# A new method for supporting public decision making on R&D: An example in energy

Gabriel Chan[*,1] and Laura Diaz Anadon[*,1]

[1] To whom correspondence may be addressed. E-mail gabe_chan@hksphd.harvard.edu or laura_diaz_anadon@harvard.edu

[*] Belfer Center for Science and International Affairs, John F. Kennedy School of Government, Harvard University, 79 John F. Kennedy Street, Cambridge, Massachusetts 02138, United States

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**Abstract**

Public R&D decision making is an important public policy issue where traditional approaches often lead to decisions supported by unsatisfying justifications and resulting in suboptimal outcomes. We propose four criteria for evaluating an R&D decision making process and then use these criteria to evaluate the current practice of allocating U.S. federal energy R&D investment at the United States Department of Energy (DOE). We then use the insights from this evaluation to propose and demonstrate a novel and implementable method to support this type of decision that performs well along the four evaluation criteria. Our method utilizes inputs from a unique expert elicitation exercise that collected inputs from 100 technology experts about the distribution of future cost and performance of 25 energy technologies conditional on several allocations of U.S. public energy R&D investments. We use the results of this exercise to parameterize the MARKAL model, a bottom-up energy system model of the U.S. economy, which we run under several policy scenarios. We then implement a novel sampling and optimization method to generate decision-relevant R&D portfolio allocations across technology areas. The results of applying our methodology indicate that (1) while there are decreasing returns to R&D investment, a 10-fold expansion from 2012 levels in the R&D budget for utility-scale energy storage, bioenergy, advanced vehicles, fossil, nuclear, and solar photovoltaic technologies can be justified by expected social economic returns; (2) the greatest social returns to R&D investment are in energy storage, solar photovoltaics, and bioenergy; and (3) at the DOE's current budget level, the optimal allocation of energy R&D funds is very different from the current allocation.

**Keywords:** decision-making under uncertainty, research policy, public R&D, energy R&D, energy technology

**(Assessing R&D Priorities)**

Public investment in research, development, and demonstration (R&D[1]) is motivated by its potential role in developing new technologies and guiding the rate and direction of economic growth (1). This makes the decision to allocate public R&D investments, and consider the tradeoffs between them, a critical public policy issue. However, understanding the implications of different public R&D investments, let alone entire portfolios of investments, is methodologically-complex (2, 3) and policymakers oftentimes do not approach this type of decision analytically. Failure to grapple with the complexity of R&D investments reduces their effectiveness, making this problem even more important in the current era of depressed public R&D funding in many countries. In this paper, we propose a set of four criteria for a decision-support tool that can feasibly and effectively improve public R&D portfolio design. We then use these criteria to evaluate how decisions are made in public energy R&D in the United Sates, while exploring some of the explanations for why policymakers in many public R&D funding agencies do not generally meet these criteria. We conclude by presenting and implementing a novel method that meets the four criteria we propose and then examine the results.

We develop our criteria and methodology in the specific context of the United States Department of Energy (DOE), but our analysis and proposed method is more broadly applicable to other areas, such as health, agriculture, and environmental R&D.  However, it should be noted that the method we present in this paper has been tailored to the specific institutional context of the U.S. Department of Energy and would need to be adapted to be useful in other contexts.

The analytical requirements of supporting an R&D decision to allocate funds to specific technology areas[2] as well as the constraints imposed by the institutional context of R&D decision making at DOE (and similar organizations) prescribe characteristics for an effective decision making process that we have grouped into four criteria. These criteria were identified based on a careful consideration of DOE's policymaking environment and the notion that a decision support tool's role is to generate analytical support for a decision rather than to directly prescribe policy actions. The first two criteria we propose

[1] Note that we use the term "R&D" as a catchall to include the full spectrum of research, development, and demonstration projects.

[2] We differentiate between R&D funding directed to specific technology areas (e.g., solar photovoltaics, nuclear energy), and R&D funding for basic science that does not consider the application of research discoveries for use. Note that even though in many ways this distinction is not ideal, most public R&D institutions throughout the world differentiate between these two activities, often under the heading of "basic" and "applied" R&D.

deal with analytical requirements and the second two criteria concern institutional feasibility of implementing a decision support tool. These criteria are detailed below and summarized in Table 1.

While R&D programs often exist to serve multiple policy goals and are judged by many criteria of success (4), we begin with the presumption that a decision-support tool should offer a justification for a portfolio of investments based on a quantitative estimate of at least one of the benefits of the aggregate investment. This places quantitative estimation of the benefits of an R&D portfolio as a central challenge to analytically supporting R&D decisions.

*Criterion 1. Technological improvement benefits of a decision must be prospectively quantified with a full account of uncertainty*

The technology improvement benefits of R&D investments needed to support decision making should meet four sub-criteria. (1) Relating the benefits of technological improvements to R&D investments requires specifying technological improvement benefits conditional on R&D investments. (2) The marginal rate of technological improvements at a given level of R&D depends not only on the level of R&D in that technology area but also on the level of R&D in related technology areas. In other words, R&D-induced improvements in different technologies can be correlated due to inter-technology spillovers. Therefore, to avoid biased estimates of aggregate benefits, benefits of individual technology improvements must be jointly specified with an explicit dependence structure. (3) The returns to R&D are often only realized over long time horizons; therefore, to fully account for the benefits of R&D investments, benefit estimates must also consider both short-run and long-run benefits. (4) The returns to R&D are ex-ante highly uncertain[3], making the estimation of the benefit of a single R&D program, let alone an entire R&D portfolio, challenging. The estimation of technological improvement benefits, therefore, requires significant technological assumptions, including an explicit representation of uncertainty with the best information available at the time. Accounting for uncertainty in the returns to

[3] Uncertainty in the returns to R&D are well-documented, with a particular strain in the literature emphasizing the skewed distribution in the returns to R&D investment (5, 6). It is also well-known that uncertainty in the returns to R&D is a feature of the R&D investment problem that makes it distinct from other investment problems (7). This uncertainty can be due to: complementary and substitute technologies leading to inter-technology dependent or “recombinant” uncertainties (8), the public goods nature of the information outcomes of R&D leading to spillovers between R&D investments by different (public/private) actors (9–11), and contingencies on other exogenous factors, such as fundamental scientific uncertainty and unpredictable macroeconomic conditions.

R&D is important because additional variance may either increase or decrease the value of conducting R&D (12, 13). Further, technological improvement benefit estimates should be developed in a framework of common assumptions. Importantly, the conditions under which uncertainty is estimated should be consistent. For example, if estimates of the uncertain technology improvement benefits in one technology area are made conditional on a specified level of economic growth, estimates for the benefits of other technologies should be made with the same condition.

*Criterion 2. Benefits to society of R&D investments must be evaluated in a common framework*

The second criterion we propose is based on the prerequisite that fair consideration of R&D tradeoffs requires a common framework for comparing benefits. Therefore, while initial technology improvement benefit estimates need not necessarily be expressed in common units, the ultimate metric for evaluating tradeoffs between investments—the societal benefits—should.

To make well-informed R&D allocation decisions, a decision-support tool must consider how the benefits of improvements in individual technologies interact (as substitutes or complements). Therefore, the benefits to society need to be estimated using a single framework to calculate the aggregate benefits of a suite of R&D investments. Under Criterion 1, we discussed the importance of considering the dependence between technological improvements, but it is similarly important to consider the dependence between the benefits of different technological improvements due to the fact that benefits of technological improvements depend on how technologies interact in satisfying demand in markets. These interactions may be positive, as is the case with the complementary role utility-scale energy storage can play with renewable technologies like wind and solar power, or they may be negative, as is the case with substitute technologies like efficient internal combustion engines and electric vehicles.

Finally, the common framework for evaluating benefits must be able to accommodate the technological improvement benefit estimates as described in Criterion 1. In other words, a common framework to evaluate societal benefits should be able to incorporate technology improvement benefit estimates conditional on R&D levels, dependence between technological improvements, sufficiently long time horizons, and explicit representations of uncertainty.

*Criterion 3. Benefit analysis should be flexible to changing assumptions*

The third criterion we propose results from the need for a decision support tool to be relevant as technological characteristics improve over time and exogenous policy decisions are made (such as setting aggregate R&D budget levels or enacting policies that complement R&D). We propose that an R&D

support tool should be made flexible to changing assumptions, allowing decision makers to update assumptions with the latest available information without reinventing the framework for analysis.

Flexibility to changing assumptions also has the added advantage of allowing decision makers to directly test the effect of assumptions by systematically varying inputs and comparing results. In the context of many R&D policy making organizations, managers of individual technology programs may hold different subjective beliefs about the benefits of an R&D program. The ability to adjust to different sets of assumptions allows for sensitivity analysis and can help focus internal deliberations on specific differing quantitative assessments rather than abstract debates about biases of individual managers[4].

*Criterion 4. Transparency in developing assumptions and analytical methods should be feasible*

The fourth criterion we propose is motivated by the institutional feasibility constraint that most R&D decision making organizations face to build procedural legitimacy both internal and external to the organization. One of the most important factors in developing procedural legitimacy in this context involves managing the transparency of inputs and methods used to support decision making. Within an organization, transparency can help build credibility of estimates from managers competing for the same pool of funds who might otherwise doubt the unbiasedness of estimates from others.

Transparency in how assumptions are developed and used can also help build procedural legitimacy, public credibility, and therefore, political support. However, public transparency often expands the scope of what a decision-making organization is accountable for. Transparency can make the process of developing quality assumptions that feed into the decision making process incentive incompatible if decision makers are held accountable for the realization of their estimates and react by systematically offering overly-conservative estimates. Further, full transparency can also create concerns about reputation loss, leading to similar bias. Lastly, public transparency can preclude the inclusion of proprietary information in developing benefit estimates, which can similarly lower the quality of estimates. Therefore, we conclude that a process to support R&D decision making must be *feasibly transparent* without prescribing whether or not the process must be both publically and privately transparent.

[4] The advantages of using a credible and transparent model in a decision making process that involves technical knowledge held by interested parties is notably discussed in the context of the Montreal Protocol and the use of the RAINS model during the negotiations (14–16). By agreeing on methodology prior to the introduction of technical assumptions, parties build credibility.

Table 1. Summary of the four criteria and their components for an R&D decision making process

| **Criteria** | **Components of Criteria** |
|---|---|
| 1. Technology improvement benefits prospectively quantified with a full account of uncertainty | • Technology benefits estimated conditional on R&D levels<br>• Dependence between technological improvements modeled<br>• Benefits over different time horizons considered<br>• Uncertainty in technology benefits of R&D modeled explicitly and estimated under common conditions |
| 2. Societal benefits evaluated in a common framework | • At least one societal benefit evaluated with common units<br>• Dependence between R&D benefits modeled<br>• Accommodation for details of how benefits were estimated |
| 3. Flexible to changing assumptions | • Flexibility to update for technological change<br>• Flexibility to update for policy changes<br>• Capability for sensitivity analysis |
| 4. Feasible transparency | • Transparency of assumptions<br>• Transparency of methods |

**Current Public Energy R&D Decision Making Evaluated Along 4 Criteria**

The well-known environmental (17), economic (18, 19), and security (20) challenges in the energy sector have been used to justify a wide array of energy policies in many countries throughout the world, such as pollution regulations, targeted subsidies, and technology standards. In order to be dynamically cost-effective, these policies require complementary technology policies (21–24). One of the most important forms of technology policy is government funding for energy R&D to support innovation projects that would not otherwise attract sufficient private investment. Toward this end, DOE has allocated approximately $5 billion per year for energy R&D since 2009 (25), making it the single largest energy R&D funding entity in the United States and the largest public energy R&D funding entity of all member countries in the International Energy Agency[5] (26). Nevertheless, several expert panels have called for greater U.S. government spending in energy R&D (27–31). (See SI for a summary of these studies).

At DOE, R&D investments are allocated in a three-step decision process. First, individual program offices at DOE submit budget requests supported by lengthy justification documents (see for example, (32)). These justifications are based on self-evaluations by program managers of the expected returns of the funding that is requested. Second, these justifications are scrutinized by analysts at the Office of

[5] IEA member countries are largely the industrialized country members of the OECD and the countries with the most reliable data for this metric.

Management and Budget (OMB), who evaluate the self-reported estimates and modify recommendations based on higher-level Executive Branch priorities. And third, the recommendations are sent to Congress where decision makers finally decide on the total level of energy R&D funds and its allocation to different technology areas.

In terms of all four criteria, current decision making within DOE, OMB, and Congress falls substantially short. In terms of the first criterion, while benefits of R&D programs are estimated conditional on R&D levels—and are occasionally considered over different time horizons—current practice does not explicitly consider the dependence in improvements between technologies nor the uncertainty in the benefits of R&D (33). Current government requirements in the United States require that DOE submit annual estimates of its program's benefits through the Government Performance and Results Act (GPRA). Yet despite robust evidence that uncertainty is a defining characteristic of R&D investment, it is neither legislative requirement (e.g. through GPRA) nor standard practice (e.g. in DOE budget justification documents) to quantify or assess the uncertainty in the benefits of R&D programs.

In terms of the second criterion, current practice has significant room for improvement. DOE's analytic strengths are rooted in its deep knowledge of R&D programs. Its comparative advantage in the three-stage decision-making process is in understanding how its R&D programs work, and therefore, DOE possesses unique information that can be used to estimate the future performance of its R&D programs. The structure of DOE makes it such that its program managers and analysts specialize in a limited range of technologies. Because of this structure, in the first stage of the process described above, justification to support funding requests is typically constructed project-by-project, program-by-program, or office-by-office, with little effort to standardize assumptions or reporting metrics. In other words, evaluation of R&D programs is done individually rather than holistically. For example, individual technology program offices (e.g., Office of Fossil Energy, Office of Nuclear Energy, Office of Energy Efficiency and Renewable Energy) often use different methods and a different set of underlying assumptions to estimate the future benefits of their office's R&D investments (34). As a result, recent observers have characterized DOE decision making as "being badly 'stovepiped,' meaning that the various offices and programs poorly communicate with one another" (35), and needing a strengthened "integrated policy assessment capability" that integrates the "analysis capabilities housed in each major program area." (36) To this end, in late 2013, the Secretary of Energy announced a new restructuring plan for DOE that will include an Office of Energy Policy and Systems Analysis.

To improve the credibility and political buy-in to its decision-making process, DOE also faces the challenge of integrating a wide array of technical assumptions and models promoted by various stakeholders (33, 37). As an example, DOE employs over 130 different quantitative models to calculate benefits of R&D program in its various program offices (38). This creates a relative weakness in current practice in assessing the benefits of DOE's holistic R&D portfolio, making it poorly equipped to evaluate tradeoffs between R&D programs—to account for the complementarities and substitutabilities between technologies in the design of the R&D portfolio. Precisely because DOE's expertise is so specific and siloed, its budget justification documents contain very little information to help policymakers assess the ***relative*** merits of R&D programs, leaving decisions to be informed instead based on disparate one-dimensional estimates of benefits that do not take into account the outcomes of simultaneously-occurring decisions.

In terms of the third and fourth criteria, current practice does not make its assumptions transparent. In turn, making it infeasible to determine if current benefit estimates are flexible to changing assumptions or capable of sensitivity analysis. In current practice, the technology assumptions used to estimate the societal benefits of individual technology programs often come from anonymous scientists or other experts within the DOE program offices, raising questions about the independence and transparency of these benefit estimates. So long as program managers benefit from additional funding, they may suffer from motivational bias and are incentivized to overestimate the effectiveness of their programs to increase the funding they receive. This sets up an adversarial "arms-race" in estimating the effectiveness of one's own R&D programs, creating a systematic bias in self-reported effectiveness. Depending on the relative benefits to a program when it overstates the effectiveness of its programs when all other programs also overstate their effectiveness, this could set up a Prisoner's Dilemma or a Deadlock game theoretic scenario, both of which predict a Nash Equilibrium to always overstate one's own effectiveness[6]. Because decision-making at the DOE (and analogous institutions in other countries[7]) is "stovepiped," technical estimates of the effects of R&D are often perceived as not credible. In many institutional settings, this leads to an erosion of trust among technical experts internal to R&D programs who hold

[6] Add in stylized game theoretic explanation: two player game, can estimate own benefits in one of two ways: unbiased or overly optimistic. Payoffs depend on relative benefits determined by a decision maker who allocates funds to the player with higher estimated returns

[7] A review of government agencies tasked with the role of creating strategic plans to promote technology innovation in the energy area in a few key countries in the world conducted by this work's authors shows that the U.S. government is not alone in failing to account for technology uncertainty and the market interactions of energy technologies. It is also not the only agency in this arena that does not utilize consistent, transparent, and independent technology assumptions as inputs into the decision making process.

detailed knowledge about specific portions of the R&D portfolio and between these experts and their funders in Congress. Without trust and a transparent integration process, including the knowledge held by internal experts across technology areas is more difficult.

At each level in the three-step public energy R&D decision making process, the technical expertise and capability for sophisticated technology analysis declines as the holistic review responsibility increases. The current process lacks integrative analysis that considers tradeoffs between programs to the detriment of its overall investment portfolio's effectiveness. In the past five years, DOE has experimented with implementing systematic approaches to evaluating R&D investments across its program offices (39), which could improve performance along criterion 2. However, these efforts have not been institutionalized, which we posit is a result of a lack of flexibility and transparency (performance along criteria 3 and 4). In the most recent budget cycles, despite requests from OMB for greater use of evidence to support agency budget submissions (40), DOE has conducted essentially no comparison of the expected benefits of its technology programs (34).

**A Methodology to Support Decisions about Public R&D Portfolios that Meets the 4 Criteria**

Understanding the strengths and weaknesses of current practices at DOE (which hold true in many other public R&D funding agencies), we propose a methodology to generate decision-relevant inputs to the R&D decision making process that satisfies the four criteria we propose. We realize that R&D funding allocation at DOE (and in nearly all other cases) incorporates many practical implementation realities, and therefore, no one approach can be used in isolation to make funding allocation decisions. Nevertheless, we propose a methodology that we believe can assist decision making and be feasibly implemented given DOE's institutional context.

Our method has three components: (a) expert elicitation to transparently parameterize technical estimates of the uncertain impacts of R&D on intermediate outcome metrics in a way that avoids motivational biases; (b) integration of intermediate outcome metrics in a well-known and publically-available bottom-up economic assessment model to quantify the benefits of an R&D portfolio; and (c) a notion of optimality that suggests at least one benefit metric to maximize used to calculate the set of optimal portfolios of R&D resource allocations under different policy scenarios. A graphical sketch of our methodology is illustrated in 6 steps in Figure 1 using public R&D investment in vehicle and storage R&D as an example.

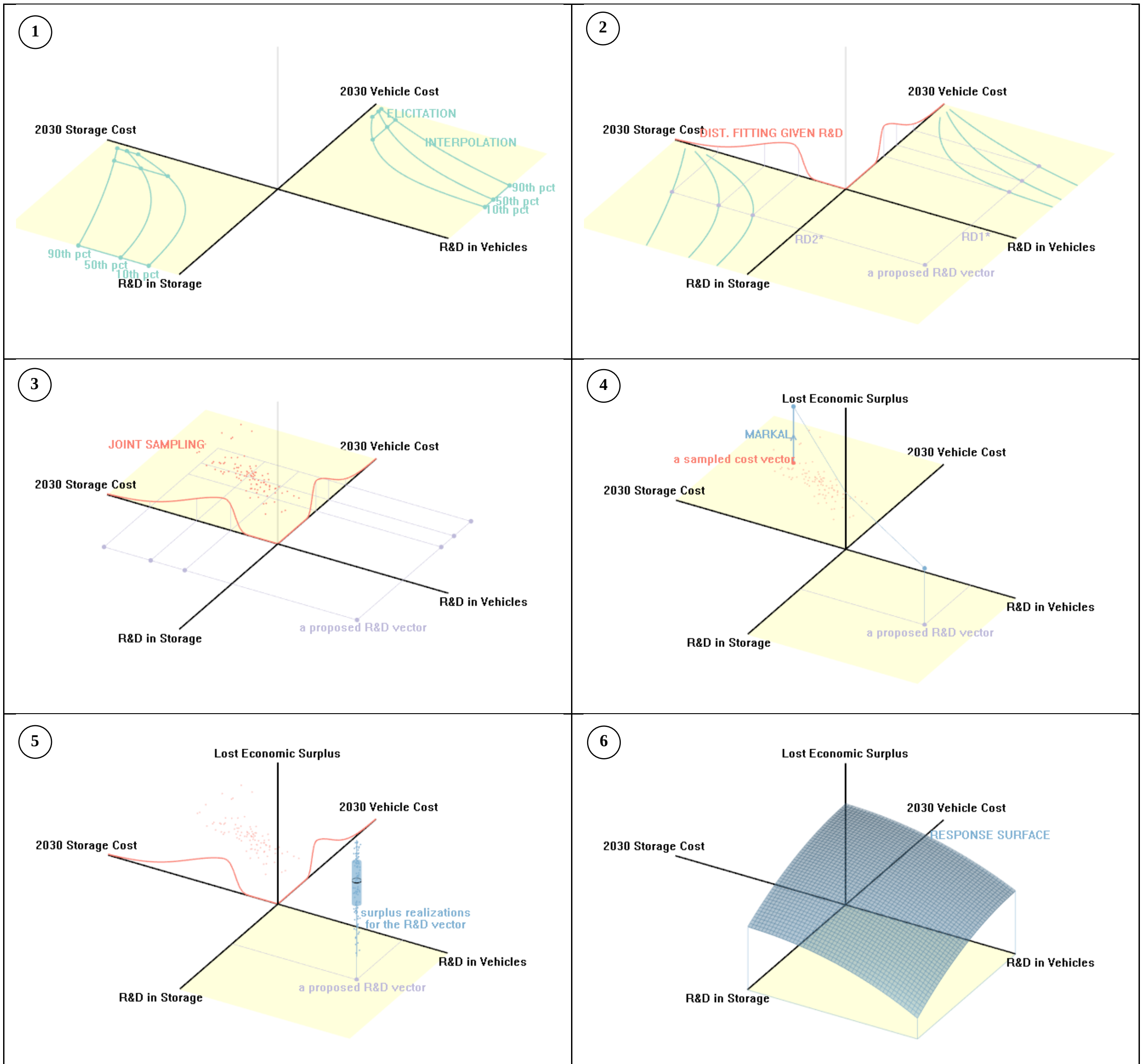


**Figure 1. Methodology sketch**. This figure is a schematic depiction of the methodology we apply in this paper using two technologies (energy storage and vehicles) as examples. From the top left, moving horizontally, (1) the expert elicitation provided estimates of the 10$^{th}$, 50$^{th}$, and 90$^{th}$ percentile of technology costs in 2030 under three R&D scenarios – these are shown with the green points in the R&D funding – technology cost space in yellow; (2) for a given R&D funding level in the two areas, RD1 and RD2, shown by the purple line perpendicular to the R&D axes, we interpolate the elicited 10$^{th}$, 50$^{th}$, and 90$^{th}$ percentiles of technology cost and then fit a three-parameter probability distribution to the percentiles for both storage and vehicles, shown in red; (3) we then sample from the joint distribution of technology cost, utilizing a dependence structure in future technology costs – samples are shown as red dots in technology cost–technology cost space; (4) for a vector of technology costs, we estimate aggregate outcomes from the two R&D investments, such as economic surplus, using MARKAL – the blue line perpendicular to the storage cost—vehicle cost plane shows this relationship; (5) with Monte Carlo sampling of various storage-vehicle technology cost combinations we can estimate the distribution of aggregate outcome metrics, as shown with the blue box plot; (6) we also use an importance sampling

technique to develop a response surface that approximates the *expected* outcome metric for a vector of R&D levels for storage and vehicle technologies, which we can then optimize over more easily – the blue surface shows the approximated economic surplus over the full space of feasible R&D investment portfolios in those two areas.

*Criterion 1*

Our method satisfies criterion 1 by using expert elicitation to quantify the returns to R&D. The expert elicitations that we utilize allow us to parameterize conditional probability distributions of the returns to R&D from 2010 to 2030 (over 20 years) for different R&D levels. These elicitations are unique in that they covered a wide range of energy technologies and were collected as part of a single study (34), allowing us to control for the same set of exogenous conditions. We also explicitly model a dependence structure between these conditional distributions to capture co-variation in the returns to R&D.

There is a considerable literature estimating the ex-post returns to R&D (see (41) for a survey), accounting for uncertainty, with a particular strand grappling with the question of attributing technological change to specific R&D projects (42). However, there is a more limited literature on methods to quantify the *ex-ante* returns to R&D, which are precisely the quantity necessary to inform R&D portfolio design. Methodologies to quantify uncertainty depend on the source of information being utilized, and there are three general classes of information proposed in the literature: (1) historic data (43, 44); (2) data on early stage, “precursor” indicators or technologies (45–47); and (3) data from technology experts.

To collect data from technology experts, the method we present in this paper utilizes data from a set of six large expert elicitations covering 25 technologies conducted in 2009 – 2011 (34). Recent research has shown that technical experts are able to consider and quantify the outcomes of R&D programs (48) and even parameterize probability distributions of outcomes (49–60). Data from technology experts has distinct advantages as an information source that feeds into a decision making process because technology experts can incorporate not only information that is publically available but also incorporate useful information that is unpublishable or proprietary. Experts also have the distinct advantage of being able to integrate historical information with specific detailed knowledge of current technical knowledge that more reductionist approaches would miss. Data elicited from technology experts allows for the possibility that technologies may advance through new pathways that endogenously depend on current decisions or in ways supported by only the most recent information. Finally, expert elicitation, formalizes the process of collecting the informed beliefs of individuals by seeking to correct for well-known cognitive biases (61) that less-formal expert consultation processes, such as advisory committee reporting, are subject to.

Expert elicitation is a structured and systematic process for collecting and assessing probabilistic estimates from individuals with particular expertise of interest (62). This method differs from surveys in that individual responses are not treated as observations from a single population, but rather as representative of a large body of knowledge. Therefore, the goal of developing a group of experts to participate in an expert elicitation is on the quality and diversity of expertise, not on the quantity of participating experts (62). To avoid unwanted interactions between experts that would obscure the true diversity of judgments (63), experts were elicited individually rather than in a group setting, as they would be in a Delphi process or expert consensus method (64).

*Criterion 2*

Our method satisfies criterion 2 by estimating aggregate benefits of an R&D portfolio by incorporating estimates of the technology improvement benefits to R&D investments in various technology areas in a single model of the U.S. energy economy. We chose an economic model with sufficient technical detail so that we could accommodate the details of how the benefit estimates were generated. In fact, our expert elicitations were designed for the explicit purpose of incorporating their results in the model we implement. The economic model allows us to evaluate societal benefits on a common set of metrics while also accounting for the interactions of technologies in satisfying market demand.

After expert elicitation of the impact of public R&D investments on future technology cost and performance, we generate estimates of the societal benefits of an R&D portfolio by introducing these estimates in the MARKAL model, a publicly-available energy-economic model with institutional buy-in from many government agencies in the United States and elsewhere, as well as from international organizations (e.g., the International Energy Agency). The model we use allows us to integrate the results from the suite of expert elicitations in different technology areas in a transparent framework with its own assumptions that can be individually assessed to estimate different societal benefits of interest (e.g., $CO_2$ emissions, energy costs, oil imports, etc.). Importantly, our method separates the technical estimates of the effects of R&D from the estimation of societal benefits.

Our method avoided the motivational bias that occurs in the DOE decision making process when self-interested program managers generate technical estimates by instead utilizing experts both external to DOE (experts from academia, venture capital investors, and private sector managers) as well as internal to DOE (current and former program managers and National Lab experts) . We propose that the incentive to systematically overstate the effect of one's own program could be removed from the process by elevating the use of independent experts who do not benefit from increased R&D funding. If our method were to be implemented in the context of the DOE, we propose that independent experts either serve as primary sources of technical assumptions or as checks to program managers.

*Criterion 3*

Our method satisfies criterion 3 by using an importance sampling technique, which allows us to flexibly update the technical assumptions of the study without repeating the prior steps of the method. We also introduce different policy scenarios in MARKAL to explore further sensitivities to a variety of climate policy scenarios.

Our importance sampling methodology allows us to readily adjust for changing input assumptions—such as different R&D levels in the different technologies in the portfolio—without requiring additional model runs, thus solving a computational constraint faced by many decision-making entities that would otherwise be only able to evaluate a small number of proposed R&D portfolios[8] (39). Additionally, our method's flexibility to different input assumptions is particularly desirable to test the sensitivity of results to assumptions from different sources (e.g., more optimistic experts, experts internal to the decision making process vs. experts from stakeholder groups, experts from different countries, etc.)[9]. In a political environment, insights from the tool that we develop may be useful because they help identify the implications of different technical and modeling assumptions and allows for a more consistent consideration of the tradeoffs between investing in different technologies.

The decision making component of our method uses the importance sampling technique to estimate the benefits of a wide range of possible R&D portfolios, interpolates these estimates, and estimates the optimal R&D portfolio (on a single outcome metric, such as economic surplus) for a given R&D portfolio. The details of this component of our method are described in the Methods section and the S.I.

*Criterion 4*

Our method satisfies criterion 4 by using a publicly available economic model and explicitly representing conditional distributions of the returns to R&D in a way that could be easily communicated to actors external to the decision making process. The names of the experts that contributed to the estimates of the impact of public R&D on future technology cost and performance are also public (34).

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[8]As stated earlier, in practice there is also an earlier problem, because decision-making entities do not estimate the benefits of a single portfolio of R&D investments due to difficulties building internal trust and buy-in, achieving external transparency and consistency, and consistently incorporating with uncertainty.

[9] Anadon, et al., 2013 compare three similarly-designed expert elicitations in nuclear energy and investigate how expert backgrounds and elicitation designs affect the outcomes of expert elicitations (65).

The flexibility in our approach to changing assumptions can be capitalized on to mitigate incentives to misreport and to adjust the level of transparency as appropriate for the decision making context.

**Results**

*Evaluating the benefits of a single R&D portfolio*

The expert elicitation studies asked experts to assess the distribution of technology costs under a range of R&D funding scenarios. We use these results as an input in estimating the distribution of outcome metrics (such as $CO_2$ emissions, economic surplus, oil imports, etc.) under specific R&D portfolios. In Figure 3, we show an evaluation of a business as usual (BAU) R&D portfolio of the six energy technology areas that we consider (solar photovoltaics, nuclear power, fossil energy with and without carbon capture and storage, advanced vehicles, utility scale energy storage, and bioenergy) using the suite of expert elicitations and our strategy for incorporating estimates into the MARKAL model. These results perpetuate current R&D investment allocations and levels using perspectives of the "middle"[10]. The SI contains the data underlying this figure as well as estimates of other outcome metrics (e.g., oil imports, and $CO_2$ prices). The results presented in Figure 2 highlight the ability of our method to quantify the uncertainty along the dimension of an evaluation criterion for different R&D portfolios. The Figure allows the estimated distribution of a particular evaluation criterion for different individual R&D portfolios to be assessed and compared as part of the R&D portfolio decision making process (66). For example, the results in the top figure show that the recommended R&D portfolio reduces the median projection of annual $CO_2$ emissions by 46 million metric tons relative to the BAU portfolio in 2030 and by 253 million metric tons in 2050. Note that even with the recommended R&D portfolio, without additional limits, our results project that $CO_2$ emissions will rise by 7% between 2010 and 2020, missing the stated goal of President Obama (67) by a wide margin. The results in the bottom figure show that the median projection of annual economic surplus is $28 billion higher in 2030 and $54 billion higher in 2050 with the recommended R&D portfolio relative to the BAU portfolio. Given that the recommended R&D portfolio has a budget $3.4 billion per year greater than the BAU portfolio, the recommended portfolio has positive and increasing net social benefits. We also find that the variance in projected economic surplus in 2030 and in 2050 is statistically greater with the recommended R&D portfolio than in the BAU

[10] "Middle" experts for each of the 6 technology areas were selected by evaluating which expert in each area had central (50$^{th}$ percentile) and uncertainty range ([90$^{th}$ percentile - 10$^{th}$ percentile]/50$^{th}$ percentile) estimates of future technology costs that that fell at or near the average values of central and uncertainty range estimates of all experts in their area. Selection of "middle" experts was made without considering the expert's R&D funding recommendation. This selection was also vetted with 23 "higher level" qualitative reviewers. (34)

case (F-test for difference in variances has p-value = 0.001 for 2030 surplus projections and 0.01 for 2050 surplus projections).

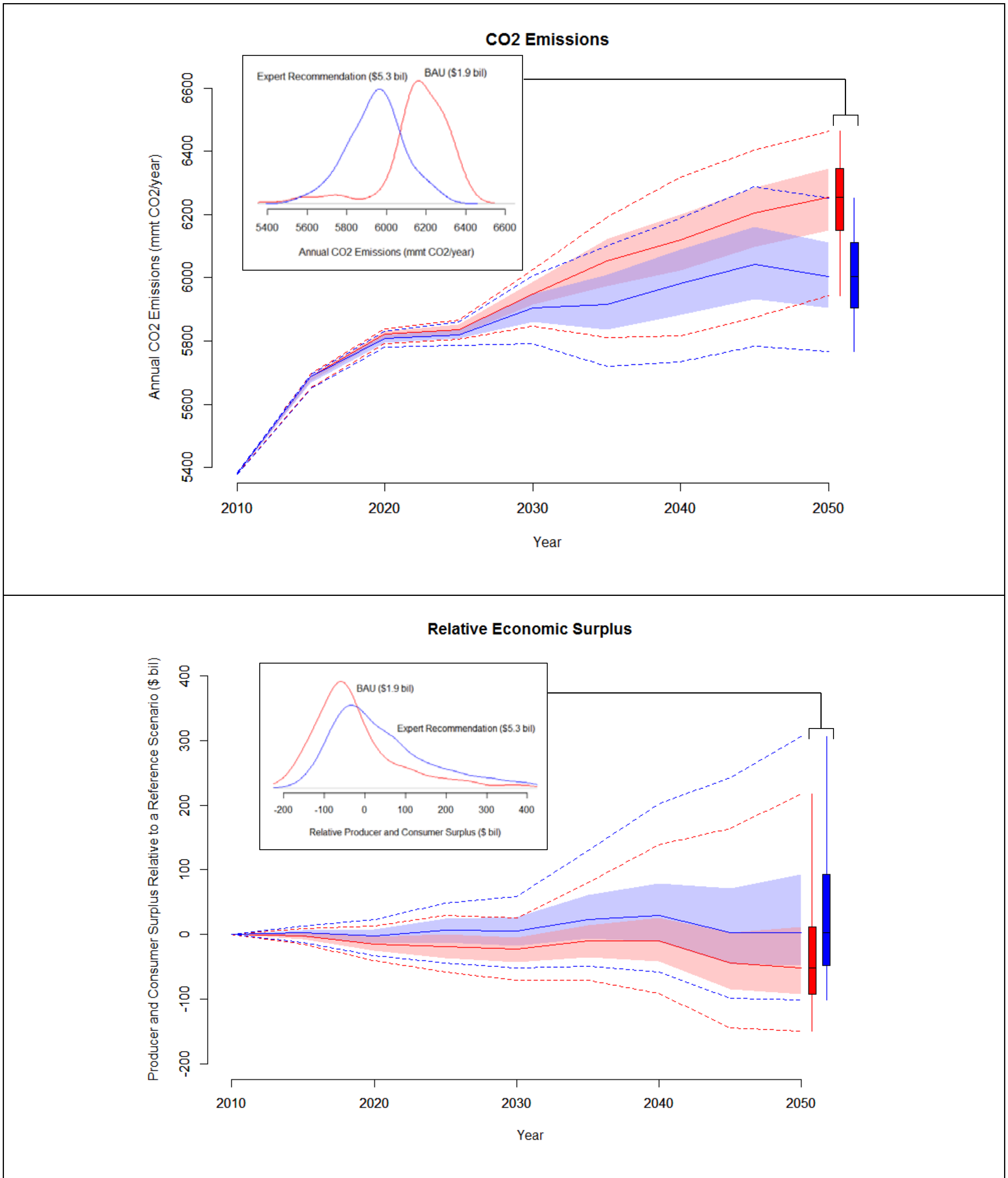


**Figure 2.** Results of societal benefit estimation of individual R&D portfolios using two different metrics:

Top panel: U.S. energy CO2 emissions; Bottom panel: change in consumer and producer surplus compared to a reference scenario. In the main figures, the dotted lines are the estimated 90% probability intervals and the lightly-shaded regions are the estimated 50% probability intervals from 400 Monte Carlo samples. The blue lines/regions show projections under the business as usual R&D funding portfolio, whereas the red lines/regions show projections under the expert-recommended R&D portfolio.

*Supporting decisions about the aggregate R&D funding level and its allocation*

We are able to estimate the mean of all outcome metrics for any R&D portfolio within the bounds of the elicited range of R&D investments—without re-soliciting input from the experts. We capitalize on this strength by estimating the R&D portfolio that maximizes the expected value of economic surplus (the evaluation criterion we use for this example), subject to a budget constraint. As mentioned earlier, there are often more than one policy goal at play when making decisions about energy R&D, leading to more than one criterion, but our method can be easily applied to estimate the optimal R&D portfolio along other dimensions beyond economic surplus, such as reducing oil imports or reducing carbon emissions. We conduct this optimization first under a no-policy scenario and then again in a scenario that includes market-based climate regulations to reduce annual $CO_2$ emissions by 83% from 1990 levels by 2050, comparable to the ambition of U.S. bill H.R. 2454, known as the “Waxman-Markey” bill[11]. The results of our analysis under these policy scenarios are shown in Figure 3. Our results yield four main insights about the optimal allocation of R&D resources across the six technology areas that we investigate.

[11] The Waxman-Markey goal and the 2020 Obama Administration were actually expressed in terms of reductions in all greenhouse gases. Tthe line shown in Figure 2 and the policy implemented in MARKAL assume a proportionate decrease in domestic $CO_2$ emissions, which is not necessarily implied by the two policy goals, as stated.

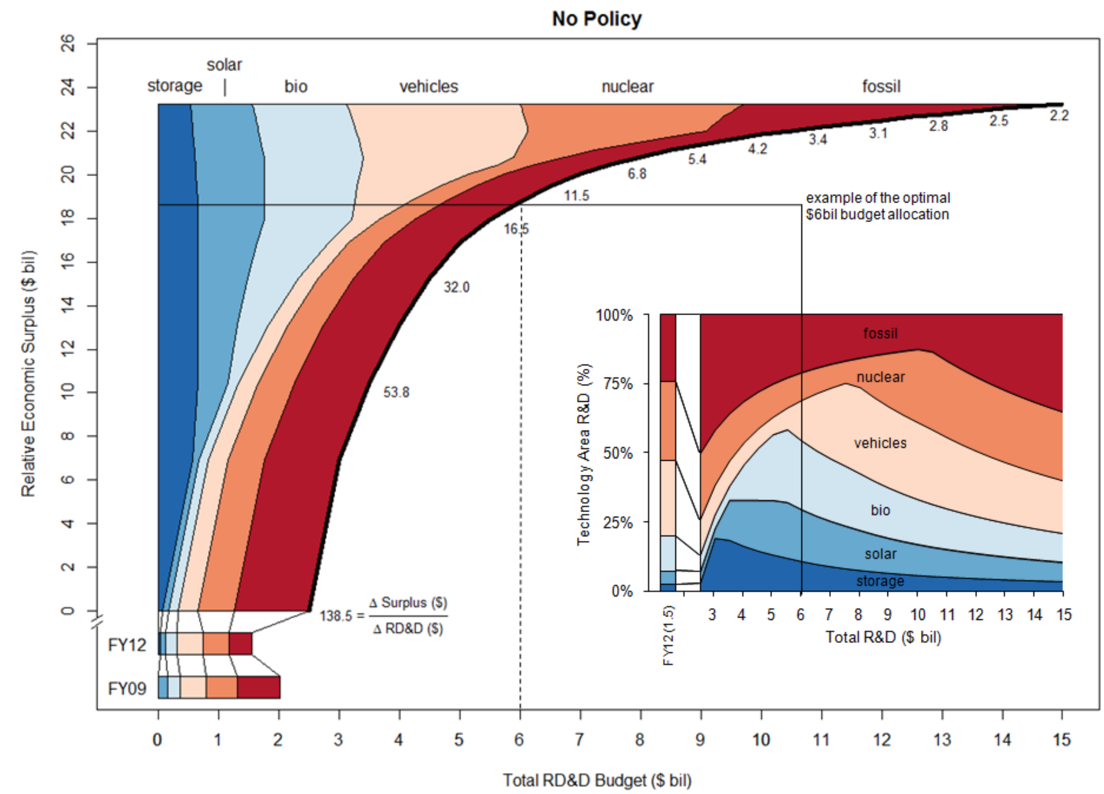


**Figure 3.** Optimal R&D portfolios under no policy. The figures show the allocaiton of R&D funding at different R&D budget constraints between $2.5 billion - $15 billion per year, relative to the Fiscal Year 2009 R&D budget allocation. The dark black line in the main plots is the maximum expected increase in economic surplus (above the an arbitrary reference point: the expected surplus in the optimal allocation for the $2.5 billion budget) that can be attained under a given R&D budget constraint. The small red numbers along the black line are estimated marginal returns on investment, calculated by linear approximations to the derivative of the optimal expected surplus at different budgets.

First, there are decreasing marginal returns to R&D. Under both policy scenarios, the incremental return to economic surplus from R&D investments is substantially higher at low levels of R&D than at high levels. In the no policy case, we estimate that the incremental returns to R&D when $2.5 billion in R&D funding is allocated optimally is $139 in economic surplus for each dollar of R&D funding; in the carbon policy case, we estimate the incremental returns to be over $80 in economic surplus for every dollar of R&D funding under a $2.5 billion budget. We find monotonically decreasing marginal returns to R&D over the full range we consider. Even though our results consider only a subjectively-defined “feasible range” of total R&D budget for the six areas considered bounded by the estimates of the expert R&D scenarios, we still estimate that there are positive expected returns to R&D even at the highest end of the range of R&D budget levels that we consider. This result implies that there are R&D portfolios with total budgets greater than $15 billion (10-times Fiscal Year 2010 levels) that can be justified solely on expected gains to economic surplus. The pattern of decreasing returns to R&D at increasing budget levels, if extrapolated to budgets beyond the range we consider, implies that our methodology would allow an identification of an optimal R&D level beyond $15 billion at which the expected marginal benefits (based on the economic surplus metric) equal the cost of R&D investment. Figure 3 shows that the current level of investment, $1.5 billion, is well below the optimum level justified by the expected benefits to economic surplus under both policy scenarios.

However, increases in economic surplus is only one of the benefits that can be expected from energy R&D (i.e., there are also indirect benefits to energy R&D, such as increased national security, decreased health costs, improved biodiversity, etc.). Therefore, the current degree of underinvestment is likely to be even greater if we include energy R&D benefits beyond expected economic surplus. In addition to changing the optimal *level* of investment, it is also important to note that the introduction of other objectives would also alter the optimal investment portfolio *allocation*.

Second, carbon policy changes the investment mix (under equivalent assumptions and still with economic surplus as the optimization quantity); however, with only a few notable exceptions, these changes are minor relative to the allocations of R&D funding at different budget funding levels within the same policy scenario. We find remarkable stability in the optimal allocation of R&D funding for most R&D budgets across policy scenarios, yet the optimal allocation of funding changes substantially with different funding levels, implying that there are general high-priority R&D technology areas. The most notable difference between the no policy scenario and the carbon policy scenario is that optimal investment would give a greater allocation towards fossil technologies in the carbon policy scenario. This is due to the fact that carbon capture and sequestration technology is deployed broadly in MARKAL in the carbon policy scenario.

Third, there is a distinct prioritization of R&D investments by technology area that appears to be robust across policy scenarios. We believe that this is due to the low current investment levels in these technologies and the high economic expected returns to R&D in these areas that are independent of policy. At the lowest R&D budget that we consider, the optimal investment mix is 50% fossil, 24% nuclear, 13% vehicles and 3-6% storage, solar, and bioenergy.[12] As the R&D budget expands, the optimal

[12]The reason why the fraction dedicated to fossil energy R&D is so large is that the BAU R&D scenario had $2.5billionin the fossil energy category and that most experts recommended high levels of R&D for fossil energy (see Figure 1). The reason for this is likely to be that the technology is largely believed to be in the demonstration phase, which requires large sums of capital to have any chance of any progress being made.

allocation shifts from these technologies first towards energy storage, then to solar energy, then to bioenergy, then to vehicle technology, and finally to nuclear and fossil energy. Because there are also decreasing marginal returns in the optimally-allocated budget, this result also implies that as the R&D budget expands, the marginal returns to R&D investments in single technology areas are greatest for energy storage, solar energy and bioenergy – although this result depends on the assumptions that R&D investments are otherwise optimally allocated.  It is also worth noting that the MARKAL model, like many other widely-used energy-economic models, does not allow a full representation of the value of utility-scale energy storage (in particular, only its peak shifting ability was considered); therefore, the value of storage R&D is likely to be even larger than we are able to estimate.

Fourth, there are important differences between the DOE's R&D funding allocation and the results of our analysis of R&D budgets close to current levels. Comparing the current allocation to our estimated optimum for a $4 billion budget, fossil energy, energy storage, and solar photovoltaic technologies are underinvested in. This implies that to maximize surplus, current R&D programs should be reallocated towards these technologies. Of these three technologies, our analysis indicates that the technology area that would yield the greatest marginal return to economic surplus, given the current allocation, is energy storage.

The results presented in this section are fundamentally contingent on the experts participating in the study. These results relied on the assessment of the identified "middle" expert, but we repeated this analysis with the assessment of more pessimistic and optimistic experts, giving consistent results about the phenomenon of decreasing marginal returns and the existence of efficient optimal portfolios with budgets greater than $15 billion.

**Discussion**

The results and methods presented in this paper offer a means and ends to supporting decisions to allocate R&D funds across technology areas for technology managers and policymakers. Importantly, our method allows for a careful consideration of the inherent uncertainty in the returns to R&D, improving upon the current best practices at the U.S. Department of Energy. Further, our method integrates an assessment of a wide range of DOE energy R&D activities while satisfying the institutional constraints of the DOE that have prevented successful integration of its in-house and external expertise.

Public R&D investment decision making often is an ultimately highly-negotiated political decision. It is difficult for policymakers to make decisions about investment levels in technology areas when co-funded technologies compete in the market (substitute goods, an example of a negative complementarity) or when a breakthrough in one co-funded technology reveals new insights in another technology (a positive spillover, an example of a positive complementarity). In addition to this complexity, the large uncertainty in the returns to R&D raises the burden on very skilled policymakers without analytic support tools to sometimes insurmountable levels.

It is worth noting that the R&D budget allocation problem shares features that are common with many other scarce resource allocation problems in other areas of policy and private sector decision making. For example, the R&D budget allocation problem involves multiple criteria for assessment, the ex-ante evaluation of investments with uncertain returns, and multiple interested stakeholders. Therefore, the methods we develop in this paper are also relevant to policy makers and budget managers in other contexts.

Public R&D investment decision making, like many other policy areas, often can be characterized by the separation of analysis from decisions (68). With this separation, considering tradeoffs across R&D investments in different technologies relies on integrating analysis that is typically only conducted on a narrow ranges of technologies. The burden of integrating disparate analyses falls to the decision-maker rather than the analyst. Historically, it may have sufficed to make R&D investment decisions without considering tradeoffs, but modern R&D investment increasingly makes progress by working across previously-separated technology areas while also competing for the same share of market demand. Historical separation may also be due to the lack of methodical tools to integrate individual R&D assessments – the exact tool that we propose and demonstrate in this paper. We hope that this work will show the need for (and help) a new kind of analyst that exists between individual technology area analysts and policymakers who make decisions about cross technology area investment strategies.

The method that we propose in this paper is not designed to completely replace existing decision making processes. Instead, we hope that the type of integrative R&D analysis we propose can be used to complement efforts such as expert panels (e.g. AAAS, PCAST, APS), individual program analyses (GPRA), and single agents in key positions of power making decisions. Integrative analysis along the lines we propose can be mutually reinforcing with these other methods for designing R&D portfolios. In tandem, these methods can reveal new important areas for future extended study, test the credibility of prior beliefs, and help incorporate new or different data, information, and assumptions into existing decision making processes.

While our method improves on current decision making practices at the DOE, there are several possible improvements outside of the scope of this paper. Uncertainties at different innovation stages lead to dynamic time-contingencies. Most simply, the R&D portfolio decision can be modeled in a static and deterministic setting with the decision modeled as a one-shot choice. More recent work has emphasized the dynamic, or process nature of the problem and has analyzed capacity and congestion effects (69) as well as strategies for search and information gathering (70, 71). This implies the need to also consider the sequencing of R&D decisions as part of a dynamic R&D decision making problem (72). Aggregate R&D portfolio decisions may have differing impacts depending on the time profile of R&D investments. For example, the large increase and then decrease in NIH funding over the past decade may have been less effective than a slow and continuous increase (73), perhaps in part due to the short-run inelastic supply of scientific expertise (74). Embedding the optimization framework we present in this paper to a multi-period repeated decision making problem would allow R&D allocations to be updated based on interim outcomes. Such a framework would likely result in allocations favoring more risky technologies. This framework would capture a fundamental aspect of the R&D allocation problem but would also require additional analytical complexity (on top of a framework that is already quite complex).

A second future direction for this work could be to include other notions of optimization. Because MARKAL is a computationally-intensive model and conducting expert elicitations is time-consuming, we relied on an importance sampling strategy to be able to consider a wide range of possible R&D portfolios. Utilizing an importance sampling strategy allowed us to consider the expected value of R&D scenarios within the bounds of the parameters of the limited number of MARKAL runs that we conducted. However, higher moments, and indeed the entire distribution, of the returns to an R&D portfolio may be policy-relevant. For example, approaches from modern portfolio and real options theory emphasize the important role of the variance in individual investments in choosing an “optimal” investment package. Application of these approaches have also emphasized the importance of the interdependence of R&D projects due to cross-technology spillovers. (88–92) An approach that quantified the distribution of the returns to R&D could also consider other notions of optimality, such as minimax, which could be particularly applicable in highly risk-averse decision making contexts.

A third direction would be to address the challenge of multiple criteria for assessing the benefits of R&D that may depend on the different values of stakeholders as well as different technical assumptions. Decision makers may disagree on which criteria to use for assessing the benefits of an R&D program. To be inclusive, decision makers may wish to implement more than one decision making criteria simultaneously (e.g. carbon dioxide emissions, oil imports, and economic growth). There is a long literature in operations research on decision making with multiple outcome criteria, sometimes referred to as multi-criteria decision-making (MCDM) in Operations Research (16, 75, 76). There is also literature on directly connecting expert opinions to R&D decision making without the use of an intermediate model of outcomes (77, 78). The method presented in this paper can provide the necessary input data to support MCDM by providing optimal portfolios and societal benefits under different optimization criteria.

It is our hope that the main ideas of our approach could be used in real-world policy making. Demand for the type of analytic tool we have developed has been voiced by policy makers in China's Energy Research Institute at the National Development Reform Commission, South Korea's KETEP (Korea Institute of Energy Technology Evaluation and Planning), Mexico's Energy Secretariat, the U.S. Department of Energy, and the California Energy Commission. These policymakers have expressed a strong interest in adopting this method or versions thereof, and they have been briefed on its intricacies over the past three years by the authors.

Having said this, the literature on the role of scientific expertise in policy making indicates that in different political settings, different types of scientific claims are perceived as authoritative. While the U.K. system of seeking expert advice has been characterized as "informal and consultative", that of the United States has been characterized as "formal and technical", making it more prone to relying on quantitative assessment (79). Quantitative evidence has generally played a greater role in policymaking in the United States, while multi-party participation and (most importantly) the public's trust in the members of expert groups making policy recommendations has played a greater role in the United Kingdom(80). Finally, it is worth noting that the method we present in this paper may be applicable to other settings that consider allocating R&D investments, including public and private sector decision makers in agriculture, pharmaceuticals (81), and biomedical research (82).

## Methods

### *Expert elicitation*

We conducted an expert elicitation of over 100 experts in six technology areas (fossil energy, vehicles, energy storage, bioenergy, solar energy, and nuclear energy[13]) as part of a broader study on the political economy of energy R&D investments and institutions in the United States (34). Estimates were collected using six distinct written and online surveys administered between 2009 – 2011. Experts were

[13] We conducted a 7th elicitation on building technology, but we were not able to utilize the results of this elicitation in this paper due to implementation difficulties in MARKAL.

selected for this study based on their contribution to the peer-reviewed literature, national academy reports and equivalent, conference participation, and recommendation by other experts..

As in other technology forecasting expert elicitations (57), each elicitation instrument began with a technology primer based on a broad survey of the engineering literature in the technology area. These primers covered current technology cost and performance, fuel costs if applicable, and a summary of current government R&D investments in the particular technology area. Experts were then presented with an overview of how to reduce their bias and over confidence and to provide a detailed self-assessment of their expertise.  Experts were then asked to recommend a level of R&D funding and propose a specific allocation of these funds within the technology area, including a description of the particular issues that the funds would mean to address. Next, and most importantly for our study, experts estimated statistics of the probability distribution of specific technology costs in 2030 under four R&D funding scenarios (business as usual and three hypothetical R&D scenarios based on multiples of their recommendations). That statistics we elicited were the 10$^{th}$, 50$^{th}$, and 90$^{th}$ percentiles of the distribution of 2030 technology costs, our preferred statistics since they can be expressed in natural units more familiar to technology experts, unlike, say, cumulative probability. They were also asked to provide estimates of technical performance (e.g., solar PV conversion efficiency), although frequently these estimates asked for a best guess (a 50$^{th}$ percentile estimate).  Finally, each elicitation instrument included a suite of qualitative questions to better understand each expert's R&D strategy. In the end, our elicitations in six technology areas yielded cost estimates for twenty-five different technologies.

Another important component of our elicitations was the way in which we formalized the dependencies between technology costs. Because technological progress in one technology is likely to spillover to another (e.g. from grid-scale batteries for energy storage to batteries used in electric vehicles), we used our research group's expertise to construct a correlation matrix of 2030 technology costs for all twenty-five technologies. For many technology-technology diodes, we did not elicit a correlation and instead assumed that technology costs would be independent.

See S.I. and (34) for a more detailed description of the elicitations we implemented, the names of participants, and the raw results of the elicitations (34). An extract of the relevant results of the expert elicitations is presented in the SI.

*Benefit Estimation*

We parameterize the results from the elicitations to use as stochastic inputs in the MARKAL model, a detailed energy system model frequently used by government planners, called the MARKet ALlocation Model, or MARKAL. MARKAL is a bottom-up, partial equilibrium model of the U.S. economy that is specifically designed to represent technological evolutions of the physical energy system occurring over 30– to 50–year periods. MARKAL is solved as a cost minimization problem where future states of the energy system are determined by identifying the most cost-effective pattern of resource use and technology deployment over time, given exogenously specified energy demands (34, 83, 84). DOE and EPA have each developed their own versions of MARKAL for their in-house policy analysis. For our study we utilized a version of the U.S. multi-region MARKAL model maintained by Brookhaven National Laboratory, one of the main operators of MARKAL for DOE.

We use the distributions based on the expert elicitation to sample technology costs in 5-year time steps from 2010-2050. To investigate individual R&D portfolios, we draw Monte Carlo samples of technology costs, conditional on the specified R&D portfolio. In the results shown above in Figure 3, we use 400 samples from a single R&D portfolio to quantify the uncertainty in outcome metrics.

*Optimization*

The R&D portfolio decision making problem is a two-part problem to determine the optimal R&D budgetary funding *level* and the optimal *allocation* of R&D funds across technology areas or projects given the aggregate budget constraint. We implement novel sampling and optimization methods that estimate the optimal allocation of R&D investments at a range of budget levels. Optimizing the R&D investment portfolio to maximize total surplus gives an efficiency interpretation to some of our results. For portfolio optimization, under each of the three policy scenarios we consider we run 1,200 MARKAL runs from Monte Carlo samples of technology cost distributions under a wide range of R&D levels that cover the full range of R&D scenarios that we consider. We then apply an importance sampling technique that allows us to calculate the expected value of outcome metrics under specific R&D portfolios that we did not have to pre-specify. We apply the importance sampler to calculate the expected outcome in over 250,000 cases that span a wide range of possible R&D portfolios. The details of the importance sampler are described in the SI.

Next we fit a polynomial to the expected outcomes from the importance sampler and use a numerical optimization algorithm to calculate the R&D portfolio that yields the optimal outcome (e.g. highest economic surplus) for a fixed R&D budget. The details of the polynomial fitting and optimization algorithm are described in the SI. While we do incorporate the uncertainty in the returns to R&D programs in estimating the benefits of a single R&D portfolio, for analytical tractability, we optimize the portfolio on the expectation of the outcome metric.

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