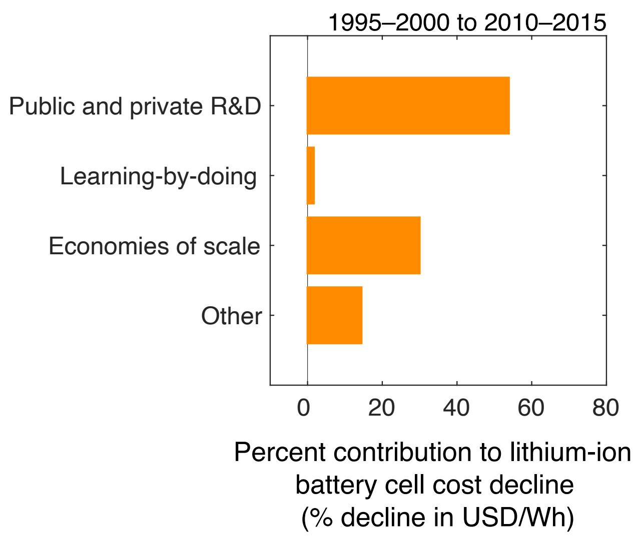

Figure 9. Contributions of high-level mechanisms to the cost decline of 18650-sized lithium-ion battery cells between the late 1990s and early 2010s.

Contributions from high-level mechanisms: We find that public and private research and development contributed just over half of the cost change observed between the late 1990s and early 2010s. Economies of scale remained significant, but contributed less, while learning-by-doing contributed little.

Of course, assigning low-level mechanisms to high-level mechanisms can be uncertain. For example, the prices of cathode materials can be influenced by changes in metal prices and improvements in mining and manufacturing processes. To account for some of this uncertainty, we assigned certain low-level mechanisms entirely to one or another reasonable high-level mechanism and examined the impacts of these extreme assignments on our results. The results of this sensitivity analysis are plotted in Figure 10.

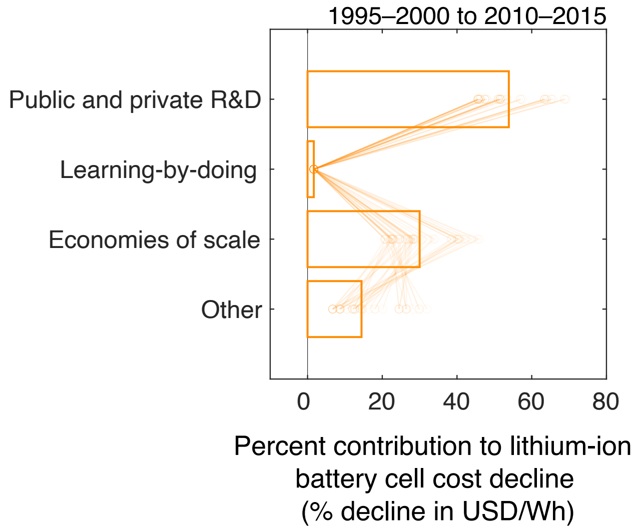

Figure 10. The results of a sensitivity analysis showing that our findings—that public and private R&D was the primary contributor to cost decline while economies of scale remain significant but still contribute less—remain robust across a full range of plausible assignments of low-level mechanisms to high-level mechanisms.

We find that our ranking of high-level mechanisms remains robust to assignment uncertainty. Research and development is nearly always the largest contributor to the cost decline of lithium-ion batteries, while economies of scale are relatively consistently the next largest contributor.

<u>Disentangling the contribution from R&D:</u> This mechanism-focused approach can also help identify which subject areas within R&D have contributed the most to the observed cost reduction in lithium-ion batteries. When we disaggregate the contribution of R&D to the cost decline, we find that advances in chemistry and materials science were responsible for the vast majority of the R&D contribution. These results are shown in Figure 11.

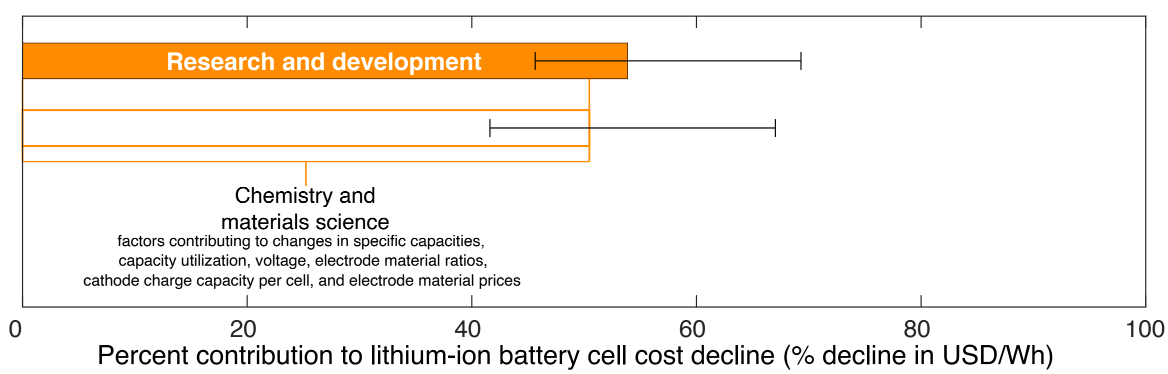

Figure 11. Contributions of research and development to cell-level cost decline between the late 1990s and early 2010s, examining both the overall contribution as well as the contribution from advances in chemistry and materials science.

This category of "chemistry and materials science" includes research and development efforts that span many traditional disciplines, including chemistry, chemical engineering, physics, and materials science and engineering. The finding that efforts within this category contributed so significantly suggests that similar efforts might substantially contribute to the improvement of other nascent electrochemical energy storage technologies.

Key insights for policymakers

- **R&D investment can be beneficial well past initial commercialization of a technology.** For both PV modules and lithium-ion batteries, we find that improvements coming from R&D activities persisted well beyond initial commercialization of the technologies. In the case of solar photovoltaics, modules for use on earth overtook those designed for use in space around 1980. Since then, R&D contributed 59% of the cost reduction. For example, improvements in energy efficiency, which resulted from R&D efforts, contributed to 24% of the cost reduction observed between 1980 and 2001, and still contributed another 12% of the reduction between 2001 and 2012. These R&D activities came from both private efforts—spurred by market-expansion policies—as well as government-funded R&D programs.

  Similarly, R&D was the largest contributor to the cost decline of lithium-ion batteries, even after their commercialization in 1991. Between the late 1990s and early 2010s, efforts to increase the energy density of cells led to considerable reductions in cost, surpassing, for example, the cost reduction contributions of lower cathode material prices and larger manufacturing plants. As with PV modules, these improvements also resulted from a combination of privately and publicly funded R&D efforts. Moreover, the case of lithium-ion batteries suggests that this support for R&D might be especially relevant when there is a diversity of options that can be explored to potentially improve a technology.

  Together, these examples suggest that sustained, and not just early-stage, R&D support can be an important driver of cost reduction for clean energy technologies. Conventional wisdom in technology policymaking is that ‘‘science and technology–push’’ processes should precede ‘‘demand-pull’’ processes. Our results are consistent with this model and provide additional insight. Our study of the underlying mechanisms reveals that technology-push policies, such as government funding for basic and applied research and development, may remain important for certain technologies even long after demand-pull processes also begin to contribute to cost reduction and other technology improvement. Additional analysis can help determine whether post-commercialization support for R&D is similarly important for other technologies and provide more guidance as to how policymakers can balance both direct support for R&D and policies that expand markets for clean energy technologies.

- **Technologies with low levels of "design complexity", or high "modularity", may be particularly well positioned to advance rapidly.** In the case of lithium-ion batteries, R&D concurrently contributed to many low-level mechanisms of cost change, which highlights a feature of lithium-ion batteries that might help explain their rapid improvement: the diversity of materials and chemistry combinations that can be used in these devices. For example, over time, as different cathode materials were identified and improved, they could be combined with a variety of different anode materials that were similarly being developed. These varied combinations of cathode and anode materials enabled lithium-ion battery cells to perform better or cost less, or both. Moreover, battery cells could be constructed using these new materials without requiring an entire redesign every time a new material was introduced. We sometimes refer to this feature of the design of lithium-ion batteries as reflecting their high modularity or low design complexity. While additional research is necessary to estimate how important this flexibility was, our results are consistent with earlier, theoretical research that suggests that technologies that allow some components to be improved without requiring changes elsewhere in a design can improve significantly more quickly than those with many dependencies between components.[51]

Case Study #3: Nuclear Fission Power Plants in the United States

Why study nuclear fission power plants? We studied nuclear fission power plants to understand why their costs, at least in the U.S. context, have risen over time.[42] Our results help identify strategies to reduce the costs of nuclear power plants, and provide insight into how to avoid increasing costs of deploying other energy technologies.

The costs of nuclear power plants built in the U.S. increased dramatically during the 1960s and 1970s (Figure 12).[42] This trend was observed not just for all plants built in the U.S., but also for individual plant designs (Figure 13), demonstrating that nominal design standardization did not lead to significant cost declines in plant construction costs. The rising costs of nuclear fission power plants provide a stark contrast to the rapid cost declines observed for photovoltaic modules and lithium-ion batteries. Understanding what has led to these increases can help us identify and mitigate similar challenges that might be encountered when deploying a range of technologies going forward.

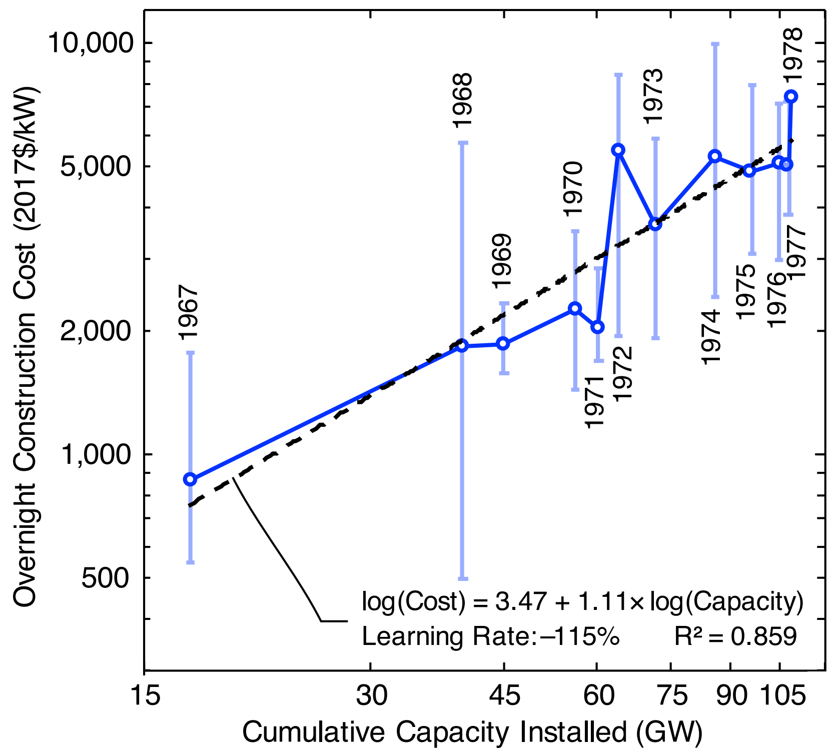

Figure 12. Trends in construction costs of nuclear fission power plants in the United States.

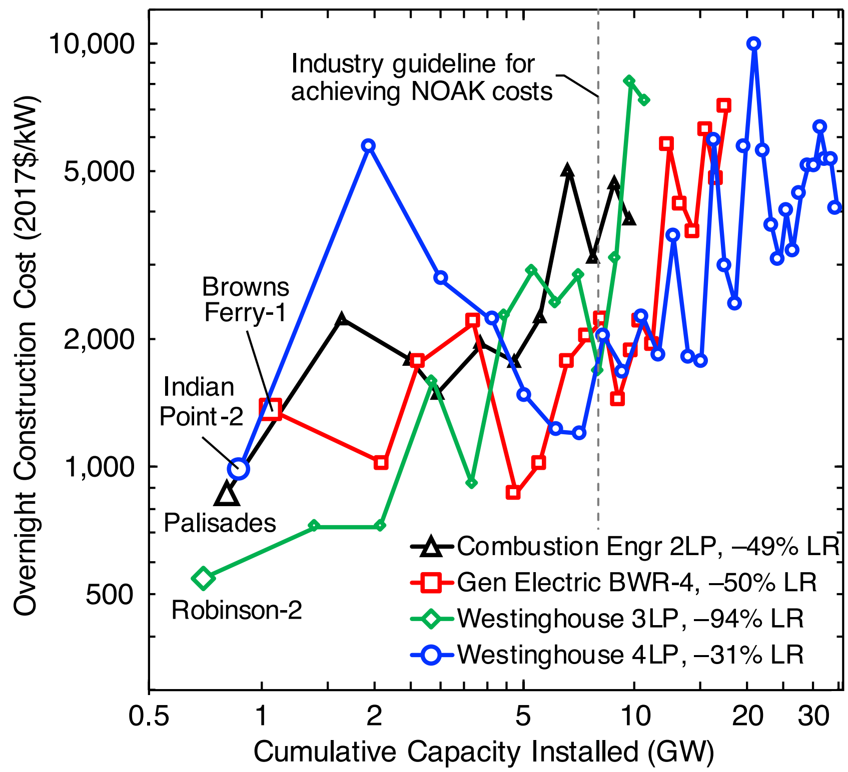

Figure 13. Trends in construction costs of nuclear fission power plants, for specific designs, in the United States.

How we applied the approach: We began by examining the drivers of the increase in the cost of construction of nuclear fission power plants for a single plant design—the Westinghouse four-loop plant.[42] In this case, the performance metric we focused on was the cost of constructing the plant, scaled by the amount of power the plant produced, in USD/kW. We chose this metric because the capital costs of plant construction compose a substantial portion of the cost of electricity from nuclear power. We then developed a cost equation that includes a variety of costs of building a plant, ranging from the construction of the nuclear steam supply system to the supervision of work in the field. We categorized these cost components as either indirect or direct costs. Indirect costs, which are largely "soft costs", include activities that support plant construction, such as engineering, administration, construction services, management, field supervision, and testing. Direct costs, include the costs of materials, labor, and equipment needed for physical components. The results are shown in Figure 14.

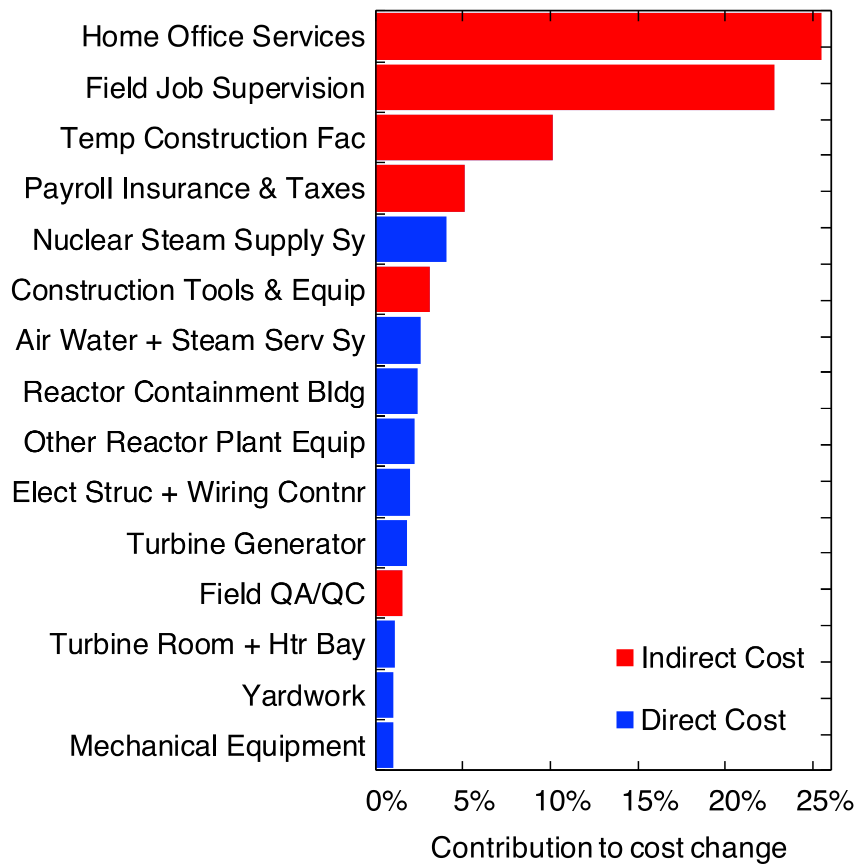

Figure 14. Contributions of low-level mechanisms of cost change in nuclear power plants of a single design between 1976 and 1987.

<u>Contribution of low-level mechanisms:</u> We found that most of the increase in construction costs between 1976 and 1987, about 72%, was due to an increase in indirect costs. Substantially less was a result of changes in direct costs.

We then estimated how different plant components contributed to this increase in indirect costs. We redistributed the indirect costs of construction to the individual plant components, and the results are plotted in Figure 15. We found that the three plant components that drove the largest change in indirect costs—the nuclear steam supply system, the turbine generator, and the containment building—also contributed heavily to direct cost increase.

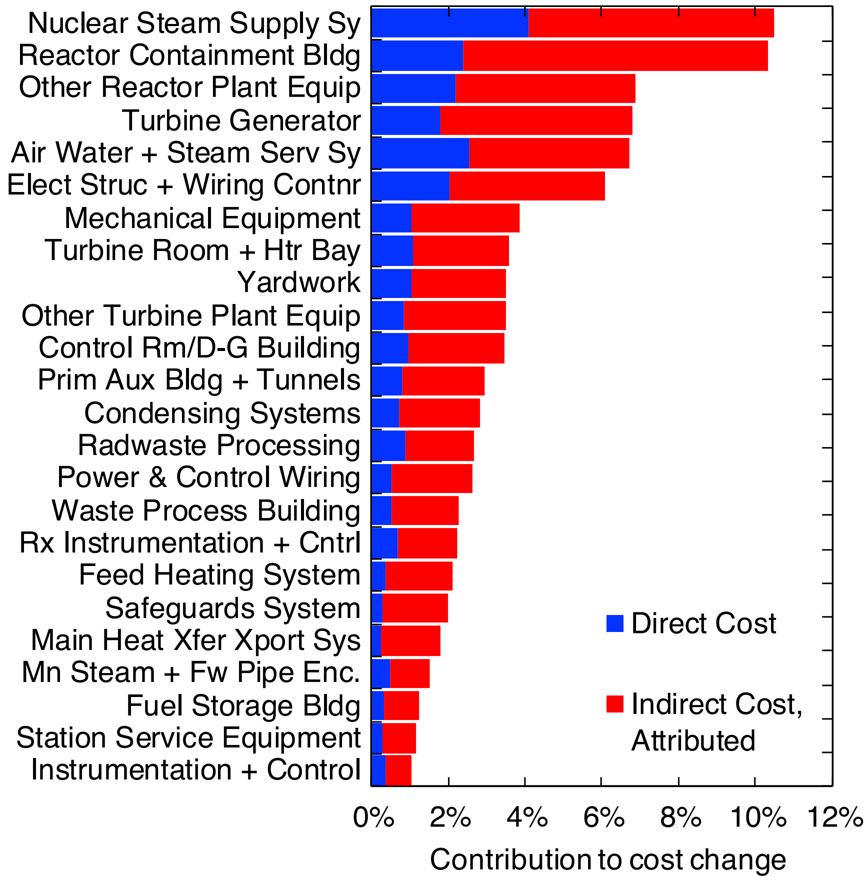

Figure 15. Contributions of low-level mechanisms of cost change in nuclear power plants of a single design between 1976 and 1987, where indirect costs are attributed to the different power plant components.

To further investigate the drivers of this cost increase, we quantified the mechanisms of direct cost change of containment building construction,[a] a major contributor to the increase in direct and indirect costs between 1976 and 1987. We focused on containment building construction in this case study in part because it is a substantial contributor to plant cost and is the largest safety-grade structure of a nuclear power plant. Elucidating the mechanisms of cost change for containment building construction allows us to examine the roles of construction challenges and changing safety paradigms. In addition, focusing on the direct costs of the containment building enables us to extend the comparison between 1976 and 1987 to 2017, so that we can investigate the impact of changes that have been implemented in the construction at the VC Summer project in South Carolina.

[a] Containment buildings are airtight structures made from steel and concrete. They form the outermost layer of a nuclear fission reactor and are designed to prevent the escape of radioactive materials during accidents, protect the reactor from external impacts, and provide structural support for the steam supply system.

The low-level mechanisms of the increase in containment building construction costs highlight the importance of deployment rates and structural design changes (Figure 16). Deployment rates are the ratios of material volumes to the quantity of person-hours required to deploy the given volume of material. Higher deployment rates reflect higher construction productivity, lower rates reflect lower productivity.

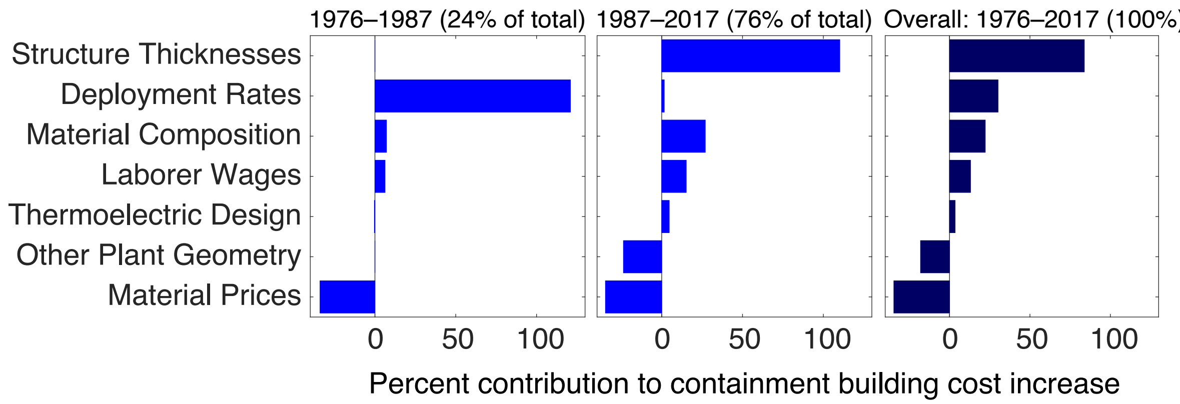

Figure 16. Aggregated contributions of low-level mechanisms of cost change for nuclear power plant containment buildings, between 1976 and 1987, 1987 and 2017, and overall.

Between 1976 and 1987, most of the direct cost increase could be attributed to a substantial drop in deployment rates, which includes both concrete and steel worker productivity in the nuclear industry. Between 1987 and 2017, much of the cost increase resulted from design changes that necessitated the construction of a much thicker steel shell.

The importance of the decline in deployment rates between 1976 and 1987 motivated further investigation of how these rates have fallen over time (Figure 17). During the early 1980s, the deployment rates estimated for nuclear construction diverged considerably from estimates for general domestic construction, with rates for recent nuclear construction dropping well below that for general domestic construction. Both the general construction and nuclear-specific construction deployment rates, which are based on empirical data, fell over the period examined and were well below those used in cost estimation guidelines employed in the nuclear industry. This disconnect between rates found in estimation guidelines and rates based on realized projects can lead to cost projections that substantially underestimate the final costs of construction.

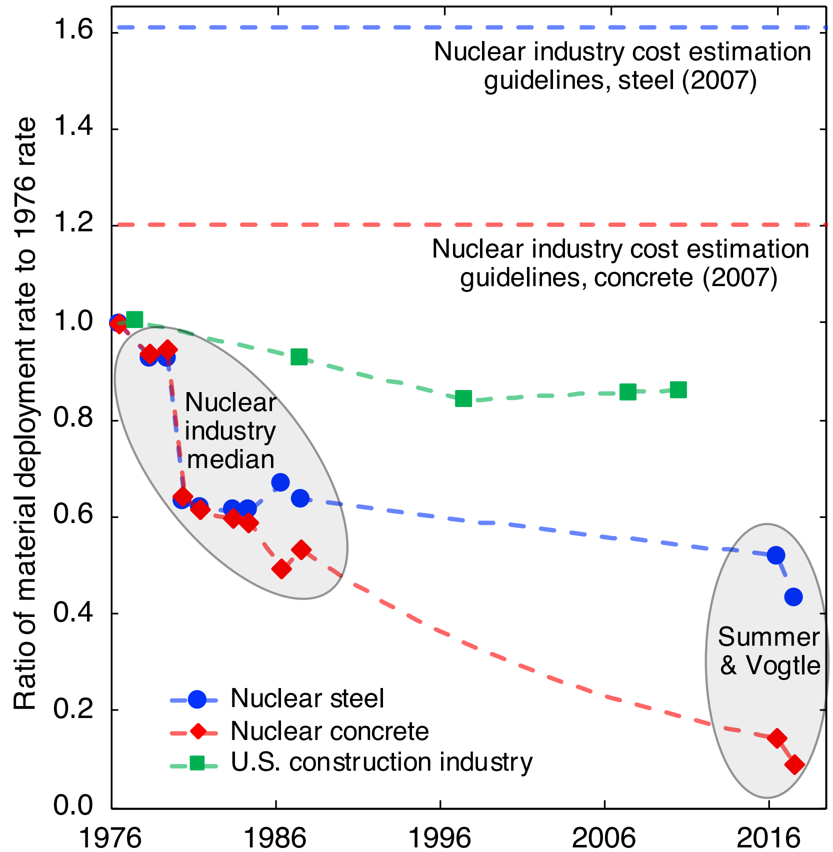

Figure 17. Historical change in construction productivity in the nuclear industry, and the construction industry at large.

As with photovoltaic and lithium-ion battery technologies, we can also examine the influence of high-level mechanisms on the increasing cost of containment building construction. However, in this case, we examine a different set of three mechanisms. The first high-level mechanism is research and development (R&D), which includes longer-term, off-site modifications to the construction process, such as design changes. For example, a switch from active to passive cooling, which was implemented to make reactors safer, required a number of design changes that are assigned to R&D in this analysis. The second mechanism we examine is "process interference, safety" (PIS), which represents the influence of on-site safety personnel, including those from the Nuclear Regulatory Commission, who interacted with the construction process. The third mechanism is "worsening despite doing" (WDD), which represents decreases in performance that can be attributed to parasitic processes, such as decreasing morale, that did not originate in construction activities and were also not counteracted by them.[b]

Contribution of high-level mechanisms: Quantitative estimates of the contributions of high-level mechanisms reveal the large influence of procedural and site-specific mechanisms, including

[b] WDD is not the same as "negative learning," which draws upon the economic definition of learning-by-doing. Learning-by-doing refers to changes that can be attributed to repetition of a construction or production activity. In worsening despite doing, the changes can also be attributed to other factors that are external to activity repetition.

both PIS and WDD (Figure 18). They also reveal that no one high-level mechanism dominated the cost increase observed for containment building construction.

One major result is that much of the cost increase, about 70%, resulted from on-site, procedural changes in plant construction, which includes both WDD and PIS. This suggests that further understanding processes that take place in the field, as these projects are constructed, could be especially important for identifying routes for reducing the costs of nuclear power.

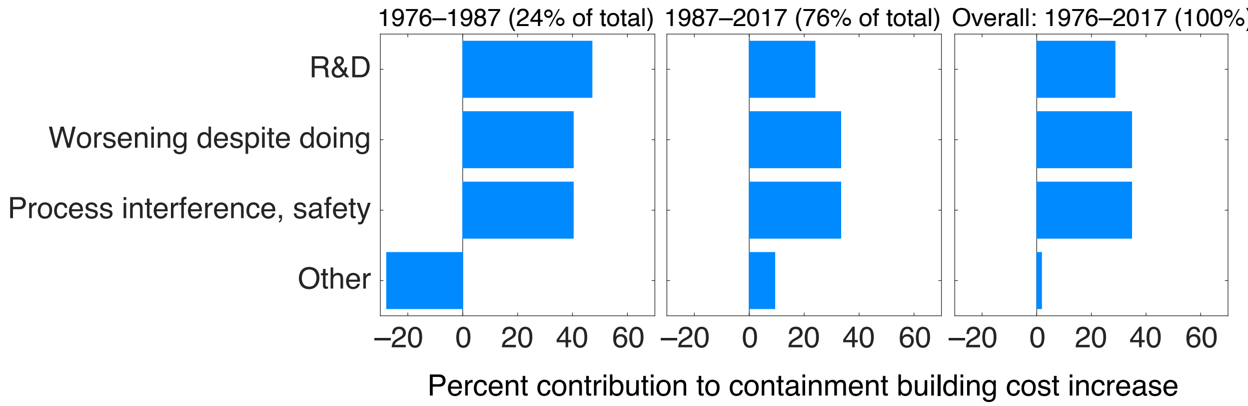

Figure 18. Contributions of high-level mechanisms of cost change to the increase in costs of containment building construction.

Safety has been a major concern for nuclear fission power plants, and our analysis allows us to estimate the influence of compliance with safety-related regulations on cost increases. While safety-related considerations permeate all of the high-level mechanisms, the mechanism most representative of compliance with relevant regulations is PIS. Our results suggest that roughly 30% of the cost increase observed between 1976 and 2017 is attributable to direct, safety-related requirements in the construction process. This finding suggests that addressing safety-related concerns in construction was not the only driver of the cost increases observed.

<u>Examining strategies moving forward:</u> We also examined three scenarios for future cost reduction to investigate whether additional innovation might be able to address the factors that led to past increases in cost (Figure 19). In this analysis, we use the same cost and cost change equations, applied to containment building construction, and estimate how different innovations might influence costs going forward.

The scenarios we examine represent hypothetical development strategies. The first scenario reflects cost improvements contributed by all of the low-level mechanisms, estimated by 20% changes in all variables in the cost reducing direction. The second scenario represents the impact of improving on-site deployment rates due to adoption of advanced techniques for manufacturing and construction management. The third scenario represents the adoption of advanced, high-strength materials in the construction of the containment building, which could reduce the quantity of commodities used like concrete and steel.

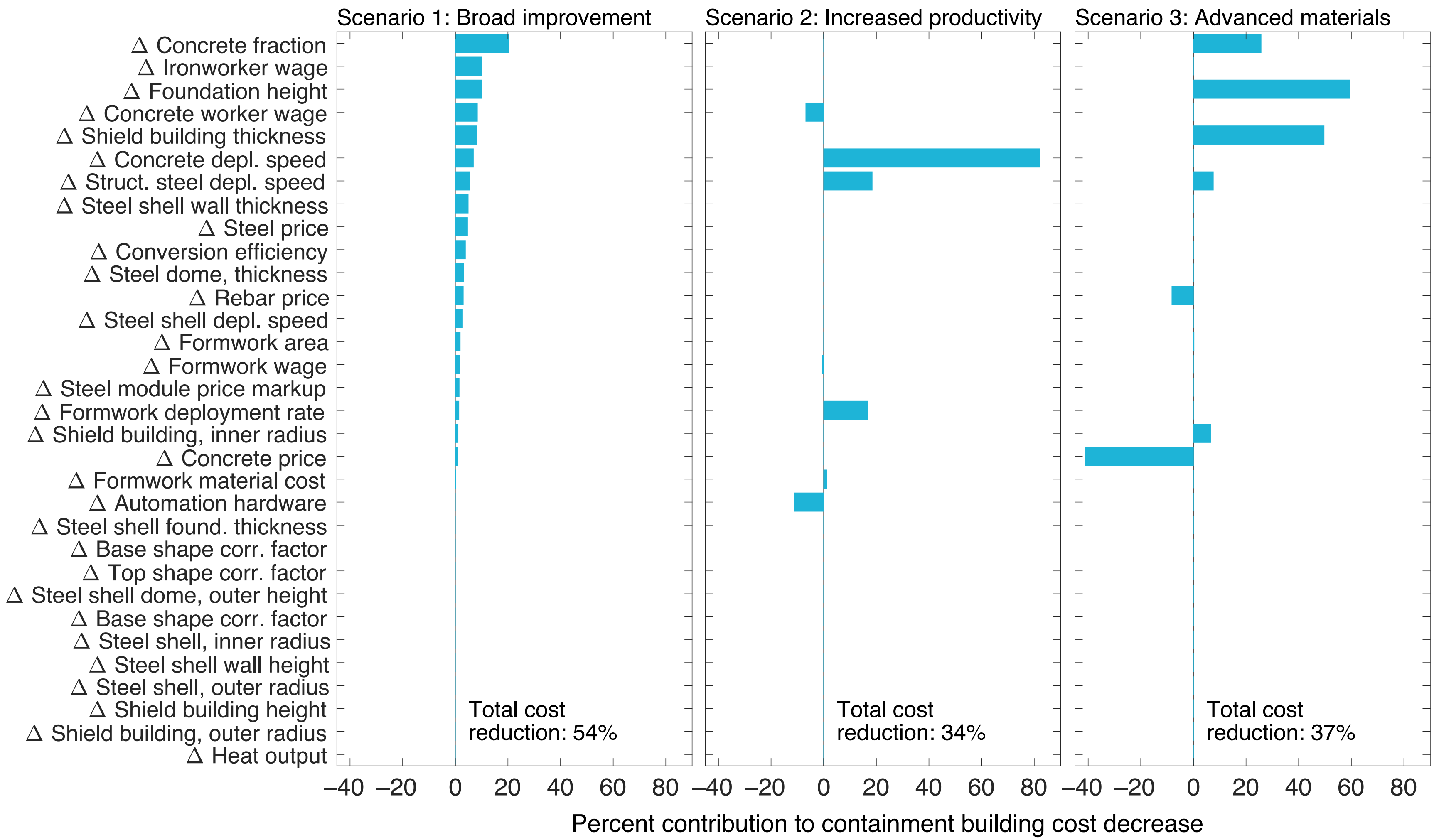

Figure 19. Contributions of low-level mechanisms to reduction in the costs of constructing containment buildings under three prospective scenarios.

Our results suggest that both reducing commodity usage and automating some of the construction process could be important goals moving forward. However, these results also highlight some of the potential limitations to reducing the costs of constructing nuclear fission power plants given current designs. Improving construction productivity (scenario 2) and introducing advanced materials (scenario 3) only lead to reductions in construction costs between 30 and 40%, relative to estimates of costs in 2017. Neither scenario demonstrates a pathway for reducing constructions costs relative to those estimated for 1976, though it is important to note that further study involving expert elicitations, detailed estimates on physical limits, and, ideally, targeted demonstration projects, is needed to determine the limits to cost reduction. Moreover, changing reactor designs offers more significant opportunities to alter the cost equation and potentially access additional cost reductions.

Key insights for policymakers

- **For some energy technologies and infrastructures, carefully designed mechanistic cost change modeling and demonstration projects could contribute substantially to technological improvement, especially through the inclusion of soft costs and soft technology variables in addition to hardware costs and hardware variables.**

  Some technologies are constructed mostly in the field rather than in manufacturing plants. Examples of such technologies include nuclear power plants, electricity transmission systems, and some proposed infrastructures for producing hydrogen gas. For those technologies, cost reducing innovations might be identified through a combination of 1) cost change modeling that connects features of technologies (represented as variables) to resulting costs and 2) building demonstration projects that can provide empirical data to refine modeling assumptions. Neglecting this approach can lead to unanticipated cost overruns, as has been observed in U.S. nuclear power plant construction.

  Demonstration does not necessarily mean a full-scale implementation of a technology, which can be costly. Modeling of the mechanisms of cost change of the kind demonstrated here can highlight potentially problematic cost categories that should be targeted through a combination of demonstration projects and adaptive designs.

  Demonstration projects paired with detailed cost change analyses can also be used to identify important drivers of cost change that diverge from expectations, which can in turn help provide guidance for future projects. For example, analysis of the increase in the direct costs of containment building construction demonstrated the importance of deployment rates. Further research revealed that the deployment rates in nuclear construction fell during the time periods examined, to levels substantially below those for the broader domestic construction industry. Moreover, the rates based on empirical data are significantly lower than those used in cost estimation guidelines for nuclear fission plants. These results suggest that guidelines for estimating the costs of nuclear plants might require updates to reflect empirical trends. Demonstration projects can similarly provide empirical data that can then be used to identify important cost contributors and improve cost estimation guidelines for larger projects or increased deployment.

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