Improving Decision Making for Public R&D Investment in Energy: Utilizing Expert Elicitation in Parametric Models

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Abstract Effective decision making to allocate public funds for energy technology research, development, and demonstration (R&D) requires considering alternative investment opportunities that can have large but highly uncertain returns and a multitude of positive or negative interactions. This paper proposes and implements a method to support R&D decisions that propagates uncertainty through an economic model to estimate the benefits of an R&D portfolio, accounting for innovation spillovers and technology substitution and complementarity. The proposed method improves on the existing literature by: (a) using estimates of the impact of R&D investments from one of the most comprehensive sets of expert elicitations on this topic to date; (b) using a detailed energy-economic model to estimate evaluation metrics relevant to an energy R&D portfolio: e.g., system benefits, technology diffusion, and uncertainty around outcomes; and (c) using a novel sampling and optimization strategy to calculate optimal R&D portfolios. This design is used to estimate an optimal energy R&D portfolio that maximizes the net economic benefits under an R&D budget constraint. Results parameterized based on expert elicitations conducted in 2009-2011 in the United States provide indicative results that show: (1) an expert-recommended portfolio in 2030, relative to the BAU portfolio, can reduce carbon dioxide emissions by 46 million tonnes, increase economic surplus by $29 billion, and increase renewable energy generation by 39 TWh; (2) uncertainty around the estimates of R&D benefits is large and overall uncertainty increases with greater investment levels; (3) a 10-fold expansion from 2012 levels in the annual R&D budget for utility-scale energy storage, bioenergy, advanced vehicles, fossil energy, nuclear energy, and solar photovoltaic technologies can be justified by returns to economic surplus; (4) the greatest returns to publicR&D investment are in energy storage and solar photovoltaics; and (5) the current allocation of energy R&D funds is very different from optimal portfolios. Taken together, these results demonstrate the utility of applying new methods to improve the cost-effectiveness and environmental performance in a deliberative approach to energy R&D portfolio decision making.

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

JEL Classification O32, O38, G11, Q48, D81

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Improving Decision Making for Public R&D Investment in Energy: Utilizing Expert Elicitation in Parametric Models[1]

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Abstract

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Introduction

The well-known environmental (IPCC, 2014), economic (IEA, 2011; WHO and UNDP, 2009), and security (Cherp et al., 2012) challenges in the energy sector have justified a wide array of energy policies, such as pollution regulations, targeted subsidies, and technology standards. In order to be dynamically cost-effective, these policies require complementary technology policies (Jaffe et al., 2005). 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, the U.S. Department of Energy (DOE) has allocated approximately $5 billion per year since 2009 towards energy R&D and basic energy science (Gallagher and Anadón, 2013).

Recently, under the heading of Mission Innovation, governments of 22 countries (and the European Union), representing more than 80% of global clean energy R&D funding, committed to doubling their R&D investments from 2015 – 2020. Allocating greatly expanded energy R&D budgets will require clarity about the goals of new R&D funds. Maximizing the probability of achieving such goals will in turn require a methodological approach to allocating funds across various clean energy technologies that systematically provides an analytic basis for assessing tradeoffs. The method presented in this paper offers one approach to supporting decisions to allocate public R&D funds across technology areas that complements existing frameworks such as comprehensive reviews of energy R&D activities (DOE, 2012), retrospective analysis (NRC, 2001), individual technology roadmaps (Geum and Park, 2013), and evaluations driven by the broader political landscape.

The method proposed and implemented here has several desirable characteristics that differentiates it from existing approaches in the literature: (1) it quantifies the anticipated improvement in technology in a way that fully accounts for the inherent uncertainty in the returns to R&D; (2) it systematically captures the interactions between R&D investments that can occur through technology spillovers or through market interactions of technology substitutes and complements, an important limitation of existing approaches (NRC, 2007a); (3) it is flexible to changing assumptions that are fundamentally subjective, such as belief distributions of the elasticity of future technology costs to current R&D investments; and (4) it is transparent, and therefore feasible to implement in public organizations that require transparency to build procedural legitimacy.

1.1 Current Process at the U.S. Department of Energy

DOE is 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 (which are largely the industrialized country members of the OECD and the countries with the most reliable data for this metric) (IEA, 2013). Nevertheless, several experts and expert panels have called for greater U.S. government spending in energy R&D (American Energy Innovation Council, 2010; APS, 2008; NCEP, 2004; Nemet and Kammen, 2007; PCAST, 2010, 1997) and U.S. political leaders have committed to greatly increasing energy R&D funds (Bodnar and Turk, 2015). Although past studies calls for additional resources to be devoted to energy R&D, none offer rigorous quantitative estimates of the expected benefits of their recommendations.

In current practice, despite the demonstrated interest of outside experts to affect DOE decision-making, DOE's decision making processes and tools do not systematically consider the benefits, and the uncertainty inherent in the benefits, of individual R&D programs or in aggregate (NRC, 2007b). Current U.S. law requires that DOE submit annual estimates of its program's benefits through the Government Performance and Results Act (GPRA). However, this program does not require DOE to consider uncertainty in its evaluation of R&D programs (NRC, 2007b), nor the interactions between the different technologies that the DOE's programs support . For example, many of the technologies that DOE R&D programs support may induce technological spillovers among them or compete in markets as either complements (e.g., utility scale energy storage and renewable technologies like wind and solar power) or substitutes (e.g., more efficient internal combustion engine vehicles and electric vehicles). Capturing these market interactions is essential for estimating the benefits of improvements in technologies in a way that appropriately accounts for available "next-best" and "enabling" technologies (NRC, 2007a). Therefore, the benefits calculated under GPRA requirements are likely to be biased. Further, to improve the credibility and political buy-in to its decision-making process, DOE also faces the challenge of integrating a wide array of non-transparent technical assumptions and models promoted by various stakeholders (NRC, 2007a; Silverman, 1981).

1.2 Design Principles for an R&D Decision-Support Tool

In this section four design principles for a decision-support tool that can feasibly and effectively improve public R&D portfolio design are proposed. While these principles are broadly applicable to R&D decision making in many contexts, they were developed based on a consideration of U.S. public energy R&D decision making and through iterative discussions with analysts involved in the DOE's policymaking environment. These principles are used 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 follow these design principles. The first two principles deal with analytical requirements and the second two principles concern institutional feasibility of implementing a decision support tool. Following a discussion of these principles, the remainder of the paper presents a method that follows the four proposed design principles and then examines the results of implementing it in the case of public U.S. energy R&D.

Principle 1: Quantifiable. *Technological improvement benefits of a decision must be prospectively quantified and account for uncertainty*

This paper differentiates "technological improvement benefits" of R&D, the change in cost and performance of technologies as a result of R&D, from "social benefits" of R&D, the changes in systemic policy objectives, such as aggregate economic surplus. Under Principle 1, technology improvement benefits are addressed; social benefits are addressed under Principle 2. The technology improvement benefits of R&D investments needed to support decision making should follow four sub-principles: (1) Relating technological improvement benefits to R&D investments requires specifying technological improvement benefits conditional on multiple levels of R&D investment; (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 (several decades); therefore, to fully account for the benefits of R&D investments, benefit estimates must also consider both short-run and long-run technology improvement benefits; and (4) The returns to R&D should account for uncertainty. In addition to these four sub-principles, technological improvement benefit estimates should also be developed in a framework of common assumptions. For example, if estimates of the technology improvement benefits in one technology area are made for one timeframe, estimates for the benefits of other technologies should be made with the same timeframe.

In U.S. energy R&D decision making, while benefits of R&D programs are estimated conditional on R&D levels—and are occasionally considered over different time horizons—current practice neither explicitly considers the dependence in improvements between technologies nor uses common assumptions to make the estimates across technology areas. Further, current practice does not consider the uncertainty in the benefits of R&D (NRC, 2007b), 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 otherwise assess the uncertainty in the benefits of R&D programs.

Principle 2: Comprehensive. *Social benefits of R&D investments must be evaluated in a common framework*

The second principle is based on the prerequisite that sound consideration of R&D tradeoffs requires a comprehensive framework for analyzing the social benefits of various R&D investments jointly and with common metrics. Therefore, while initial technology improvement benefit estimates need not necessarily be expressed in common units, a necessary condition to evaluate tradeoffs between R&D investments is that the ultimate metric for comparison—the social benefits—should be expressed in common units.

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). These interactions may be positive, as is the case with the complementary role utility-scale energy storage can play in smoothing out the intermittent supply of electricity from 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 that compete for the same market share. Therefore, the benefits to society need to be estimated using a single framework that allows the aggregate benefits of a suite of R&D investments to be estimated.

In terms of the second principle, current practice in U.S. energy R&D has significant room for improvement. DOE justifications to support funding requests are typically constructed project-by-project, program-by-program, or office-by-office, with little effort to standardize assumptions or reporting metrics. 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" (Cho, 2013), and needing a strengthened "integrated policy assessment capability" for the "analysis capabilities housed in each major program area." (Moniz, 2013) To improve the credibility and political buy-in to its decision-making process, DOE also faces the challenge of integrating the wide array of technical assumptions and models it has access to (NRC, 2007b; Silverman, 1981). DOE's 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.

Principle 3: Adaptive. *Benefit analysis should be flexible to changing assumptions*

The third principle 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). 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 conduct sensitivity analysis, directly testing the effect of different assumptions. 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 can help focus internal deliberations on specific quantitative assessments, or the choice of model and metrics to estimate social benefits, rather than abstract debates about biases of individual managers. Experience has shown that by agreeing on a flexible methodology prior to the introduction of technical assumptions, parties can build credibility (Parson, 1998).

Principle 4: Transparent. *Transparency in developing assumptions and analytical methods should be feasible*

The fourth principle 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 reliability of estimates from others. Transparency in how assumptions are developed and used can also help build external (public) credibility, and therefore, political support. However, public transparency can preclude the incorporation of proprietary information, which can lower the quality of technical estimates. Therefore, a process to support R&D decision making must be feasibly transparent but not necessarily actually both publically and privately transparent.

Current U.S. energy R&D decision making practice does not make its assumptions and process transparent, making it infeasible to determine if current benefit estimates are flexible to changing assumptions or amenable to sensitivity analysis. In current practice, the technology assumptions used to estimate the social benefits of individual technology programs often come from anonymous scientists or other experts within the DOE program offices, raising questions about the independence 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 had led to an erosion of trust among technical experts internal to R&D

programs who hold detailed knowledge about the R&D portfolio and between these experts and their funders in Congress.

The four design principles and their components are summarized in Table 1.1.

Table 1.1: *Summary of Four Design Principles for an R&D Decision Making Process*

Principle	Components of Principle
1. **Quantifiable**: Technology improvement benefits prospectively quantified with a full account of uncertainty	• Technology benefits estimated conditional on R&D levels • Dependence between technological improvements modeled • Benefits over different time horizons considered • Uncertainty in technology benefits of R&D modeled explicitly and estimated under common conditions
2. **Comprehensive**: Social benefits evaluated in a common framework	• At least one social benefit evaluated with common units • Dependence between R&D benefits modeled • Accommodation for details of how technology improvement benefits were estimated
3. **Adaptive**: Flexible to changing assumptions	• Flexible to update for technological change • Flexible to update for policy changes • Capable of sensitivity analysis
4. **Transparent**: Feasible transparency	• Transparency of assumptions • Transparency of methods

1.3 Proposed Methods in the Literature

Several studies in the literature on U.S. public energy R&D have proposed approaches to estimating the value of supporting energy technology R&D using a variety of analytical methods. Schock et al. (1999) and Nemet and Kammen (2007) estimate the appropriate level of energy R&D as the difference between the cost of meeting CO_2 emissions targets using assumptions of a business-as-usual (BAU) and an advanced technology scenario of costs. Davis and Owens (2003) use the concept of real options to estimate the value of investments in renewable energy R&D. Blanford (2009) estimates the optimal allocation of R&D funds for renewable energy, nuclear energy, and coal with CCS by defining two states for the cost of those technologies (BAU and low) and assuming that the probability of achieving the low-cost technology is an exponential function of R&D. All of these approaches, however, are based on assumptions that are not grounded in empirical data about the degree of technological innovation that will result from increased R&D investment. Other studies have used expert elicitations to determine the relationship between technology-specific public R&D and technology cost and performance in the United

States and the European Union (Anadón et al., 2012; Baker et al., 2009a, 2009b; Baker and Keisler, 2011; Bosetti et al., 2012; Chan et al., 2011), but have not made the additional step of quantifying aggregate benefits of a portfolio of R&D investments. The National Research Council (2007a) proposed a method to evaluate individual DOE R&D programs using expert-assessed probabilities incorporated in a decision-tree framework to capture key uncertainties coupled with models to quantify benefits. However, this report does not propose a method to assess the aggregate benefits of an R&D portfolio in which the benefits of individual programs are contingent on each other. Nevertheless, the insights on assessing individual R&D programs were important for shaping this proposed approach to quantifying the benefits to energy R&D.

1.4 The Challenges of R&D Benefit Estimation

The uncertainties in the returns to R&D make estimation of the benefit of a single R&D program, let alone an entire R&D portfolio, challenging. Benefit calculation requires significant technological assumptions including an explicit representation of uncertainty. 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 (Pakes, 1986; Scherer and Harhoff, 2000). It is also well-known that uncertainty in the returns to R&D is a feature of the R&D resource allocation problem that makes it distinct from other investment problems (Arrow, 1962). This uncertainty can be due to: complementary and substitute technologies leading to inter-technology dependent or "recombinant" uncertainties (Fleming, 2001), the public goods nature of the information outcomes of R&D leading to spillovers between R&D investments by different (public/private) actors (David et al., 2000; Griliches, 1992; Keefer, 1991), and contingencies on many other factors (e.g., unpredictable demand, changing macroeconomic conditions, dependencies on markets in other countries, changing patterns of scientific/technical human capital etc.). Accounting for uncertainty in the returns to R&D is important for benefit estimation because greater uncertainty may either increase or decrease the value of conducting R&D (Bloom and Van Reenen, 2002; Santiago and Vakili, 2005). There is a considerable literature estimating the ex-post returns to R&D (see Hall et al. (2010) for a survey), with a particular strand grappling with the question of attributing technological change to specific R&D projects (Hall, 1996). 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 assess in designing an R&D portfolio.

Different methods in the literature can be classified in how they utilize information to quantify uncertainty ex-ante: (1) historic data (McNerney et al., 2011; Nemet, 2006; Wiesenthal et al., 2012); (2) data on early stage "precursor" technologies (Martino, 1987; Roper et al., 2011); and (3) data from technology experts. Methods that utilize data from technology experts have distinct advantages as an information source that feeds into a decision making process concerning R&D investments. Data 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. Further, technology experts can incorporate useful information that is unpublishable or proprietary.

Approaches to quantifying uncertainty typically represent probability distributions stylistically. Methods that utilize any of the three sources of information described can estimate notions of uncertainty parametrically (e.g. first and second moments) or non-parametrically (e.g. selected percentiles). Therefore, uncertainty analysis that requires propagating the uncertainty of estimated input parameters through a model typically depends on additional assumptions and appropriate sampling techniques. This is a particular challenge when there are multiple uncertain and non-independent parameters (such as the impact of R&D in various energy technologies that interact in the market), requiring an explicit representation of co-variation in parameters.

2. Methods

Inspired by an examination of the strengths and weaknesses of current practice in allocating U.S. public energy R&D investments, this paper proposes a methodology to generate inputs to an R&D decision making process that satisfies the four proposed principles. This method has six components, detailed below and in Figure 2.5 (which uses public R&D investment in just two technology areas as an example).

This paper develops and applies a method to support public energy R&D investments in the context of decision making at DOE. The first stage of this method is a major expert elicitation exercise that collected inputs from 100 experts in a range of sectors about the probabilistic distribution of the future cost and performance of 25 energy technologies conditional on different DOE R&D investment levels and allocations. Conditional probability distributions then parameterize the MARket ALlocation (MARKAL) model, a bottom-up energy system model of the U.S. economy with internal buy-in at DOE (as demonstrated by its use by the DOE Office of Policy and International Affairs in the past). The conditional probability distributions are introduced into MARKAL with a targeted sampling strategy to approximate joint distributions, allowing us to run Monte Carlo simulations to approximate the distribution of several outcome variables of interest, such as economic surplus, pollution emission levels, and crude oil imports. The final step of the methodology uses an importance sampling and optimization approach to estimate optimal R&D portfolios for varying aggregate budgets.

2.1 Expert Elicitation

Recent research has shown that technical experts are able to consider and quantify the outcomes of R&D programs (Ruegg and Feller, 2003) and even parameterize probability distributions of outcomes (Chan et al., 2011; Catenacci et al., 2013; Bosetti et al., 2012; Fiorese et al., 2013; NRC, 2007a; Baker and Keisler, 2011; Baker et al., 2009b, 2009a; Curtright et al., 2008a; Abdulla et al., 2013; Jenni et al., 2013; Baker et al., 2010). Following the first design principle, the method proposed in this paper uses expert elicitation to parameterize probability distributions of technological improvement returns conditional on several R&D levels. Data from technology experts is collected through an expert elicitation of over 100 experts in six technology areas (fossil energy, vehicles, energy storage, biofuels, solar energy, and nuclear energy)[2], covering 25 technologies[3]. R&D funding in these six technology areas totaled approximately

[2] These elicitations were conducted as part of a broader study on the political economy of energy R&D investments in the United States. The full results of this study are published in Anadón et al. (2011) and Anadón et al. (2014a). A 7th elicitation on building technology was also conducted but not utilized in this paper due to implementation complexities in MARKAL.

[3] Vehicles technology included fuel cell vehicles, battery-electric vehicles, plug-in hybrid vehicles, hybrid vehicles, and advance internal combustion vehicles. Solar photovoltaics (PV) included utility PV, residential PV, and commercial PV. Biofuels included bioenergy for electricity, and biochemical and thermochemical biofuels for jet fuel, diesel, and gasoline (thermochemical biofuels

$2.1 billion in 2009 and $1.8 billion in 2012, equivalent to over half of total DOE-funded applied R&D investment[4]. Estimates were collected using six distinct written and online surveys administered between 2009 – 2011. Experts were selected for this study based on their contribution to the peer-reviewed literature, conference participation, and employment at research laboratories and universities. See Appendix A.1 for a more detailed description of the elicitation protocol and Anadón et al. (2014b) for even further detail, including the names of participants and the raw results of the elicitations.

Expert elicitation is a structured and systematic process for collecting and assessing subjective probabilistic estimates from individuals with particular expertise of interest (Anadón et al., 2012; Baker et al., 2009a; Chan et al., 2011; Cooke, 1991; Curtright et al., 2008b; Morgan, 2014; Morgan and Keith, 1995). This method involves in-depth engagement with experts to extract their subjective beliefs about uncertain parameters. This 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, expert elicitation seeks to include a group of participating experts of the highest quality and diversity of expertise, not the greatest quantity of viewpoints (Cooke, 1991). To avoid unwanted interactions between experts that would obscure the true diversity of judgments (Oppenheimer et al., 2007), experts were elicited individually rather than in a group setting, as in the related Delphi process or expert consensus methods (Dalkey, 1969).

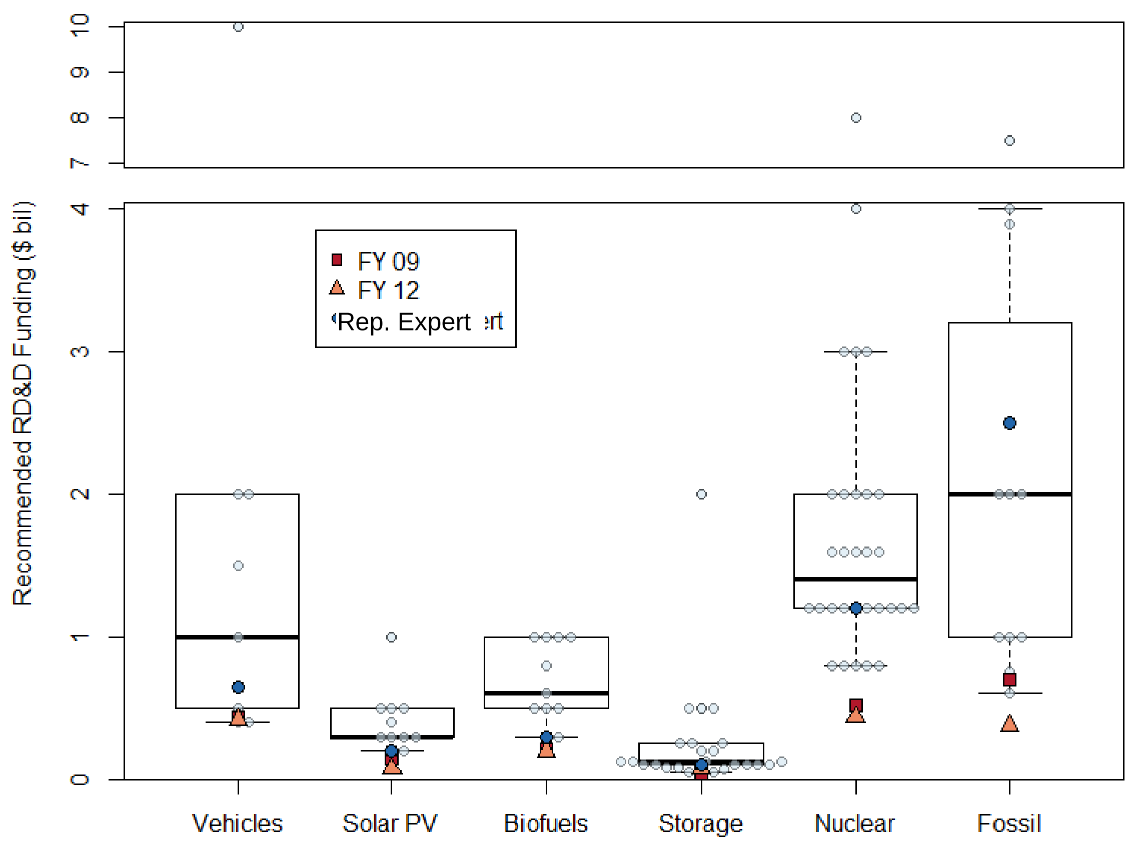
As in other technology forecasting expert elicitations, each elicitation instrument utilized in this study began with a technology primer based on a broad survey of the engineering literature in the technology

for jet fuel was excluded). Energy storage included grid-scale lithium ion batteries, sodium-sulfur batteries, flow batteries, flywheels, and compressed air energy storage. Nuclear technology included modular nuclear reactors, Generation IV reactors, and Generation III/III+ reactors. Fossil energy included natural gas power plants with and without carbon capture and coal power plants with and without carbon capture.

4 In FY 2009, DOE's R&D portfolio in the six technology areas considered allocated $214 million to bioenergy, $440 million to vehicles (including hydrogen technology), $172 million to solar PV, $701 million to coal and gas fossil energy, $514 million to nuclear energy, and $83 million to energy storage. These totals exclude program direction and management and represent 59% of the total DOE energy technology R&D budget. The remaining $1.5 billion (41%) of the energy R&D budget not covered by the elicitations was comprised primarily of program direction and management ($425 million across all technology R&D areas), nuclear fusion ($395 million), other renewable energy R&D ($323 million across wind, geothermal, hydropower, Indian renewables, renewable energy facilities, and Congressionally directed projects), and other energy efficiency areas ($153 million across industry, distributed energy resources, and congressionally directed projects). In addition to these funding streams, DOE funding for basic energy sciences was $1.5 billion in 2009 and 2012 and DOE funding for environmental and biological R&D was $0.6 billion in 2009 and 2012. (Gallagher and Anadón, 2016)

area (Curtright et al., 2008a). These primers covered current technology cost and performance, fuel costs – if applicable, a summary of previous studies about future costs, and a summary of current U.S. federal government R&D investments in the particular technology area (primarily, but not exclusively, these investments were managed by DOE). Experts were then presented with an overview of heuristics to reduce their bias and overconfidence and asked to provide a detailed self-assessment of their expertise.

After this background material, experts were asked to provide their estimates of 2010 technology costs. Next, they were asked to recommend a level of R&D funding for the technology area that the study considered and propose a specific allocation of these funds to specific technologies and research pathways within the technology area. These recommendations were made without a consideration of the tradeoffs between technologies and without a presupposed policy goal (although experts were asked to describe their strategy for allocating funds to specific technology areas and along different technology development stages). Figure 2.1 displays the results of the R&D funding recommendation portion of the expert elicitations. Recommendations for R&D funding in the six technologies consisted of R&D in several sub-technologies and across different stages of development; for these specific results see Anadón et al., (2014b). From a methodological perspective, these results can be compared to the results from expert panels discussed above (American Energy Innovation Council, 2010; APS, 2008; NCEP, 2004; PCAST, 2010, 1997). In every technology area, the majority of experts in this study recommended funding levels greater than current allocations.



The box plots are the expert-recommended funding levels (with empty grey circles denoting individual recommendations). The blue circles are the recommendations of the chosen "representative expert." The representative experts in each technology area were selected not on the centrality of their RD&D budget recommendation, but instead on the centrality of their cost estimates (see Section 2.2 for detail). These representative expert recommendations form the basis of much of the subsequent analysis (see footnote 7 for the budget recommendation of the "representative expert"). The red and orange markers are the FY 2009 and FY 2012 DOE budget allocations to particular R&D areas, respectively.

Figure 2.1: *Comparison of Expert-Recommended R&D Levels*

In the next step of the elicitations, experts provided estimates of their subjective belief distribution for 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). The elicitation results are constrained by the way in which technical experts are able to consistently understand and interpret probabilistic statements. Specifically, experts estimated their belief distributions by reporting the 10^{th}, 50^{th}, and 90^{th} percentiles of the distribution of 2030 technology costs. Belief distributions were not elicited this way because percentiles can be expressed in the natural units of technology costs, which are more familiar to technology experts (unlike the inverse problem of estimating the cumulative probability of a given technology cost). Further, the inverse problem requires pre-specifying technology cost levels which could induce bias through anchoring or could be far from experts' beliefs and therefore not informative. Three percentiles were elicited to limit the number of parameters experts had to grapple with while still providing enough information to recover an estimated continuous distribution. This was a conscious decision in light of the limited patience and attention of participating experts and the tradeoff between more precisely estimating a smaller number of belief distributions or more imprecisely estimating a larger number of distributions. The elicitations concluded with a suite of qualitative questions to better understand each expert's R&D strategy.

2.2 Formalizing Elicitation Results

This subsection uses the following notation to describe the steps of how the expert elicitation outputs were translated into inputs for the MARKAL model: t indicates specific technologies which are grouped into technology clusters, $c(t)$; p indicates the specific percentiles, α_p, used in the expert elicitation; r indicates the R&D budget multipliers, γ_r, used in the expert elicitation; $R_{c(t)}$ is the expert-recommended R&D levels for the $c(t)$ technology cluster; RD are specific R&D funding levels; $x_{t,p,r}$ is the cost of a technology t at the p percentile under the r R&D level. The $c(t)$ technology clusters group the 25 technologies into 6 R&D clusters based on how aggregate R&D investments are allocated to the specific technologies. For example, R&D investments in solar photovoltaic technologies are allocated to utility photovoltaics, residential photovoltaics, and commercial photovoltaics.

The outputs of the expert elicitations were: R&D budget recommendations for each technology-cluster (R_c), technology cost estimates at three points on the inverse cumulative distribution (the 10th, 50th, and 90th percentiles) in 2010 and in 2030 at each of three multiples (0.5, 1, and 10) of recommended R&D levels. In 2030, the cost parameters, $x_{t,p,r}$ for each of the $t = 1, \dots T$ ($T = 25$) technologies were estimated by experts at three points on the inverse cumulative distribution function of cost:

$$x_{t,p,r} = Q_t(\alpha_p; RD_{c(t)} = \gamma_r R_{c(t)}) \tag{2.1}$$

In the above expression, $c(t)$ is the R&D cluster of technology t, $RD_{c(t)}$ is the R&D level in the $c(t)$ cluster, $R_{c(t)}$ is the expert's recommendation for $RD_{c(t)}$, $p = 1,2,3$ index three percentiles ($\alpha_1 = 0.1, \alpha_2 = 0.5, \alpha_3 = 0.9$), and $r = 1,2,3$ index three R&D multipliers ($\gamma_1 = 0.5, \gamma_2 = 1, \gamma_3 = 10$). 2010 costs were elicited as in Equation (2.1) and do not depend on R&D levels. With estimates for 2030 technology costs for twenty five technologies at three percentiles and three R&D levels, and estimates for 2010 technology costs at three percentiles, this amounts to a minimum of 300 total parameter estimates from the expert elicitation exercise.

An explicitly modeled dependence structure between these conditional distributions is represented as the $\boldsymbol{V}_T$ Spearman correlation matrix of 2030 costs, capturing co-variation in technology improvement benefits that could be due to technological spillovers (e.g. from grid-scale batteries for energy storage to batteries used in electric vehicles). Spearman correlation, rather than Pearson correlation, is appealing for expert elicitation because it is cognitively more natural to think of relationships between uncertain quantities in terms of their strength of monotonicity rather than their strength of linearity. For many technology-technology diodes, a correlation in the $\boldsymbol{V}_T$ matrix was not elicited and instead it was assumed that technology costs would be independent.

Similarly, T estimates of ρ_t, are estimated time rank correlations for each technology. The ρ_t time correlations take into consideration how much information relative 2010 technology costs provide for relative 2030 technology costs. These longitudinal (rank) correlations will be high for most technologies ($0.7 \leq \rho \leq 0.9$), as experts assumed that it is unlikely that a technology on the high end of costs in 2010 will be on the low end of costs in 2030.

In the vehicle technologies elicitation instrument, experts were asked to provide information that could be used to empirically estimate joint probability distributions of costs that were related to batteries. After asking experts to provide their 10^{th}, 50^{th}, and 90^{th} percentile cost estimates in 2030 under the various R&D scenarios, experts were asked to assume as fixed a given cost of a technology in 2030 and then re-estimate the distribution of costs for a different technology in 2030. Through this conditional reestimation, experts provided information that could be used to estimate a correlation between the future costs of the two technologies. However, these suites of questions were not implemented in all surveys because these were mentally taxing questions on an already fatiguing exercise. Therefore, a Delphi process within the research group was used, which had significant technology expertise, to propose a correlation matrix of 2030 technology costs for all twenty-five technologies. For many technology-technology diodes, it was assumed that technology costs would be independent (See the Appendix A.2 for the correlation matrix used in this work).

The elicitations utilized included subjective belief distribution estimates from over 100 experts. The full results of these elicitations are available online[5] and are summarized in Anadon et al. (2014b). However, the objective of this paper is not to summarize the implications of these elicitations, but rather to demonstrate the utility of a methodology that connects the results of expert elicitations in general with an optimization and decision framework. With the emphasis on methods, we elect to simplify the use of elicitations by selecting a single representative expert for each of the six elicitations. Other approaches to simplifying the use of elicitations include averaging expert assessments, other methods of combining elicitation results based on expert confidence or expertise, and exploring sensitivity to expert assessment that is either more optimistic or pessimistic. These alternative methods are discussed in the context of inter-expert reliability (Anadón et al., 2013; Keith, 1996) and the factors that affect expert confidence (Nemet et al., 2016).

We selected the "representative expert" for each of the 6 technology areas by evaluating which expert in each area had central estimate, $x_{t,2}$, and uncertainty range indicator, $(x_{t,3} - x_{t,1})/x_{t,2}$, 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 representative experts was made without considering the expert's R&D funding recommendation (see Figure 2.1). This selection was also vetted with 23 "higher

[5] The full results from the elicitations upon which this study are based are available at: http://belfercenter.ksg.harvard.edu/publication/21528/transforming_us_energy_innovation.html

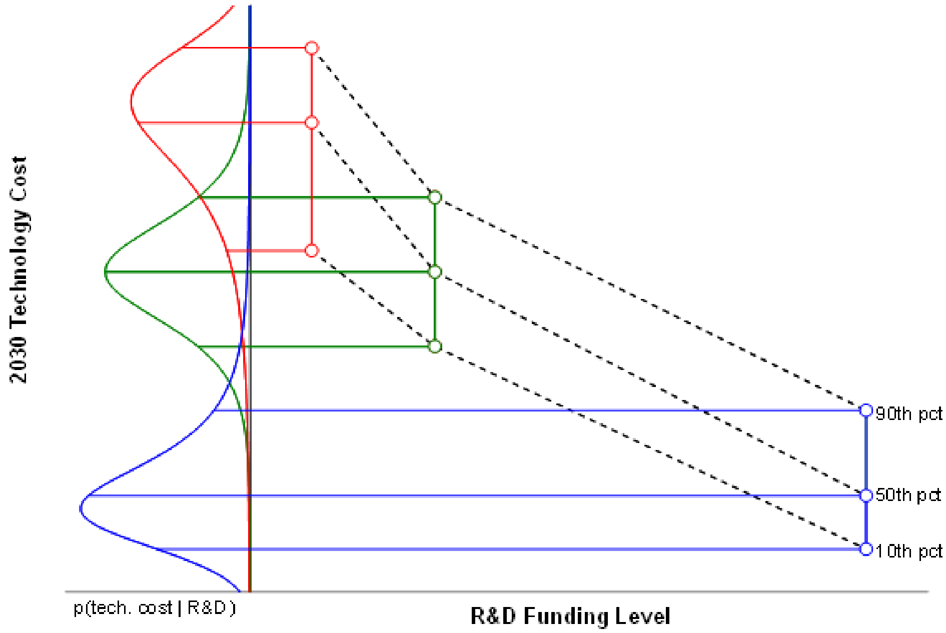
level” qualitative reviewers with experience in the management of large scale technology programs (Anadón et al., 2014b).

2.3 Sampling Strategy

Using the expert elicitation results from the selected representative experts, estimates of the benefits of an R&D portfolio are generated by introducing these estimates in the MARKAL model, a publicly-available energy-economic model (see Section 2.4 for detail of the model). A key challenge is to translate the expert elicitation results into congruent probability distributions that could efficiently estimate outcome distributions given the computational cost of MARKAL. Because MARKAL is so computationally expensive due to the level of technical detail it incorporates, this sampling strategy is constrained to a finite number of model simulations (1,200 scenarios in the final implementation used in optimization). To overcome the limits of this constraint, samples from the distributions of technology costs were drawn using Latin Hypercube sampling (LHS) (McKay et al., 1979) and in a way to cover the full range of possible R&D realizations. LHS reduces the total variance in the sampled values of uncertain quantities by fixing the probability mass between all sampled values but does not introduce bias. The variance reduction property of LHS allows us to decrease the total number of samples (and therefore total number of model simulations) that are needed to run in order to sufficiently describe the variance in the output quantities of interest. However, the tradeoff in using LHS is that the samples drawn from the process are no longer independent and therefore, each sample viewed by itself is difficult to interpret.

A shifted-log-logistic (SLL) functional form is imposed to interpolate and extrapolate the expert elicited percentiles as full probability distributions. The SLL distribution has three parameters, allowing us to exactly identify a continuous probability distribution that maximizes the information content of the elicitation results. Equation (2.2) shows the quantile function parameterization of the SLL distribution conditional on $\boldsymbol{x_t}$ in terms of the three values of $x_{t,p}; RD_{c(t)}$ at a given level of R&D, allowing us to sample values of p. A graphical depiction of the SLL fitting is shown in Figure 2.2 for percentiles estimated by experts at three R&D levels.

$$Q_t(p|\boldsymbol{x_t}; RD_{c(t)}) = \frac{(x_{t,3} - x_{t,2})(x_{t,1} - x_{t,2})}{2x_{t,2} - x_{t,3} - x_{t,1}} \left[\left(\frac{1-p}{p} \right)^{\log\left[1 + \frac{2x_{t,2} - x_{t,3} - x_{t,1}}{\log(9)(x_{t,3} - x_{t,2})}\right]} - 1 \right] + x_{t,2} \tag{2.2}$$



A graphical depiction of representative sets of expert-elicited percentiles for three R&D scenarios (shown separately in red, green, and blue white-filled circles) and conditional probability distribution fitting with the SLL distribution (on the left side of the y-axis).

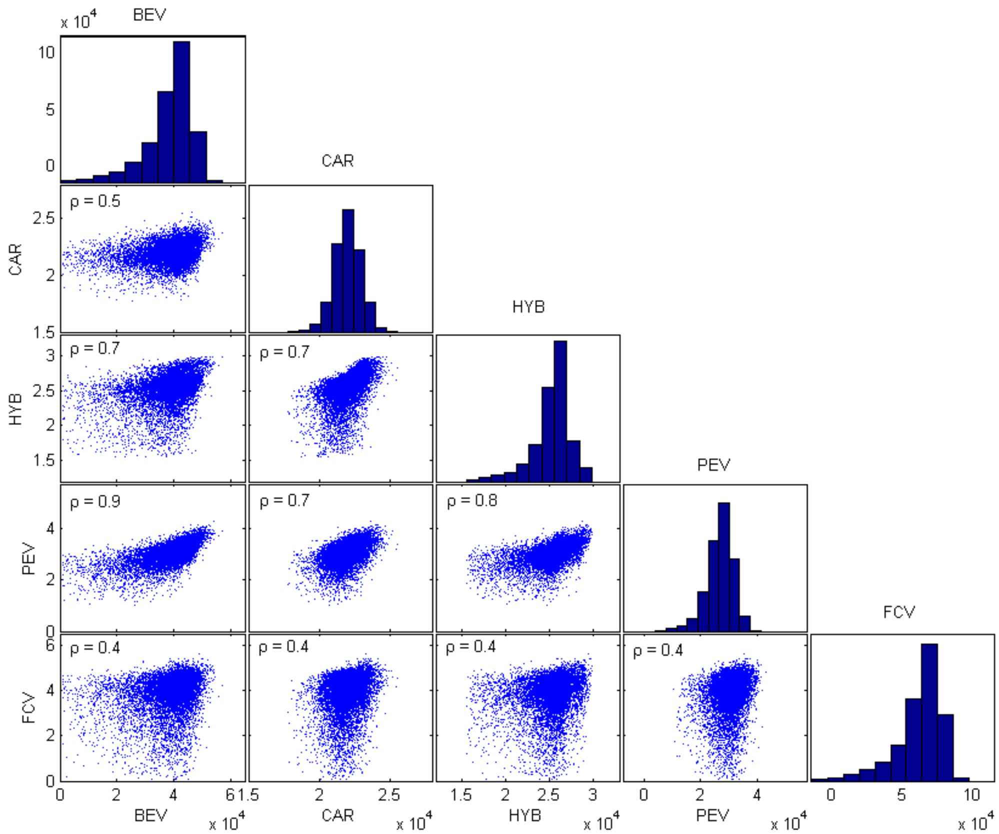
Figure 2.2: *Distribution-Fitting to Expert-Elicited Percentiles*

While there are many probability distributions with three parameters, the SLL distribution is relevant for this application because it is a smooth distribution that can allow for skewness. A disadvantage of the SLL distribution is that it is almost always bounded on one side and the bounds are determined by the three parameters. While there may be conceptual reasons to include bounds in the distribution of costs (e.g. forcing costs to be greater than zero), bounds could also be elicited directly, although this would add to the number of parameters included in elicitations. Ultimately, the choice of any probability distribution that can fit the three percentiles exactly is arbitrary since a three parameter distribution fully utilizes the information content of the elicited beliefs.

Our elicitation methodology included a process for estimating a Spearman correlation matrix of 2030 technology costs, $\boldsymbol{V}_T$. Using the T-dimensional Gaussian copula, $C_{\boldsymbol{V}_T}^{Gauss}$ for each sample, T samples from Unif(0,1) with the specified $\boldsymbol{V}_T$ Spearman correlation matrix are drawn. Then, correlated samples from the joint distribution of cost given a fixed level of R&D can be found by evaluating the quantile function given in Equation (2.2) at the correlated variates using $\left(\boldsymbol{x_t}; RD_{c(t)}\right)$ as calculated in Equation (2.1). More formally, joint samples of 2030 technology costs, $\boldsymbol{x}^*$, are drawn from a joint distribution such that the variates are distributed as described in Equation (2.3).

$$F(\boldsymbol{x}^*|\boldsymbol{RD}) \sim C_{\mathbf{V}_T}^{Gauss} \qquad (2.3)$$

Because $\left(x_{t,p}; RD_{c(t)}\right)$ is weakly monotonic in $RD_{c(t)}$, the rank correlations as sampled from the copula are maintained under this transformation. An alternative to this approach proposed by Iman and Conover (1982) essentially approximates the Gaussian Copula with less precision. Figure 2.3 shows example joint samples for 5 vehicle technologies with correlated costs.

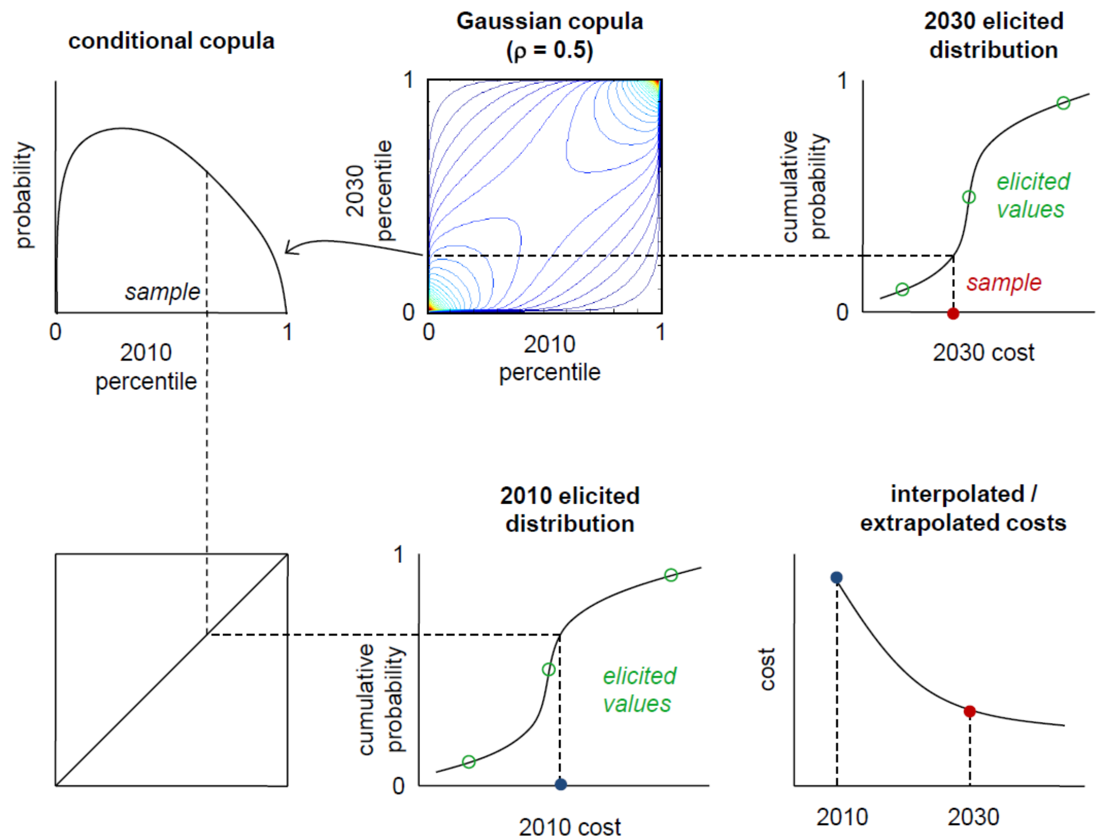


An example sample from the joint distribution of 2030 costs for five technologies in 2010 USD: battery electric vehicles (BEV), advanced internal combustion vehicles (CAR), hybrid vehicles (HYB), plug-in electric vehicles (PEV), and fuel cell vehicles (FCV). Marginal sample distributions are shown as histograms in the diagonal plots and joint samples between all pairs are shown in scatter plots off the diagonals along with the corresponding rank correlation coefficients, □.

Figure 2.3: *An Example Sample from the Joint Distribution of Five Technology Costs*

Next, for each sample the 2010 and 2030 cost draws are interpolated and extrapolated to construct a vector of costs for 2010–2050 in 5-year time steps. This step is necessary to conform to the required inputs of the MARKAL model. Because the elicitations only provide estimates of costs in two years (2010 and 2030), additional assumptions are required, which have a substantial effect on the 2030–2050 extrapolation region. With the 2030 costs sampled, 2010 costs conditional on 2030 costs are sampled using the estimated time correlation, ρ_t and the expert-elicited probability distribution for 2010 costs, fit in the same way as the 2030 distribution. To calculate a sample's 2010 cost, a 2-dimensional copula with rank correlation ρ_t is sampled, conditioning on the 2030 sample's quantile (which was sampled from a T-

dimensional copula). This approach samples from the 2-dimensional copula, representing time-dependence, conditionally using a numerical approximation at 10^{-5} precision. Then, the resulting quantiles for 2010 are transformed by Equation (2.2), using the $\boldsymbol{x_t}$ values elicited for technology t in 2010. Note that for 2010 estimates, there is no need to condition on R&D levels since R&D is constant by definition in 2010. For each sample, if the 2030 draw is greater than the 2010 draw, costs are linearly interpolated and extrapolated; otherwise, an exponential functional form is imposed. The choice of functional form is of little practical consequence in the interpolation region (2010–2030), but has important consequences for the extrapolation region (2031–2050). The choice of a linear functional form for scenarios with cost increases is consistent with cost increases due to institutional causes, such as increasing permitting and licensing costs, which are unlikely to evolve at nonlinear rates. The choice of an exponential functional form for cost decreases is conservative in the sense that the rate of cost decrease declines from 2030–2050, relative to the rate of cost decrease from 2010–2030. See Figure 2.4 for a graphical depiction of these steps.



A graphical depiction of dependent sampling of 2010 costs conditional on a sampled 2030 cost. Moving from the top right to the left, the 2030 cost is sampled (shown in red) from the estimated distribution based on elicited percentiles (in green). In the top center figure, the 2-dimensional Gaussian copula at the 2030 sampled cost defines a conditional probability distribution of 2010 cost percentiles, shown in the top left subfigure. The bottom left figure reflects the 2010 cost percentiles, which are then transformed across the 2010 elicited distribution, shown in the center frame of the bottom row. These two samples together are then used to interpolate costs between 2010 and 2030 using a linear functional form for scenarios with cost increases and an exponential functional form for cost decreases. To extrapolate costs to 2050 it is assumed that between 2030 and 2050 costs follow the same functional form as between 2010 and 2030.

Figure 2.4: *Graphical Depiction of Dependent Sampling*

2.4 Modeling with MARKAL

The method proposed in this paper parameterizes the results from the elicitations to use as stochastic cost inputs in MARKAL, a detailed energy system model (Fishbone and Abilock, 1981; Loulou et al., n.d.). This approach also uses elicited point values of performance metrics, which were held constant across samples at expert-elicited values but varied over time. Other model parameters not included in the elicitations were held constant at their default values based on the U.S. Energy Information Administration’s Annual Energy Outlook (EIA, 2009). 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 (Anadón et al., 2014b; Fishbone and Abilock, 1981; Loulou et al., n.d.). DOE and EPA have each developed their own versions of MARKAL for their in-house policy analysis. This study utilizes a version of the U.S. multi-region MARKAL model maintained by Brookhaven National Laboratory, one of the main operators of MARKAL for DOE.

MARKAL was chosen for this study for its technical detail which allows us to accommodate the nuances of the impact of the technology improvement benefit estimates generated in the expert elicitations. For example, MARKAL allows us to include the specific performance characteristics of technologies that the experts conditioned on when estimating costs, the solar irradiation profile and underground CO_2 storage space in each of MARKAL's 10 geographic regions, and the interaction between different vehicle types in satisfying aggregate vehicle demand. Further, MARKAL allows us to evaluate social benefits along a common set of metrics while also accounting for the interactions of technologies in satisfying market demand.

The MARKAL model 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[6]; MARKAL is publically-available and many government agencies implement the model themselves. A MARKAL scenario run produces hundreds of outcome metrics of potential interest (e.g., CO_2 emissions, energy costs, oil imports, etc.), many of which could be used to evaluate an R&D portfolio.

2.5 Optimization

[6] 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 Long Range Transport of Atmospheric Pollutants (LRTAP) Protocol and the use of the RAINS model during the negotiations (Figueira et al., 2005; Parson, 2002, 1998). By agreeing on methodology prior to the introduction of technical assumptions, parties built credibility.

Our approach implements a sampling and optimization method that allows for the estimation of the optimal allocation of R&D investments at a range of budget levels. For these results, 1,200 MARKAL Monte Carlo samples of technology costs are run under a wide range of R&D levels that cover the full range of R&D scenarios considered. An importance sampling technique is applied that allows for the calculation of the expected value of outcome metrics under specific R&D portfolios that are not pre-specified (Morgan and Henrion, 1998). This importance sampling approach allows for the flexibility to update the technical assumptions of the study without repeating the prior steps of the method, satisfying the third design principle. The importance sampling strategy allows one 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 only be able to evaluate a small number of proposed R&D portfolios (Pugh et al., 2011). Additionally, this method's flexibility to different input assumptions may be particularly useful in testing the potentially important sensitivity of results to assumptions from different sources (e.g., more optimistic experts, experts internal to the decision making process, experts from stakeholder groups, or experts from different countries) and elicitation strategies (e.g., in person interviews, or written surveys) (Anadón et al., 2013).

Using this importance sampling strategy, a response surface of the expected returns across a continuous range of R&D levels can be constructed–as represented in subplot F of Figure 2.5. The final step of this method is to fit a polynomial response surface to the expected outcomes from the importance sampler and use a numerical optimization algorithm to calculate the R&D portfolio allocation that yields the optimal outcome (e.g. highest economic surplus) for a fixed R&D budget. This approach optimizes the portfolio on the expectation of the outcome metric. This method follows Principle 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 (Anadón et al., 2011).

Our approach inputs stochastic realizations of technology cost parameters conditional on randomly drawn R&D levels and holds all other model parameters constant across model runs at their default values (i.e. technology performance parameters, which were held constant across samples at expert-elicited values but varied over time, and other model parameters not included in the elicitations, which were held constant at their default values). While the MARKAL model outputs many metrics for a given sampled cost vector, this method uses only one outcome metric in the optimization stage, denoted $S(\boldsymbol{x}^*)$.

The first stage of the optimization is to use the relationship between R&D funding and technology costs from the expert elicitation and the relationship between technology costs and the outcome metric, $S(\boldsymbol{x}^*)$, from many samples, to estimate the expected value of the outcome metric at any specified R\&D level in the feasible range. Formally, for a given R&D vector, $\boldsymbol{RD}$, the goal is to find the expression in Equation (2.4).

$$\mathbb{E}[S(\boldsymbol{x}^*)|\boldsymbol{RD}] = \int S(\boldsymbol{x}^*)p(\boldsymbol{x}^*|\boldsymbol{RD})\, d(\boldsymbol{x}^*|\boldsymbol{RD}) \tag{2.4}$$

However, the distribution $p(\boldsymbol{x}^*|\boldsymbol{RD})$ is computationally intractable for integration due to the complexity of the expert-elicited distributions. While this distribution could be simplified to allow for a more direct evaluation of the expectation in Equation (2.4), doing so would undermine the integrity of the expert assessments. Instead, this approach uses an importance sampling strategy to evaluate the expected value in Equation (2.4), using $p(\boldsymbol{x}^*|\boldsymbol{RD})$ as the "target distribution." The importance sampler is represented in Equation (2.5) where γ indexes the n=1,200 MARKAL model runs that computational constraints allow, and $k(\boldsymbol{x}_{\boldsymbol{\gamma}}^*)$ is a kernel approximation to the entire joint "sampling distribution" of 2030 costs, described in Equation (2.3). The kernel approximation is used to calculate the "sampling probability" to reduce computational requirements and is of little practical consequence.

$$\mathbb{E}[S(\boldsymbol{x}^*)|\boldsymbol{RD}] \approx \frac{1}{n}\sum_{\gamma}^{n} \frac{p\left(\boldsymbol{x}_{\boldsymbol{\gamma}}^*|\boldsymbol{RD}\right)}{k\left(\boldsymbol{x}_{\boldsymbol{\gamma}}^*\right)} S\left(\boldsymbol{x}_{\boldsymbol{\gamma}}^*\right) \tag{2.5}$$

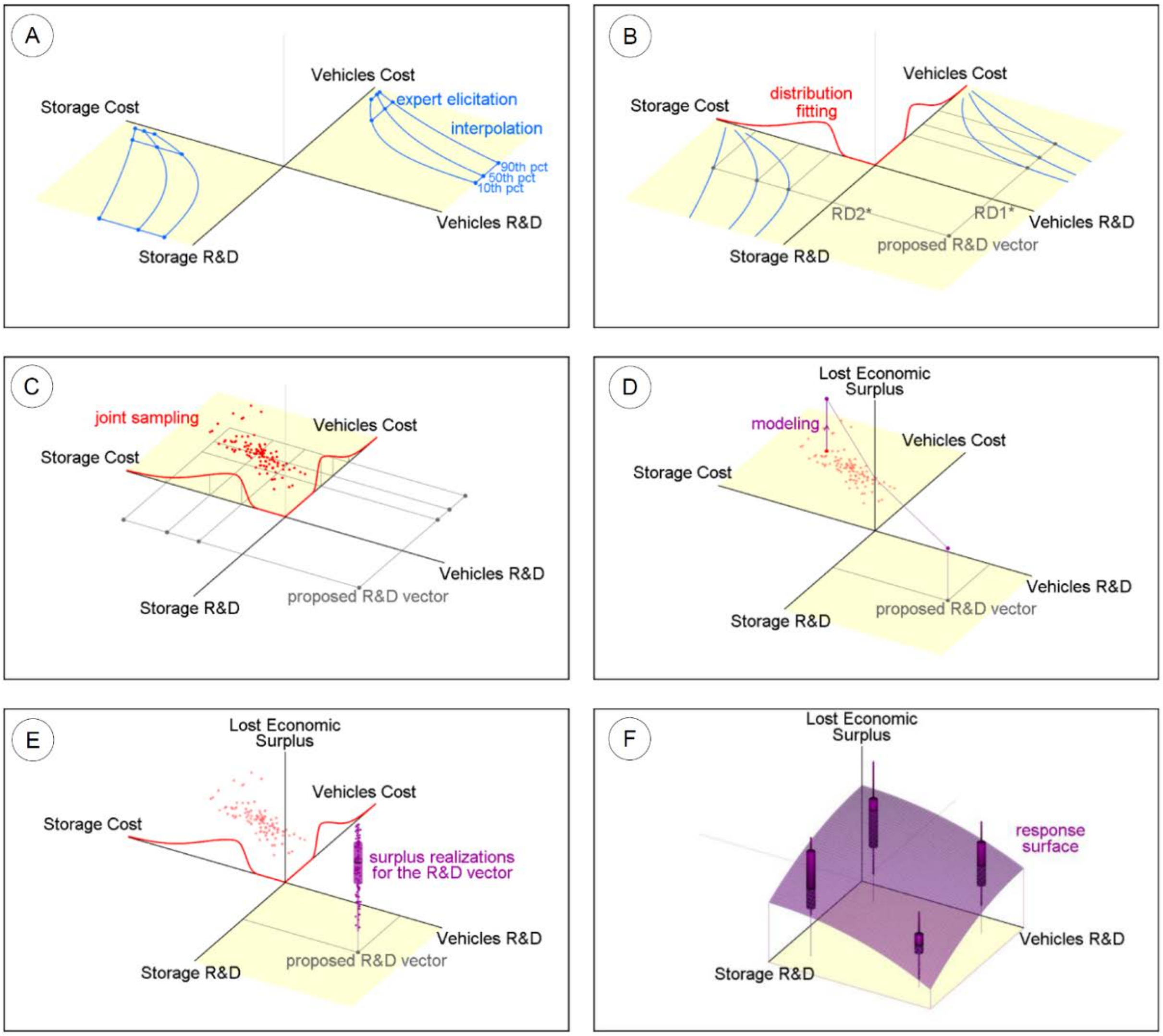
In the second stage of the optimization, the importance sampling strategy is applied to a grid of R&D vectors that span the feasible R&D space to calculate the expected outcome metric over the full range of possible R&D portfolios. An 8-unit grid in the 6-dimensional R&D space is used, yielding importance sampling calculations at 8^6 = 262,144 R&D vectors. The grid constructed evaluates all permutations of R&D levels at γ = 0.5, 0.75, 1, 1.5, 2, 5, 7.5, and 10 multiples of the expert-recommended R&D level. These levels were chosen to give higher resolution to R&D levels close to the recommended levels while still informing higher R&D levels. Repeating the importance sampling strategy is the most computationally expensive step of the method. Future work could address this by investigating techniques to reduce the computational burden of evaluating the importance sampler's sampling distribution.

In the final stage of the optimization, a high dimensional polynomial is fit to the grid of expected outcome metrics. In the results presented in the paper a least-squares fit is used to find a “response surface” of the expected outcome metric using the six first-order R&D terms, the thirty six second-order R&D terms (including squared terms and interactions). Since the polynomial fits the expected values of the outcome metric, the predicted values along the response surface can be thought of as a double expected value or a predicted value of an expectation, as shown in Equation (2.6).

$$\mathbb{E}[\widehat{S|\boldsymbol{RD}}] = \hat{\beta}_0 + \sum_{c}^{6} \hat{\beta}_c RD_c + \sum_{c}^{6}\sum_{c'}^{6} \hat{\beta}_{c,c'} RD_c RD_{c'} \tag{2.6}$$

The estimated polynomial in Equation (2.6) is used in an optimization scheme to find the vector $\boldsymbol{RD}^*_{\boldsymbol{\Omega}}$ that maximizes $\mathbb{E}[\widehat{S|\boldsymbol{RD}}]$ under the constraints $\sum \boldsymbol{RD} \leq \Omega$, where Ω is a budget constraint, and that all R&D levels are within their feasible ranges. The results of repeating this optimization at many levels of Ω are shown in Figure 3.2.

Figure 2.5 summarizes the six steps of this method using an example of two technology areas. The figure shows the collection of expert belief distributions, fitting probability distributions, sampling from the joint distribution, modeling with MARKAL, the Monte Carlo interpretation of modeled results, and finally the response surface connecting the set of Monte Carlo results.



This figure utilizes projections across relevant dimensions to visualize a schematic example of the methodology described in this paper using two technologies as examples, energy storage and vehicles. Subplots (A) and (B) replicate the key features of Figure 2.2, namely probability distribution fitting to the expert-elicited cost percentiles at a given level of R&D. The expert elicitation provided estimates of the 10th, 50th, and 90th percentile of technology costs in 2030 under three R&D scenarios – these are shown with the blue points in the two R&D funding–technology cost spaces highlighted in yellow. For a given vector of R&D funding levels in storage and vehicle technologies (RD1*,RD2*), shown by the grey line perpendicular to the R&D axes, the approach fits the three-parameter SLL probability distribution to the interpolated percentiles for technologies, shown in red. In subplot (C), then the joint distribution of technology costs is sampled, utilizing a dependence structure for technology costs – samples are shown as red dots in the highlighted storage cost–vehicle cost space; this replicates the key features of Figure 2.3. In subplot (D), for a vector (pair) of technology costs, aggregate outcomes, such as lost economic surplus, are estimated using the MARKAL model–the purple line perpendicular to the storage cost—vehicle cost plane shows this relationship. In subplot (E), using a LHS approach over storage cost—vehicle cost combinations, the distribution of outcome metrics is estimated, as shown with the purple vertical dot plot and superimposed box plot. The boxplot replicates the key features of Figure 3.1. Finally, in subplot (F) a response surface is built connecting the box plots that can be used to find the portfolio that optimizes the expected outcome metric under a budget constraint.

Figure 2.5: *Summary of Methodology from Elicitations to an Optimal Portfolio*

3. Results

This section evaluates the results of the suite of model runs parameterized by the expert elicitations in several ways. This section considers, in turn, system benefits (e.g. aggregate economic surplus and CO_2 emissions), technology diffusion (e.g. deployment of renewable energy), and uncertainty analysis (e.g. high and low percentiles of outcome metrics and the variance in outcome metrics). Each of these three classes of methods can be useful inputs to support public energy R&D investment decision making. These results are summarized in Figure 3.1, which focuses on a comparison of a BAU R&D portfolio that perpetuates Fiscal Year 2009 R&D investment allocations and levels at $2.1 billion (see footnote 4) and the "representative" expert-recommended R&D portfolio with a total investment of $5.3 billion[7]. We emphasize in this section the results from analysis parameterized by the representative expert of the suite of expert elicitations conducted in 2009 – 2011. We discuss the policy relevance of these findings noting that expert assessment of energy technology costs have likely changed since the elicitations were conducted. Still, given the long time lags in technological change, these results may still be qualitatively relevant for current decision making. More importantly, we hope to illustrate the utility of the methodological approach we have described by showing in detail the type of results that could be obtained with such an analysis parameterized by new expert elicitations.

3.1 System Benefits

In Figure 3.1, the top subplot shows 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. Even with the recommended R&D portfolio, without additional limits, results project that CO_2 emissions will rise by 7% between 2010 and 2020, inconsistent with the stated goal of President Obama (Executive Office of the President, 2013) of a 17% reduction of total greenhouse gas emissions below 2005 levels by 2020.

[7] The representative expert-recommended R&D portfolio allocates $300 million to bioenergy, $650 million to vehicles, $200 million to solar PV, $2,850 million to fossil energy, $1,200 million to nuclear energy, and $100 million to energy storage.

In terms of other environmental performance metrics, median projected NO_x emissions under the recommended R&D scenario are 2% lower relative to the BAU scenario in 2030 and 5% lower in 2050. SO_2 emissions show smaller differences – in 2030 they are virtually equivalent, and in 2050, the recommended scenario has median projected emissions 3% lower than the BAU scenario.

The results in the middle subplot of the figure show that the median projection of annual economic surplus[8] is $29 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 $3.2 billion per year greater than the BAU portfolio, the recommended portfolio has positive net social benefits.

3.2 Technology Diffusion

The results in the bottom subplot of Figure 3.1 show that median renewable energy deployment (energy generated by hydroelectric, wind, solar, and biomass) under business as usual R&D is expected to increase from 2010 levels by 160% by 2030 and by over 230% by 2050. Under the recommended R&D scenario, these growth rates increase to 170% and 250%, respectively. In levels, the BAU R&D scenario increases renewable energy deployment from 2010 levels (approximately 485 TWh) to 770 TWh in 2030 and 1,130 TWh in 2050, while the recommended portfolio increases renewable energy deployment to 810 TWh and 1,190 TWh, respectively. This shows that secular trends in renewable energy deployment are much larger than the incremental deployment induced by the recommended additional R&D. However, these estimates only represent changes due to R&D in a subset of renewable technologies since other potentially important renewable energy sources, such as geothermal, solar thermal, and wind, are not considered in the elicitations.

Unlike for renewable technologies, R&D in coal technology is unlikely to substantially alter projected deployment rates from 2010-2030 (perhaps due to the long-term nature of coal power plant construction

[8] Net (producer and consumer) economic surplus is estimated by MARKAL as the area between the supply and demand curves for the full set of goods in the model and does not include most environmental externalities, such as greenhouse gas emissions.

and the other institutional factors that build inertia into the system of coal utilization). Projections through 2030 for coal deployment are virtually identical under the BAU R&D scenario and the recommended R&D scenario, with both scenarios estimating a median growth rate between 2010-2030 in coal energy of 22-24%[9] (10.7-10.9 EJ in 2030 relative to 8.8 EJ in 2010). Taken together, these results indicate that R&D policy alone is unlikely to substantially affect the deployment of coal energy.

For crude oil imports, as with coal, high inertia in the system limits the ability of R&D to affect outcomes in the short run. In 2030, the recommended R&D scenario has median projected oil imports 2% lower than the BAU scenario. However, in 2050, this number increases to 10%. While median projected crude oil imports are projected to decrease from 2010 to 2035, even under the BAU scenario, they are still projected to increase from 2035 to 2050. Median crude oil price projects are within 2% of each other under the two R&D scenarios from 2010-2050. Taken together, this suggests that other non-R&D policies would likely be needed to perpetually reduce net oil imports.

3.3 Uncertainty Analysis

Figure 3.1 highlights the ability of this method to quantify the uncertainty in evaluation criteria of R&D portfolios. The figure allows the estimated distribution of evaluation criteria in different individual R&D portfolios to be assessed and compared as part of the R&D portfolio decision making process (DOE External Expert Peer Review Panel, 2006). For example, the proposed method allows for the quantification of high and low percentiles of outcome metrics. Relative to the business as usual R&D scenario, if the 5th percentile or 95th percentile of economic surplus is realized, the benefits of the recommended R&D scenario could be \$48.2 billion and \$89.7, respectively. As another example, under the BAU R&D scenario, the difference between the projected 95th percentile and 5th percentile of CO_2 emissions in 2050 is as large as 60% of the difference in median projected CO_2 emissions for 2050 and 2010.

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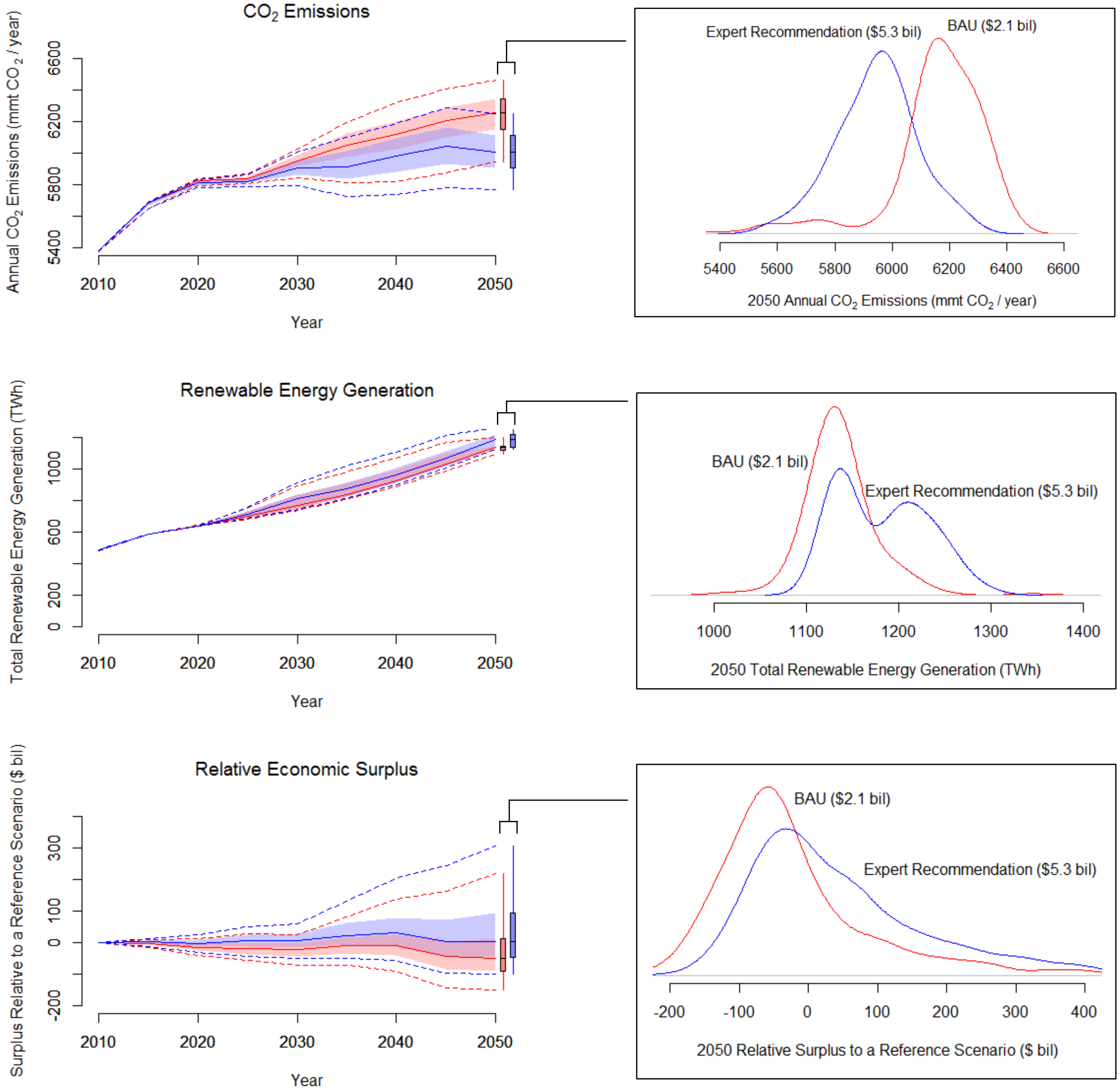
[9] Note that the model and expert elicitations were conducted during a period before natural gas prices were forecasted to decline as rapidly as they have in recent years due to large shale gas production.

Uncertainty can also be evaluated by looking at the variance in outcome metrics. These results show 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 case (F-test for difference in variances has p-value = 0.001 for 2030 surplus projections and 0.01 for 2050 surplus projections). This demonstrates that while greater R&D has positive expected benefits, additional R&D also creates more uncertainty in outcomes.



Estimation of benefits of individual R&D portfolios in terms of CO_2 emissions, relative economic surplus, and renewable energy generation. In the left figures, the dotted lines encapsulate the estimated 90% probability intervals (5^{th} – 95^{th} percentiles) and the lightly-shaded regions are estimated 50% probability intervals (25^{th} – 75^{th} percentiles) from 400 Monte Carlo samples using the "representative experts" for each of the 6 technology areas. 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. In the right plots, kernel density approximations to the distribution of benefits in 2050 are shown under the same two R&D scenarios. The top subplot shows CO_2 emission benefits; the middle subplot shows economic surplus benefits, and the bottom subplot shows renewable energy generation.

Figure 3.1: *Distribution of Benefits under Two R&D Scenarios*

Greater expected benefits combined with greater uncertainty under greater R&D investments also translates into a quantifiable larger probability of desirable outcomes. For example, this analysis can be used to estimate that under the BAU R&D scenario, the probability that CO_2 emissions in 2050 will be below 6 Gt-CO_2 is 9%, while under the recommended scenario the probability would increase to 66%. The use of probabilistic language to talk about the uncertain benefits of R&D through a combination of expert elicitations and models using a transparent process would be a positive development in the decisions about budget allocations, as it would help move debates away from the credibly of final estimates towards the technical assumptions that matter, which are usually less politically vulnerable.

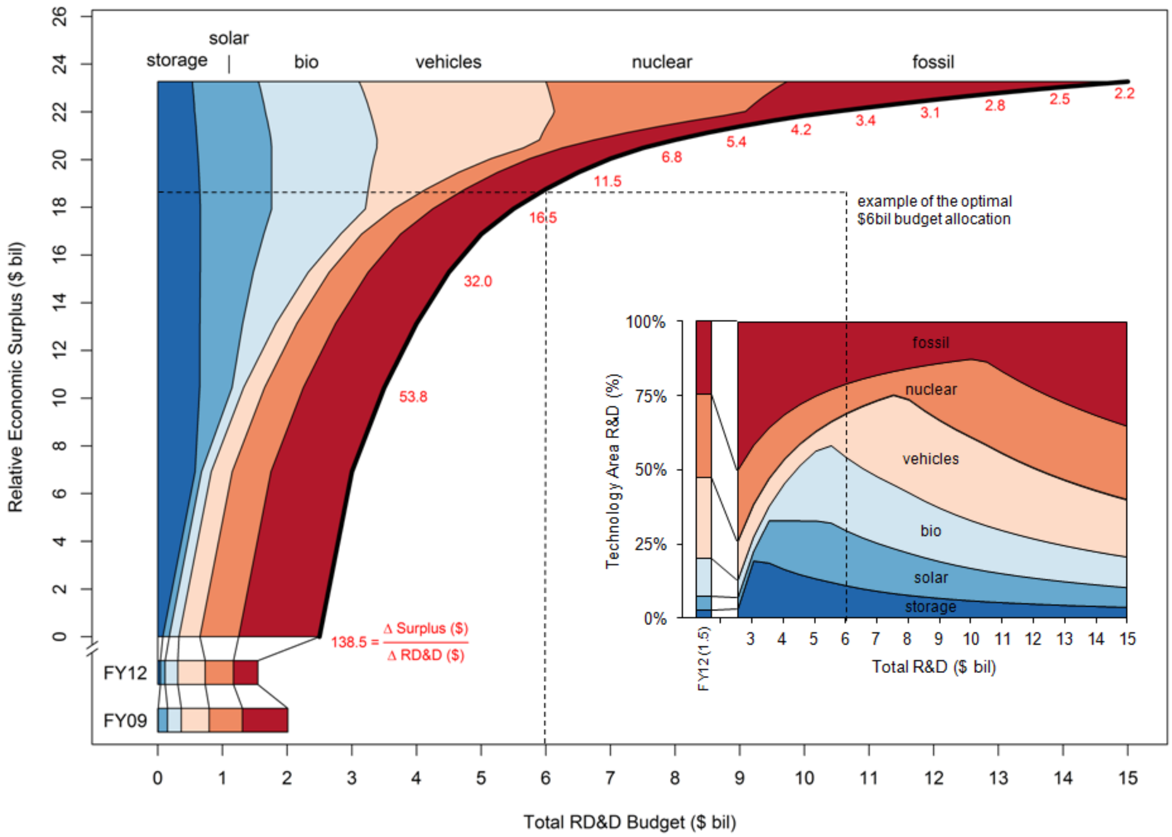
3.4 Optimized R&D Portfolios

This section presents an analysis of optimal R&D portfolio allocation under a no-policy scenario, shown in Figure 3.2. Overall, results yield four main insights about the optimal allocation of R&D resources across the six technology areas that investigated.

First, there are decreasing marginal returns to R&D. The incremental return to 2030 economic surplus from R&D investments is substantially larger at low levels of R&D than at high levels. In the no policy case, results show that incremental returns to R&D when $2.5 billion in R&D funding is allocated optimally are $139 in economic surplus per year in 2030 for an additional dollar of yearly R&D funding allocated to the technology areas with the highest marginal returns at that budget level. Further, there are monotonically decreasing marginal returns to optimally-allocated R&D funds over the full range considered, a subjectively-defined “feasible range” bounded by the estimates of the expert R&D scenarios. However, these results also indicate that there are positive expected returns to economic surplus from R&D even at the highest end of the range of R&D budget levels considered. This result implies that there are R&D portfolios for the six areas investigated with total budgets greater than $15 billion (more than 10-times Fiscal Year 2012 levels) that can be justified solely on expected gains to economic surplus realized by 2030. If extrapolated to budgets beyond the range considered, this implies an “optimal” R&D level beyond $15 billion at which the expected marginal benefits to economic surplus equal the marginal cost of R&D investment. However, this method is not able to capture the marginal cost of raising public funds through revenue-generating policies, such as taxes. The method also does not capture the welfare effects of other externalities associated with energy use, such as pollution and energy resource import dependency

Second, there is a distinct prioritization of R&D investments by technology area. As the R&D budget expands, the optimal allocation shifts first towards energy storage, then to solar energy, then to bioenergy, then to vehicle technologies, 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. This prioritization of R&D investments appears to be robust across policy scenarios (optimization for minimizing CO_2 emissions reveals strikingly similar results). This is likely due to the low current investment levels in these technologies and the high expected economic returns to R&D in these areas.

Third, there are important differences between the current U.S. public energy R&D funding allocation and the results of this analysis for R&D budgets close to current levels. Comparing the current allocation to the estimated optimum for a $4 billion budget, fossil energy, energy storage, and solar photovoltaic technologies are underinvested in. Of these three technologies, this analysis indicates that the technology area that would yield the greatest marginal return to economic surplus, given the current allocation, is energy storage.



The figure show the allocation 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 plot is the maximum expected increase in 2030 economic surplus (above an arbitrary reference point: the expected 2030 surplus in the optimal allocation for the $2.5 billion budget) that can be attained for a given R&D budget constraint. The red numbers along the black line are estimated marginal returns on investment, calculated by linear approximation to the derivative of the expected 2030 surplus. At the lowest R&D budget considered, $2.5 billion, the optimal investment mix is 50% fossil, 24% nuclear, 13% vehicles and 3-6% storage, solar, and bioenergy. Because this method is constrained by the range of R&D levels that experts considered, at low levels of total R&D investment estimates are directed towards the technology areas that received expert recommendations for capital-intensive demonstration projects (fossil and nuclear).

Figure 3.2: *Optimal R&D Portfolios under a No Climate Policy Scenario*

The range of R&D portfolios considered is tied to the elicitations: to reduce model dependence, expert-elicited relationships between R&D and technology improvements are not extrapolated, and therefore constrain the analysis to only the R&D ranges that experts explicitly considered. In some cases, this implies that at low and high R&D budgets, optimum portfolios cannot equate marginal benefits across technology areas (see Figure 3.3) because the implied optimum investment level is outside of the range considered by experts.

	Vehicles	Fossil Energy	Energy Storage	Solar PV	Bioenergy	Nuclear Energy	Total
allocation	$0.33 bn	$1.25 bn	$0.08 bn	$0.1 bn	$0.15 bn	$0.6 bn	$2.5 bn
marginal returns	$31	$8.1	$190	$95	$73	$15	
allocation	$0.33 bn	$1.25 bn	$0.66 bn	$0.98 bn	$1.19 bn	$0.6 bn	$5.0 bn
marginal returns	$20	$5.1	$26	$26	$26	$9.1	
allocation	$2.27 bn	$1.25 bn	$0.61 bn	$1.15 bn	$1.62 bn	$0.6 bn	$7.5 bn
marginal returns	$7.7	$4.0	$7.6	$7.7	$7.7	$6.8	
allocation	$2.8 bn	$1.25 bn	$0.57 bn	$1.1 bn	$1.62 bn	$2.65 bn	$10.0 bn
marginal returns	$3.9	$3.5	$3.7	$3.9	$3.9	$3.9	
allocation	$2.87 bn	$3.13 bn	$0.55 bn	$1.06 bn	$1.59 bn	$3.3 bn	$12.5 bn
marginal returns	$2.8	$2.8	$2.8	$2.8	$2.8	$2.8	
allocation	$2.89 bn	$5.27 bn	$0.53 bn	$1.02 bn	$1.56 bn	$3.73 bn	$15.0 bn
marginal returns	$2.1	$2.1	$2.0	$2.1	$2.1	$2.1	

The figure shows the optimal allocation and marginal returns to economic surplus from R&D at six example budget levels. Corner solutions imposed by the limited range of R&D scenarios considered by experts lead to unequal marginal returns for low budget levels.

Figure 3.3: *Optimal Allocation and Marginal Returns by Technology Area*

4. Conclusions and Discussion

R&D decisions are complex, require integration of multiple assumptions and metrics, and are important for public policy. This paper shows that current practices in energy R&D decision making in the U.S. could be improved. The new method developed in this paper is based on a consideration of four design principles for an R&D decision making process. This method also highlights the need for analytic capability that exists between technical experts and funders of R&D portfolios.

The method developed in this paper advances the current state of methods available in the literature. By operationalizing this method on data from a large set of expert elicitations, the distribution of different types of benefits under different R&D portfolios can be estimated – while fully propagating the elicited uncertainty and accounting for multiple interactions among technologies. Results quantify the aggregate benefits of an R&D portfolio in terms of system benefits (e.g. reduced pollutant emissions and economic surplus), technology benefits (e.g. the deployment of certain desirable technologies), and uncertainty analysis parameters (e.g. statistics of the distribution of other output metrics – such as variance of economic surplus or the probability that an R&D portfolio does not increase CO_2 emissions above certain levels). This method also allows analysts to test the sensitivity of the results to key assumptions, including functional form assumptions, the degree of spillover across technologies, the experts engaged in parameterizing the technology improvement distributions, the R&D investment levels, and other parameters in MARKAL. A transparent presentation of the assumptions that drive the calculation of benefits could help focus new work on important questions that are unresolved.

The method presented in this paper also improves on current decision making practices at the DOE and several other government organizations, which have demonstrated interest in adopting this type of method. However, there are several possible improvements outside of the scope of this paper. First, R&D investments could be modeled more realistically. Uncertainties at different innovation stages lead to dynamic time-contingencies in the benefits of R&D investments that occur over time. This paper models the R&D portfolio decision in a static setting with R&D investment occurring at a single point in time. More recent work has emphasized the dynamic, or process nature of the R&D investments and has analyzed capacity and congestion effects (Terwiesch and Loch, 1999) as well as strategies for search and information gathering (Dahan and Mendelson, 2001; Loch et al., 2001). This implies the need to also consider the sequencing of R&D decisions as part of a dynamic R&D decision making problem (Granot and Zuckerman, 1991; Santen and Anadón, 2014) because 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 federal funding for the National Institutes of Health over the past decade may have been less effective than a slow and continuous increase (Jaffe, 2012), perhaps in part due to the short-run inelastic supply of scientific expertise (Goolsbee, 1998). A dynamic R&D decision-making framework would capture a fundamental aspect of estimating the benefits of an R&D portfolio but would also require additional analytical complexity (on top of a framework that is already quite complex). In particular, the burden on expert participants would likely be very high.

A second direction for future work 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 consider 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) (Figueira et al., 2005; Greening and Bernow, 2004; Stewart, 1991). There is also literature on directly connecting expert opinions to R&D decision making without the use of an intermediate model of outcomes (Hsu et al., 2003; Liberatore and Titus, 1983). The method presented in this paper can provide the necessary input data to support MCDM by providing estimates of social benefits measured by several individual criteria.

The approach presented in this paper could be used in modelling efforts that help justify and improve decision making on R&D beyond the particular application to the DOE that is presented in this work. To generate quantitative estimates of the ex-ante benefits of an R&D portfolio, this method relies on expert judgment, which is inherently subjective in nature. While the inputs to any ex-ante policy assessment require scrutiny, the use of this method to evaluate impacts in a probabilistic fashion can advance public debate in many other cases in which the propagation of uncertainty and the interactions between policy instruments are important. Beyond R&D investment decisions, there are many contexts in which decision making can be supported through the use of a complex model of outcomes with uncertain parametric inputs; for example, earth systems models for decisions about mitigating environmental impacts, structural economic models for decisions about economic incentives, and engineering systems models for decisions about risk mitigation. The approach presented in this paper has a more generalizable core that addresses the common challenge in utilizing these types of models of representing uncertainty in parameters and summarizing probability distributions of outcomes that propagate uncertainty (Morgan and Henrion, 1998; Raiffa, 1968).

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Appendix

A.1 Expert Elicitation Protocol

This appendix provides additional details on the protocol we developed and followed to conduct a suite of energy technology expert elicitations in 2009-2010. This protocol is described in greater detail in Anadón, et al. (2014b), which forms the basis for this appendix.

A.1.1 Technology Selection

We designed and conducted expert elicitations with more than 100 experts[10] on seven technology areas: fuels and electricity from biomass (bioenergy, for short); different types of utility scale energy storage (or storage); residential, commercial, and utility scale photovoltaic technologies (solar); efficiency in commercial buildings (buildings); nuclear power from Generation III/III+, Generation IV, and small and medium reactors (nuclear); coal and natural gas electricity production with and without carbon capture and storage (fossil); and vehicle technologies (vehicles). We were unable to include other energy technologies in DOE's investment portfolio – notably wind power, geothermal power, concentrated solar power, advanced lighting, and industrial energy efficiency – in this study owing to limited resources. Due to the design of the buildings elicitation, we are not able to quantify uncertainty in building technology parameters in MARKAL, and therefore the results of the buildings elicitation are not included in our analysis in this paper.

A.1.2 Expert Selection

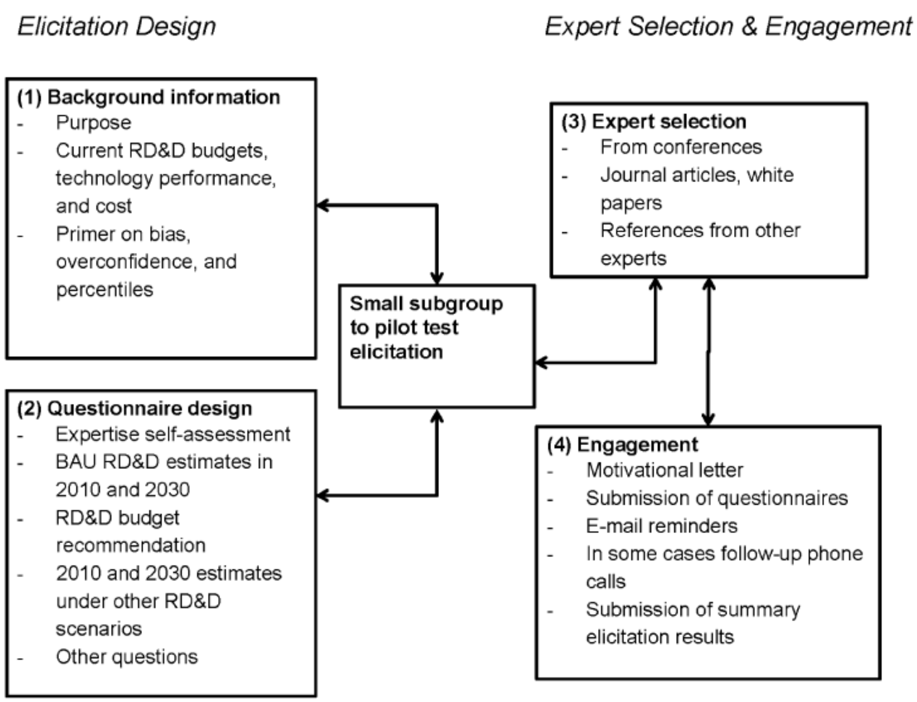
We invited leading researchers and practitioners in each of the seven fields from academia, the private sector – including small and large firms – and the U.S. national laboratories to give us their input. We asked these experts to estimate technical cost and performance metrics in 2030 under a BAU scenario for federal R&D funding for that technology, to recommend the level of annual R&D funding and allocation

[10] 108 experts gave total and partial answers to the different surveys: 30 participated in the nuclear survey, 25 in the storage survey, 12 in the bioenergy survey, 9 in the buildings survey, 9 in the vehicles survey, 12 in the fossil energy survey, and 11 in the PV survey.

that would be necessary to increase the commercial viability of the technologies in question, and to revise their 2030 technology projections under different hypothetical budgets.

A.1.3 Expert Elicitation Protocol

Our seven elicitations were carried out using a consistent methodology. We examined four energy supply technology areas (fossil, nuclear, solar, biofuels), two energy demand technology areas (vehicles, buildings), and one enabling energy technology area (energy storage). Figure A.1 illustrates the different tasks that were involved in the design and execution of each of the seven elicitations. Designing and fielding each elicitation took between four and eight months. The first phase involved conducting extensive research into each technology, which we summarized for expert participants in a background information section.



Adapted from Anadón et al. (2014b).

Figure A.1: *Schematic of the Protocol for Expert Elicitations*

In the second phase, we designed the questionnaires for each technology. The questionnaire first asked experts to self-assess their expertise in a wide range of technology subfields; we used this information to explore potential biases in experts' technical assessments. The questionnaire also asked experts to recommend an aggregate level of R&D funding, and then to estimate cost and performance metrics once in 2010 and then again in 2030 under four scenarios of R&D funding: BAU, half of the recommended budget, the recommended budget, and 10 times the recommended budget. The results of this suite of conditional cost and performance metrics allowed us to explore the sensitivity of the cost and performance estimates to different public R&D investments. A small subgroup of experts (typically two to three) was then used to test and refine the first elicitation draft to increase our confidence that each elicitation instrument draft would be correctly interpreted by the experts (and that it would provide information in the right form to be of use in the next stages of the method). This second phase of fielding the final elicitation instrument took between two and three months.

In the third phase, we collected the names of experts from a range of sources by examining the peer-reviewed literature, national laboratory programs, university research programs, conference participation, and referrals from other experts and our own program's advisory board. The participant pool we assembled covered a range of perspectives and included technical experts from the private sector, academia, and the national laboratories.

In the fourth phase, we engaged experts through email solicitations for participation. For willing participants, survey responses were conducted by mailed hard copy or through an online platform. In many cases it was necessary to send reminders and hold follow up phone calls to clarify specific questions from the participants. On average, experts invested between two and five hours to complete our study's elicitations, not including the interaction with researchers in the cases in which it took place. Designing and fielding an expert elicitation is a very labor-intensive process for both study designers and participating experts.

We now turn to describing in more detail the structure of the elicitation instruments. The elicitations began an extensive background section divided into four subsections: (i) a summary of the purpose of the elicitation (reminding experts of the rationale explained in their invitation via e-mail and phone) and a note encouraging experts to contact researchers at all times to answer questions; (ii) a technology primer of material on current technology cost and performance, fuel costs if applicable, a summary of current government R&D investments in the technology area, and future cost projections found in the literature; (iii) a short tutorial on bias and overconfidence, which included a graphical example on expert's overconfidence estimating the speed of light, and instructions about how to reduce overconfidence, including the provision of the expert's 10th and 90th percentile estimates before the 50th percentile estimate, and including the importance of imagining alternate scenarios wherein the true value is outside the ranges the expert provided (which should lead to expert to broaden his/her estimates); and (iv) an explanation of percentiles, including text using language like that used in the remainder of the elicitation, and a graphical representation of interpreting percentiles (Baker et al., 2014).

The background material served to ensure that all experts had the most recent literature fresh in their minds and to encourage them to think consistently about the variables that we would ask them to estimate, which included costs, efficiency, and government R&D investments and programs. The elicitation device was then divided into four or five sections of questions.

In Part 1, experts were asked to assess their expertise on specific technologies, components, and ancillary topics such as feedstocks, specific technology areas, materials, products, and enabling technologies.

In Part 2, experts were asked to identify commercially viable technologies in 2010, as well as the projected cost and performance that would result from a continuation of 2010 federal funding and private investments through 2030, assuming no new government policies are implemented. This scenario was defined as the BAU scenario.11

In Part 3, experts were asked to recommend a total annual federal R&D budget for the technology area in question. The experts were asked to allocate their recommended budget among basic research, applied research, development, and demonstration investments for specific technologies within the general class of technologies being assessed (e.g., oxy-fired carbon capture technology was one specific technology in

[11] The BAU scenario in this work includes all current deployment policies modeled in the Energy Information Administration's (EIA) Annual Energy Outlook 2010 (EIA, 2010a). Anadón et al. (2011) summarizes the status quo policies in the BAU scenario and other future policies categorized into power standards, building codes, transportation policies, and climate policies. It also describes the scenarios used to estimate the impact of oil and gas prices.

the fossil elicitation). These questions asked experts to visually allocate R&D funds into different technology areas and development stages. Experts were also asked to indicate potential coordination with other areas of energy technology research, as well as industries that could provide “spillover” innovations. In most surveys, experts were also asked to provide their insights into the technological hurdles that could be overcome by research in the areas where they recommended the largest investments, and to recommend research areas for cooperation with other countries.

In Part 4, experts were asked to update their BAU 2030 technology cost and performance estimates under three scenarios of R&D funding. These scenarios were defined in relation to the level of R&D recommended by the experts. First experts estimated 2030 cost and performance metrics assuming their recommended annual federal R&D budget was implemented and held constant over the next 20 years. Then, experts updated their 2030 estimates under two additional R&D scenarios: a 50% proportional reduction in their recommended budget and a 10-fold proportional increase in their recommended budget. Having experts re-estimate future technology cost and performance was a crucial part of this analysis because it allowed us to estimate the sensitivity of technology outcomes to R&D funding. In the online elicitations, technology cost questions under different R&D scenarios were visualized in one graph enabling and encouraging respondents to adjust their answers as they were completing the elicitation.

In Part 5, which was not formally a part of all the elicitations we conducted, experts were asked to estimate deployment levels that could be achieved under the four R&D budget scenarios. These elicitations also asked experts to think through deployment policies that would contribute to commercializing novel energy technologies. In those surveys where deployment was not examined in a separate section, experts were asked similar questions about deployment in Parts 2 and 4.

Four of the elicitations (the bioenergy, fossil, storage, and vehicles surveys) were conducted using a written device, which was mailed to participants. The remaining three elicitations (the nuclear, buildings, and solar surveys) were conducted online. Online elicitations improve the ability of experts to modify their answers and to visualize them as they input their estimates. We included several graphics that allowed the experts to see the uncertainty ranges they specified as well as their estimates of cost and performance under different budget scenarios alongside each other. Online elicitations also accelerated the data collection and analysis process, which would be beneficial for future elicitations conducted on a more frequent or broader scale.

At the end of the elicitations, all experts were provided with a written summary of the responses of all participating experts, with the ability to change theirs. For the elicitation on nuclear energy, we also convened a workshop of the participants in the elicitation we conducted and the participants from a similar expert elicitation conducted by the Fondazione Eni Enrico Mattei (FEEM). These experts were given the possibility of revising their responses in private after each workshop session. The details of the workshop and the lessons learned are described in Anadón et al., 2012 (Anadón et al., 2012).

For reference, the nuclear energy expert elicitation is publicly available online at https://erd3.cloudapp.net/nuclear_energy.

A.1.4 Qualitative Reviews of Elicitation Results

We complemented the seven elicitations with qualitative interviews (two to six per elicitation) in which we presented the elicitation results to a set of 23 additional experts who were not involved in the first round of elicitations but had expertise managing R&D budgets for each technology area and experience thinking about investments on a range of technology projects. In these conversations, which lasted from one to two hours, we showed the program experts the technology area experts' recommended budgets and technology cost and performance parameter estimates. Their affiliations included DOE programs, venture capital firms, and U.S. Congressional committees. These qualitative reviews helped us interpret the elicitation results and served to expand expert input in our work. These additional experts gave their views on how to synthesize the entire set of results from each of the elicitations and helped identify a representative expert in each survey (see Section 1.2.2).

A.2 Correlation of Future Technology Cost Improvements

In Section 1.1.2, we describe the requirements for and the process we used to construct a correlation matrix relating the 2030 costs of the 25 technologies considered in this paper. Table A.1 displays this correlation matrix, expressed as a Spearman correlation matrix.

Table A.1: *Estimated Cross-Technology Spearman Correlations*

index		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
tech code		GTC	DTC	JTC	ETC	COL	GAS	CCS	GCC	GBC	DBC	CAS	BLI	BNS	FLO	BEV	CAR	HYB	PEV	FCV	THR	FOR	MOD	PVR	PVC	PVU
Cross-Tech Correlation	GTC	**1.00**	0.95	0.95	0.70	0.60	0.60	0.70	0.70																	
	DTC	0.95	**1.00**	0.95	0.70	0.60	0.60	0.70	0.70																	
	JTC	0.95	0.95	**1.00**	0.70	0.60	0.60	0.70	0.70																	
	ETC	0.70	0.70	0.70	**1.00**	0.70	0.70	0.65	0.65																	
	COL	0.60	0.60	0.60	0.70	**1.00**	0.70	0.90	0.70																	
	GAS	0.60	0.60	0.60	0.70	0.70	**1.00**	0.70	0.90																	
	CCS	0.70	0.70	0.70	0.65	0.90	0.70	**1.00**	0.80																	
	GCC	0.70	0.70	0.70	0.65	0.70	0.90	0.80	**1.00**																	
	GBC									**1.00**	0.70															
	DBC									0.70	**1.00**															
	CAS											**1.00**														
	BLI												**1.00**	0.50	0.30	0.50	0.10	0.10	0.50	0.10						
	BNS												0.50	**1.00**	0.50	0.30	0.10	0.30	0.30	0.05						
	FLO												0.30	0.50	**1.00**	0.30	0.10	0.30	0.30	0.05						
	BEV												0.50	0.30	0.30	**1.00**	0.50	0.70	0.90	0.40						
	CAR												0.10	0.10	0.10	0.50	**1.00**	0.70	0.70	0.40						
	HYB												0.10	0.30	0.30	0.70	0.70	**1.00**	0.80	0.40						
	PEV												0.50	0.30	0.30	0.90	0.70	0.80	**1.00**	0.40						
	FCV												0.10	0.05	0.05	0.40	0.40	0.40	0.40	**1.00**						
	THR																				**1.00**	0.60	0.70			
	FOR																				0.60	**1.00**	0.60			
	MOD																				0.70	0.60	**1.00**			
	PVR																							**1.00**	0.95	0.90
	PVC																							0.95	**1.00**	0.92
	PVU																							0.90	0.92	**1.00**

Estimated cross-technology Spearman correlations for the following technologies: GTC: gasoline-substitute from biomass or a mixture of biomass and coal through thermochemical conversion pathways; DTC: diesel-substitute from biomass or a mixture of biomass and coal through thermochemical conversion pathways; JTC: jet fuel-substitute from biomass or a mixture of biomass and coal through thermochemical conversion pathways; ETC; electricity from biomass or a mixture of biomass and coal through thermochemical conversion pathways; COL: coal power without carbon capture and storage; GAS: combined cycle natural gas power without carbon capture and storage; CCS: coal power with carbon capture and storage; GCC: combined cycle natural gas power with carbon capture and storage; GBC: gasoline-substitute from biomass through a biochemical conversion pathway; DBC: diesel-substitute from biomass through a biochemical conversion pathway; CAS: compressed air energy storage; BLI: utility-scale lithium-ion-based batteries; BNS: utility-scale sodium-sulfur-based batteries; FLO: utility-scale flow batteries; BEV: light-duty battery electric vehicles; CAR: light-duty advanced internal combustion engine vehicles; HYB: light-duty hybrid vehicles; PEV: light-duty plug-in hybrid vehicles; FCV: light-duty fuel cell vehicles; THR: Gen III/III+ nuclear power; FOR: