Integrating uncertainty into public energy research and development decisions

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Abstract

Public energy research and development (R&D) is recognized as a key policy tool to transform the world's energy system in a cost-effective way. However, managing the uncertainty surrounding technological change is a critical challenge for designing robust and cost-effective energy policies. The design of such policies is particularly important if countries are going to meet the ambitious greenhouse gas emissions reductions goals set by the Paris Agreement and the required harmonization with the broader set of objectives dictated by the Sustainable Development Goals. The complexity of informing energy technology policy requires, and is producing, a growing collaboration between different academic disciplines and practitioners. Three analytical components have emerged to support the integration of technological uncertainty into energy policy: expert elicitations, integrated assessment models, and decision frameworks. Here we review efforts to incorporate all three approaches to facilitate public energy R&D decision-making under uncertainty. We highlight emerging insights that are robust across elicitations, models, and frameworks, relating to the allocation of public R&D investments, and identify gaps and challenges that remain.

Introduction

Predicting the future is extremely difficult[1], yet it is nonsensical to ignore the knowledge and understanding we can acquire from experts when making decisions. It is well understood that using experts, and using them wisely, is a key component of evidence-based policy making[2].

In the energy sector, policy makers are faced with a number of near-term decisions, such as balancing technology R&D, performance standards, and subsidies; or designing energy technology R&D portfolios. Designing these policies involves managing the significant uncertainty that exists about how technologies will evolve with and without different policies[3]. In the wake of the December 2015 Paris Agreement, in which countries agreed to put in place national action plans to reduce greenhouse gas emissions, and in the context of tight government budgets around the world, designing robust and cost-effective energy innovation policies in the face of technological uncertainty has become more pressing.[4] The question of how to design portfolios of R&D investments across a range of energy technologies has received much attention, most recently after the launch of the Mission Innovation and Breakthrough Energy Coalition pledges to increase public energy R&D funding and follow-on private investments in energy technologies. The R&D decision literature typically approaches this problem in two stages: first considering how R&D investments affect future technology costs[5], then considering how future technology costs affect energy and climate policies (e.g., EMF28[6]) .

One method for informing policy decisions is to perform expert elicitations (a structured process for eliciting subjective probability distributions from subject-matter experts[7]). Over the past 10 years a number of researchers have performed expert elicitations to characterize the uncertainty around future cost and performance of various energy technologies, often subject to assumptions about public R&D investments. This information, however, is just one of the pieces of analysis needed to inform the design of optimal energy R&D portfolios. Supporting R&D policy decisions requires knowledge in a multiplicity of domains, ranging from forecasts for multiple technologies, the economics and engineering of integrating technologies in the energy system, the relationship between economic activities, emissions and the climate, and the role of risk and hedging strategies. For this reason, there has been an effort to integrate the data from expert elicitations about the future of energy technologies into integrated assessment models and decision making frameworks to provide results that can serve to support energy R&D decisions. Until recently, these three domains, illustrated by the analytical components in Figure 1, had largely resided in different literatures.

The components in Figure 1 have been used to inform a range of questions, including both energy infrastructure planning and energy technology R&D policy. Expert elicitations have been used to calibrate deterministic analysis in both integrated assessment and energy-economic models (both of which we will refer to as IAMs from now on) through the use of means or medians. (Box 1 includes a description of IAMs and a discussion of the challenges associated with their use.) The greatest value of expert elicitations is that they allow researchers and policy makers to explicitly use probabilistic data to characterize uncertainties in their analysis, permitting the design of policies capable of hedging against particular risks[8–10]. Having an explicit characterization of uncertainty is particularly important when the problem or question under consideration includes non-linearities. Non-linearity may characterize preferences, as in the case of risk aversion, where a decision maker is willing to give up something, such as money or enjoyment, to avoid some level of risk. Such preferences are represented by concave utility functions in economic models[11]. Non-linearities can also reside in the underlying problem itself. In the case of energy R&D investments, there may be non-linearities in the impact of R&D investments on energy technology costs, in the competition and complementarity among technologies in the market, and in irreversibilities or tipping points that might characterize environmental damages. A third type of non-linearity emerges when decision makers can make additional decisions in the future once uncertain outcomes have been revealed. As has been demonstrated[12], when future options are available, near- term decisions that avoid lock-ins or irreversible effects are more welfare enhancing than those that naively maximize the expected net present value. Collectively, these non-linearities make it important to consider the full distribution of outcomes from decisions, including the tails and not just average values. This applies to multiple types of energy planning problems; the literature, however, has focused this kind of analysis on R&D problems. While in some cases the full stochastic treatment does not yield significantly different results from a simple best guess[13–15], at other times[16,17] it does; unfortunately it is difficult to know a priori when it is important.

An important distinction we make in Figure 1 is to classify integrated uncertainty modeling efforts into Learn-then-Act (comprising sensitivity analysis and uncertainty analysis) and Act-Learn-Act (which are often simply called Act-then-Learn in the literature and comprise one-stage and multi-stage decision making under uncertainty, DMUU). Learn-then-Act frameworks combine elicitations with IAMs; Act-Learn-Act frameworks also integrate decision theory models (sometimes within IAMs themselves [18], sometimes in a multi-model framework[8]).

The differences between Learn-then-Act and Act-Learn-Act frameworks are related to when decisions take place in relation to when uncertainty is resolved. The key uncertainty in the papers we review is technological outcomes. Learn-then-Act frameworks take near-term actions as given (in this case a particular level of public energy R&D investment), and explicitly model decisions which take place only after uncertainty has been realized (deployment decisions which take place within IAMs). Act-Learn-Act frameworks are more realistic, explicitly modelling near-term decisions that must be made before uncertainty is resolved; the full probability distribution is taken into account when choosing an alternative. In all of the papers reviewed, the near-term decision is investment in public energy R&D. The remaining later stage decisions, including deployment, take place within the IAMs.

In this Review, we discuss work combining expert elicitations on energy technologies with IAMs and frameworks for decision making under uncertainty to support public energy technology R&D policy decisions in the face of technological uncertainty. The insights stemming from the types of integrated quantitative analysis depicted in Figure 1 and described in this Review are, of course, just one input to public policy. There are many other factors, such as politics, stakeholder values, and the interactions between policies in the energy sector and other sectors that require government investment, to name a few. Nevertheless, insights about optimal public energy R&D portfolios arising from integrated quantitative analysis can usefully support decisions, by clarifying the presence of non-linearities and by providing clarity about assumptions, goals and tradeoffs of different investments. The aim of this Review is three-fold: to summarize and categorize recent research incorporating expert elicitations and IAMs in decision making frameworks; to highlight the most relevant insights coming from this literature for the design of public energy R&D portfolios; and to identify gaps and key research areas going forward.

Expert Insights about the Future of Energy Technologies

Before delving into the integrated approach presented in Figure 1, we review the literature on energy technology expert elicitations.

Verdolini et al. [19] provide a review of 29 expert elicitation studies performed between 2007 and 2012, covering eleven energy technology categories. The range of studies reviewed there (plus two additional recent wind studies, making it a total of 31 papers) are summarized in Table 1 and the key challenges and gaps associated with energy technology expert elicitations are summarized in Box 2. It is important to note that none of the elicitations explored alternative scenarios of private-sector R&D investment due to a large extent to the lack of information regarding current private energy R&D investments by technology.

The analysis of 31 papers included in Table 1[3,19] provides robust evidence of the significant uncertainty surrounding future energy technology cost and performance. The uncertainty characterized by elicitations goes beyond the uncertainty estimated from forecasting methods based historical data (e.g. learning or experience curves, as a function of deployment[20] or of time[19]). For example, using 20 year windows of historical data on solar photovoltaic (PV) module costs from Fraunhofer[21] , the average annual cost reduction ranges between 2.7% and 4.6%, depending on the start date of the window; the average annual cost reduction over a 25 year period (1980-2015) is 2.8%. For comparison, using individual expert answers from the Harvard solar PV expert elicitation[22] on module costs, implied average annual cost reductions between 2010 and 2030 show a much wider range, from 0.1% to 4.7%. This range of uncertainty does not seem to depend on the level of R&D investment.[5,23] It is also worth noting that most of the elicitations sought to isolate the impact of R&D, recognizing that there are factors beyond R&D, such as input prices, learning-by-doing and economies of scale that have driven previous cost reductions. This has, for example, been demonstrated for solar PV [20].

According to the studies in Table 1 and the related discussion in Box 2, on average, with significant variation across technologies, experts expect that higher levels of R&D would lead to cost reductions of over 50% between 2010 and 2030. Looking at the tails of the distributions, however, it is possible to detect non-zero probabilities of more significant breakthroughs leading to sustained cost reductions on the order of 10% per year until 2030[3]. Examining only the medians or means would result in ignoring low probability, high-impact events in decision making. Among the studies, results vary by technology in terms of forecast rates of cost improvements; however, the uncertainty within and between studies dominates.

When comparing the rate of change in the future cost of technologies implied by the expert elicitation studies to projections based on historical data, it was found[19] that the technologies differ in the degree to which the experts see the future as being similar to the past. For example, the median expert forecasts for nuclear power and biofuels are similar to historical data, while expert forecasts for bioelectricity are relatively pessimistic. This is consistent with the possibility that expert judgments represent a semi-independent source of information: experts are influenced by historical trends as well as by their personal experiences and beliefs about future technological developments.

There are many challenges and gaps associated with energy technology expert elicitations (see Box 2). Nevertheless, elicitations provide a systematic way, using the best available knowledge, to provide information on future technological change unavailable from other types of analyses.

Modelling and Managing Technological Uncertainty

It is not enough to have an understanding of the uncertainty surrounding the future cost and performance of energy technologies. The design of efficient and cost-effective energy policies requires understanding the broader social impact of changes in these technologies, including the impact of interactions across technologies and between R&D and other policies. A large body of literature has explored the importance of technological costs on future mitigation pathways under uncertainty without using inputs from expert elicitations (see for example refs [24,25,26]). In this section, we review studies that explicitly combine elicitation-based uncertainty on energy technology cost and performance with IAMs to support the design of energy technology policy.

Table 2 classifies modeling efforts into Learn-then-Act and Act-Learn-Act, categories introduced in Figure 1. Sensitivity analysis, which takes the energy R&D investment decision as given, addresses technological uncertainty by experimenting over a range of technological scenarios. The result of sensitivity analysis is a range over the standard outputs of IAMs (e.g. investment levels, climate mitigation costs). Most sensitivity analysis efforts do not rely on expert elicitations, but Table 1 includes some sensitivity analysis studies that do.

Uncertainty analyses also take the energy R&D investment decision as given, but move a step further, using probability distributions of future technology costs and performances as inputs, and providing outputs from IAMs as probability distributions. The most well-known method of uncertainty analysis is Monte Carlo analysis.

The last two columns of Table 1 move into the realm of DMUU, which provides insight into near-term strategies given the current state of information. In the 1-stage DMUU approach, as illustrated in Figure 1, key decisions (in this case R&D investment decisions) are made before uncertainty is resolved. Multi-stage DMUU approaches, on the other hand, allow for "recourse" — key decisions are revisited after uncertainty is revealed, including future climate policies or results from the previous energy R&D investments. Thus, multi-stage DMUU models can identify near-term decisions or policies with option value[12]. Among multi-stage DMUU frameworks, it is most common to have two stages, but some models include a larger number of downstream decisions. The two most common methods for implementing multi-stage models are Dynamic Programming [27] and Stochastic Programming. Dynamic Programming is increasingly being implemented with high-dimensionality solution techniques, such as Approximate Dynamic Programming (ADP)[28]. In general, computational challenges are difficult in all multi-stage frameworks due to the "curse of dimensionality": while stochastic programming needs to manage the number of future uncertain states; ADP models need to manage the number of state variables. Some have argued that the addition of decision stages beyond two may not provide considerable insight[25,29]. In all

DMUU studies here, IAM-based deployment decisions take place after uncertainty is resolved. DMUU differs from sensitivity and uncertainty analysis, as the uncertainty explicitly feeds back into the near-term decision.

Sensitivity to Energy Technology Costs

While expert elicitations have been used to calibrate IAMs, this does not fully utilize the probabilistic data assembled in expert elicitations. In Table 1, we include sensitivity analysis studies that use the range of values elicited from experts to analyze the impact of technology scenarios on model outputs. Typically, sensitivity analyses vary technology input parameters one at a time to assess the range of societal outcomes associated with extreme technology assumptions. This helps to identify critical uncertainties and to bound results. Pugh et al.[30] performed an informal expert elicitation over various technical outcomes across a wide range of technologies, and used the results to assess emissions reductions and return on investment. Ricci et al.[31] and Iyer et al. [32] each perform a simple sensitivity analysis to bound possible future costs and efficiency of a single technology (carbon capture and storage and nuclear, respectively) and its economic implications. Barron and McJeon[33] investigate how much technologies would need to improve to significantly reduce the cost of climate change mitigation. Olaleye and Baker[34] perform a large scale, multi-parameter scenario analysis to identify technologies that are complements or substitutes in terms of utility.

In recent years, there has been an effort to go beyond conventional sensitivity analysis, by allowing various input parameters to change together, thus capturing interaction effects. Such approaches can use elicited probability distributions for random draws [35] and are referred to as global sensitivity analysis. Bosetti et al.[36] perform a multi-model global sensitivity analysis of energy technology costs, drawing on three elicitation studies over five technologies. Their results, robust to the choice of the IAM, indicate that when there is no climate policy, among the technologies considered, nuclear cost assumptions are the biggest technology cost determinants of projected societal energy costs and baseline emissions, complementing findings about the role of nuclear with climate policy[37]. Sensitivity analysis is more computationally-tractable than the methods we discuss later, and is appropriate for identifying areas of interest that could be the subject of additional research. It has descriptive value and its results can be easily presented to policy makers or other users, usually in the form of scenarios representing particular narratives. Sensitivity analysis represents a first step towards understanding the resilience of a particular policy. It has the weakness, however, of not taking into account many of the non-linearities mentioned above. Thus, researchers and analysts should consider going beyond sensitivity analysis, even if this presents challenges to communication, because "decision makers are often far better served by examining the diversity of opinion" [38] and thinking about the robustness of policy approaches to the uncertainty.

Towards Understanding Uncertainty

Expert elicitation data can also be used in uncertainty analysis, most commonly Monte-Carlo analyses. Monte-Carlo type analyses use random draws from probability distributions as inputs to models, such as IAMs, resulting in probability distributions over the outputs of interest. Gillenwater[39] uses an elicitation on wind to estimate the effect of policies on the probability of private sector deployment investment. A similar, but more sophisticated method, Latin Hypercube Sampling (LHS)[40], can reduce the number of needed simulations while preserving the probabilistic interpretation of the model outputs. Chan and Anadon (2016)[41] account for the dependency between R&D-induced energy technology improvements across a set of twenty-five technologies (some of which are interrelated) using LHS. The results include probability distributions of future CO_2 emissions, oil imports, consumer and producer surplus and other metrics under different R&D scenarios, with and without specific demand-side policies.

Another method of uncertainty analysis is to propagate probability distributions through a model. Olaleye[42] uses large scale scenario analysis to estimate probability distributions over welfare for different R&D portfolios, by associating each technological outcome with a conditional probability derived from elicitations. Lemoine and McJeon[43] combine energy technology elicitation results with an IAM to investigate the probability distributions of climate damages and mitigation costs. Several elicitation studies use deterministic runs of an IAM combined with elicited probabilities of particular technology costs to derive conditional probability distributions over the impacts of R&D on the Marginal Abatement Cost curve, with a focus on the different ways in which different technologies impact the curve[44–46].

Nemet and Baker[47] combine the results of a solar expert elicitation with a technology-economic model that allows them to derive probability distributions over the cost of solar conditional on both technology R&D and technology subsidies. Similarly, a set of interrelated papers propagate elicited distributions of the outcomes of R&D in carbon capture and storage (CCS) technology through different techno-economic models to produce probability distributions of the future technology costs and overall CO_2 avoidance for various R&D investment and deployment policies [48,49,50].

Uncertainty analysis forces researchers and policy makers to think about probabilities, with the added benefits (and added complexities) that this entails[51]. However, similarly to sensitivity analysis, uncertainty analysis by itself does not directly inform near-term decision-making, such as the optimal amount and allocation of R&D investments.

Modelling Insights from DMUU Frameworks

The studies presented in Table 3 and discussed in Box 3 show that there are tradeoffs involved in selecting DMUU strategies, involving the number of technologies that are explicitly modelled as uncertain, the number of decision stages, the representation of R&D, and use of reduced form decision models. Baker and Solak (2014)[52] consider only three technologies, but solve a technologically-detailed stochastic programing version of the IAM DICE, where investments into R&D impact the marginal abatement cost curve and are the first stage decision. All papers with 4 or more technologies feed outputs from IAMs into reduced-form decision models. Chan & Anadon (2016)[41] include continuous public R&D levels for 6 technology areas that affect the cost and performance of 25 individual technologies, but only one-stage DMUU. Six papers in Table 3 use two-stage DMUU[8,42,53–56], but only have 3-6 technology categories; all but one[56] use discrete R&D investment levels. Santen & Anadon (2016)[17] use ADP to solve a four-stage DMUU, but consider R&D dependent uncertainty in only one technology (which competes with 3 others for deployment). Most of the multi-stage DMUU frameworks include R&D as a first stage decision and deployment in later stages; Santen & Anadon (2016)[17] include decisions on R&D and deployment in all 4 stages. Some studies optimized given one or several budget constraints[41,42,53,57], others solved for the optimal budget level[8,17,52], and others do both[54–56,58].

It is important for researchers and users of information to be aware of the crucial design decisions being made when conducting this analysis and to understand what tradeoffs are being made and why. Key design decisions are the number of technologies that are modelled with R&D dependent uncertainty, the number of decision stages, whether or not R&D funding is continuous, and the decision framework.

Another question for researchers and policy makers is whether one piece of the analytical framework depicted in Figure 1 is driving the results. Is it enough to look at the results of expert elicitations to determine which R&D investments are best to achieve a particular policy goal? Or, on the other hand, do the built-in assumptions of IAMs swamp the assumptions stemming from expert elicitations? We find evidence that both components influence results, along with the decision framework. A comparative analysis[8] reported in Figure 2 shows that the expert elicitation data matters: the IAM and decision frameworks were identical yet the R&D portfolio results vary by elicitations. Figure 3 shows that the inclusion of more technologies (for example, some studies include vehicles and some do not) also has an impact on results about optimal energy R&D portfolios. Figures 2 and 4 both show that the decision framework matters. Comparing the results in Baker et al. (2015)[8] that use the UMass elicitations with the McJeon study[53] in Figure 2 shows that while both studies employ the same IAM and elicitation data, they have different results. Santen & Anadon (2016)[17] also find that the decision framework matters: the results presented in Figure 4 show that deterministic, Monte-Carlo, and 5-stage DMUU lead to different levels of R&D vs technology deployment investments. Finally, Barron (2015)[57] shows that the choice of the IAM matters, with GCAM and MESSAGE providing different optimal R&D portfolios using the same elicitations and decision frameworks.

Policy Insights

One important dimension that emerges when thinking about designing optimal energy R&D portfolios is to what extent they depend on the context, including other policies or policy goals. In particular, climate policy stringency, and the availability of resources for R&D investments and for deployment of energy technologies are key factors prevalent in policy debates in the energy sector.

We now turn to reviewing the insights for policy that emerge from the literature introduced above. We organize these insights into three areas: the impact of climate change targets on optimal R&D portfolios; the impact of R&D budget constraints on the allocation of R&D investments; and a comparison between funding allocated to public R&D and to technology deployment.

Optimal R&D Portfolios under Different Climate Targets

Figure 2 summarizes a range of studies investigating the extent to which different climate constraints affect optimal R&D portfolios. Results are organized into Groups with common elicitations, IAMs, and decision methods. Of the six Groups analyzed, which come from 4 major studies[41,53,56,59], four Groups (1-4) compare a baseline "no policy" scenario with either a lenient and stringent climate stabilization scenario or with just a stringent climate stabilization scenario (the Figure caption provides information about the specific studies), Group 5 compares a lenient and a stringent climate stabilization scenario and Group 6 presents the optimal R&D allocation under a lenient climate stabilization policy. Although the climate scenarios are not entirely comparable, we group them into the broad categories of stringent and lenient climate target scenarios; details and assumptions are reported in Table 3 and in Box 3.

There are five technology-specific results that emerge from the analysis presented in Figure 2. First, solar gets the smallest share of R&D and its role slightly decreases as the target gets more stringent. This is mainly due to the different magnitude of solar R&D investments compared to the other type of technologies. Second, the stricter the climate constraint, the greater the share of CCS in energy R&D portfolios, with the exception of one study[8] using the UMass elicitations. CCS is critical for negative emissions (bioenergy plus CCS), which in turn is an increasingly important strategy for stricter climate targets. Third, stricter climate constraints lead to an equal or smaller share of nuclear in energy R&D portfolios, with the exception of one study[8] using the Anadon et al. (2014) [22] elicitations. This appears to be due to large nuclear investments under low-stringency targets, with less room to grow as target gets more stringent. Fourth, all studies that include vehicles find that a significant share of the overall budget is devoted to advanced vehicles R&D, ranging from 30 to 80% of the total R&D investments; this fraction increases with stricter climate constraints. Fifth, R&D funding for utility scale energy storage, a technology area included in only one study, increases with stricter climate constraints.

It is important to note that this is a summary of emerging insights, and many gaps and challenges exist, such as model biases and missing or poorly modeled technologies, making it difficult to extract recommendations about the precise level of R&D investments into specific technologies. However, one general conclusion does appear: technologies which provide flexibility see higher R&D investments as climate stringency increases. CCS allows for ex-post emission decreases from fossil plants; storage allows higher penetration of intermittent technologies; and vehicles allow abatement to reach into the transportation sector. The fact that we do not see this pattern for biofuels reflects elicitation results, particularly in the US studies, which may in turn reflect high existing levels of R&D.

Optimal R&D Portfolios for Different R&D Budget Constraints

Another pressing question in the minds of policy makers, particularly in times of financial crisis, is how R&D investment portfolios should change for different public energy R&D budget constraints. Figure 3 summarizes the results of seven papers[22,42,52,54,56,58,41] that consider multiple public energy R&D budget constraints.

Results show that with tighter R&D budgets, portfolios become less diverse, with some technologies not funded at all. Among the four studies that include vehicles[41,22,42,53] there is a decrease in the share of vehicles R&D with greater R&D budgets. This is likely because vehicle R&D (in particular batteries) get a large share to begin with in constrained budgets; and because the marginal improvement seen in the elicitations above and beyond those levels is smaller than that of other technologies, especially CCS. Among the three studies that include bioenergy[41,42,56] the fraction of R&D devoted to total bioenergy (the combination of biofuels and bioelectricity) stays relatively constant, driven to some extent by assumptions about the availability and cost of biomass.

Solar plays an interesting role in these portfolios. First, we note that, as the R&D budget constraint is relaxed, and consequently the number of technologies considered grows, the share of R&D for solar decreases precipitously (more so than nuclear, CCS, or vehicles). Moreover, the share of solar is non-monotonic in a number of studies, more prominently than any of the other technologies. This may indicate that solar plays the role of a kind of "filler" technology in these portfolios. The problem of finding an optimal portfolio subject to a constraint is what is known as a "knapsack problem". It is well known that knapsack problems can lead to non-monotonic results as the constraint (in this case the total energy R&D budget) relaxes. Solar R&D plays this role since, especially in comparison to CCS and nuclear, it can be productive even at lab scales. On the other hand, in the absence of cost-effective storage technologies, solar PV has a limited impact on the overall economy, due to structural assumptions about intermittency in many of the IAMs.

The main disagreement in the results in Figure 3 is for the fraction of R&D devoted to nuclear versus CCS. In two of the papers[42,54] nuclear increases at the expense of CCS as the R&D budget grows; while for the other 4 papers[41,52,53,58] that include both technologies this trend is reversed. Nuclear and CCS tend to be strong substitutes; thus, depending on the specific IAM assumptions, different technologies take a larger share. Both of these technologies are associated with significant socio-technical issues that are difficult to model, such as public acceptance. Thus, factors embedded in IAMs beyond future cost (e.g., limits on the rate of deployment) are likely to play a role on whether one or the other technology receives the largest share of R&D portfolios.

We can also ask to what degree R&D expenditures are justified: what amount is the right amount? This question has been asked in the theoretical literature using hypothetical probability distributions or the comparative statics of risk (see [60] for a review). Some of the papers reviewed here have taken on this question using elicitation-based distributions. McJeon[53] finds that the savings in abatement costs are 2-3 orders of magnitude higher than the R&D investment costs for all portfolios considered; Anadon, Chan, and Lee[22] find that current US public energy R&D budgets could be increased by at least an order of magnitude and still be cost effective in terms of consumer and producer surplus; there are similar results in other papers, especially when opportunity costs are low, potential benefits are high, and a limited set of projects is available. Most papers, however, find that the optimal investment in R&D includes only a subset of the total available projects. Thus, the opportunity cost of R&D investment does play a role. A few papers have found that R&D is more valuable in second-best worlds [8,52,61]; that under-investment may be more costly than over-investment [52]; and that the optimal investment decreases in the discount rate and the opportunity cost, and appears to be non-monotonic in risk, first increasing then decreasing as risk increases [52,54].

R&D vs. Deployment Expenditures

A key debate in innovation and climate policy is the question of how to balance public support for R&D as opposed to technology deployment. A recent study[67] highlighted this as one of the hardest questions in crafting comprehensive energy policy. In Figure 4 we highlight the ratio of (mostly public sector) R&D investments compared to the long term (mostly private sector) investments in deployment resulting in some of the elicitation-based studies. Figure 4 shows the proportion of R&D investment to the total investment (including R&D and all deployment costs, such as capacity investments and government subsides) between 2010 and 2040; this proportion ranges between 0.1 – 9.2%.

While the innovation literature has highlighted the need for both technology-push and market-pull technology policies[63], and the energy economics literature has discussed the need for two instruments to address two market failures of environmental and knowledge externalities[64], we are not aware of any attempt to obtain an estimate of what the optimal range of public R&D is when compared to total deployment costs, given our current knowledge. While the range, including uncertainty, spans over one order of magnitude, no study found that the fraction of R&D should be more than 9.2% of the total investment, with the median result around 3.5%. For reference, this ratio for solar PV in the United States in 2015 was roughly 1.1% (this estimate was calculated[65] using a federal R&D investment in solar PV in 2015 of US$231 million; and a rough deployment investment of US$20.6 billion--estimated from a total of 7.3 GW of installed solar capacity, approximately 4.3 GW for utility scale solar and 3 GW for non-utility scale solar[66], and assuming average solar costs in 2015 of 2 US$/W for utility scale solar (about 4.3 GW) and 4 US$/W for non-utility scale solar[67]). The question of R&D vs deployment is a ripe area for future research, since only limited studies were available for this analysis.

In addition to shedding light on these three areas, the existing literature also includes a few studies that investigate different questions. Ziolkowska[68] combines a biomass and bioenergy elicitation with a multi-objective decision framework, considering economic, environmental and social policy objectives in evaluating different biomass feedstocks to inform energy policy. Bistline[61] investigates the optimal electricity capacity investment portfolio under uncertainty about technology prices derived from elicitations. Using a two-stage stochastic program, the paper finds that natural gas prices and the stringency of climate policy are the main risks associated with capacity expansion planning.

Gaps and Challenges in Combining the three Approaches

We have discussed the insights that can be drawn about public energy technology R&D policy through an integrated analytic approach which combines expert elicitation, IAMs, and DMUU frameworks. We now address some gaps in knowledge and methodology and potential challenges to this combined approach.

First, the combined approach is necessarily limited by the availability of expert elicitations and the limitations of IAMs. The set of technologies that can be included in a combined framework is limited to those for which elicitations have been performed and which IAMs represent in some detail. In addition, the representation of the energy system in IAMs can strongly influence results. For example, the result that solar PV plays a small role in many R&D portfolios may be related to how IAMs model the challenges of grid integration. Recent work[69] has revisited the representation of wind and solar across multiple models, leading to higher shares of these technologies in more recent versions of the models. It will be important to test expert elicitation data on this new generation of IAMs. Beyond these gaps, the limitations of IAMs and expert elicitations (discussed in Boxes 1 and 2, respectively) affect the combined analysis, and thus must be considered when interpreting results.

A second issue relates more generally to all optimization frameworks used in policy assessments: how, and by whom, is the objective function defined? The papers reviewed here are primarily aimed at a high level, relevant to national governments or international agencies. However, much decision-making takes place at lower levels, such as sub-national agencies. Moreover, it has long been acknowledged that the problem of identifying an objective function, even in the case of a single decision-maker, is quite challenging[70]. This becomes even more challenging when the problem is in the public realm and consists of multiple policy goals[71], stakeholders[72], and long timeframes. The role of optimization and decision frameworks in this case is not to provide a single optimal solution, but rather to shed light on the impact of decisions, uncertainty, and preferences in a quantitative framework; ultimately decision-makers are faced with value judgments over particular optimization criteria. There are considerable gaps in the objectives that have been explored by this approach in the literature so far. Most of the papers employing DMUU either minimize the cost of achieving a climate goal (such as a particular stabilization scenario) or minimize the combined cost of abatement and damages. A few papers explore other objectives, such as maximizing consumer and producer surplus, reducing carbon price, or reducing CO_2 emissions in the US[22]. Ziolkowska[68] uses a multi-criteria approach, including criteria such as economic efficiency, reducing GHGs and water use, and supporting local communities. The wide range of possible policy objectives (which might vary based on the geographical and socio-economic context of the decision maker) has yet to be explored using these frameworks. Some objectives of interest may be general economic development, reduction of inequality or poverty, energy access, and many others. To truly address this gap, researchers must collaborate with policy-makers to support decisions in specific contexts. Nevertheless, there is the danger of "lamp-posting" — of only addressing questions that current models are set up to answer.

A third area that could help address some of the limitations of the combined approach is to perform structured multi-model comparisons; including sets of IAMs with different assumptions about technology diffusion, built-in objectives, and decision frameworks, as well as multiple elicitation studies to parameterize technological uncertainty performed using different methods. Structured multi-model comparisons have shown great promise in increasing the robustness of insights in the context of IAMs and the Energy Modeling Forum (EMF) studies[6,69,73], and could help increase the robustness of existing insights from the integrated approach presented here, or provide new policy insights.

A fourth area in need of additional attention by the research community is that of understanding the private sector response to government policy, both in terms of R&D investments and the challenges to the commercialization of technologies[74], and on the interaction between innovation in different technologies through spillovers. While some headway has been made using patent studies[75], little is known about private R&D spending, its effectiveness, and its relation to public R&D and other policies[76]. Thus, this important piece of the puzzle often gets left out of technology policy analyses. Similarly, the challenges related to spillovers — between locations and between energy R&D and other areas — are not included in the reviewed papers due to the limited availability of data and analysis. A particular concern is a lack of representation of R&D in emerging economies, and related international spillovers. Most broadly, it is important to note that these important mechanisms, including private R&D response and first phase deployment challenges, have not been considered in expert elicitations nor are well-represented in IAMs. These mechanisms have an important role, and thus are ripe for more research.

Current decision making on public energy R&D investments is generally opaque: it is unclear to external analysts, stakeholders, or taxpayers where assumptions about future costs and R&D effectiveness come from, and what goal or goals are being prioritized[22]. The type of analytical approach presented here can serve as a complement to inform and scrutinize public decisions, since the source of the technology assumptions (the names of the experts) is clear, and the models and optimization criteria are specified. However, this approach is only useful to the degree that policy makers buy in to the results and insights. This is a major challenge, not just for this combined framework, but for all approaches that explicitly include uncertainty in the analysis. And thus, a fifth and final area for future work is in uncertainty communication, including two-way communication with policy makers through a process of research co-design, so that frameworks, such as those we have reviewed here, are informed by both the insights of policy makers and responsiveness to their needs.

Outlook

Governments are increasingly turning their attention to questions about energy technology R&D portfolios and energy innovation policy. The U.S. Department of Energy recently created the Office of Technology Transitions, responsible for developing and overseeing delivery of strategic vision[77] and goals around technology commercialization, including considerations about R&D portfolios. Various global efforts are emerging aimed at improving energy technologies, including Mission Innovation, the Breakthrough Energy Coalition, and the UNFCCC Green Climate Fund.

Decisions about how to best support innovation in energy technologies are hard for a number of reasons, but among the most important is the deep uncertainty about the outcomes of R&D and other policies, the interactions of technologies, and the science of climate change. The approach we review in this paper —

integrating expert elicitations, IAMs, and decision frameworks — is complex. Yet the transition pathway ahead of us demands radical changes in policies and in the economy, as well as strategies to enable such radical changes, in all their complexities. Thus, governments have an imperative to acquire, integrate, and use the best available information in order to support this important decision making process. Many governments are developing capabilities in IAMs, allowing them to use this set of tools to inform decisions (for example, the U.S. Department of Energy[78], and the UK Department of Business, Energy and Industrial Strategy [79,80]). It would be worthwhile for governments to develop capabilities similar to those presented in this paper to understand the full ramifications of expert elicitations alongside other data, and DMUU frameworks[81].

Of course, expert elicitations, IAMs, and decision frameworks, while crucial, are themselves only part of the full range of available information and analytic tools that can be used to inform policy decisions. An open question for the future is how to go beyond the already complex and integrative approach presented here, as additional data becomes available. This additional information could come from sources as diverse as prediction markets, increased computing power, and hybrid data-human based forecasting methods. The challenge rests in incorporating this body of information while all the while maintaining a firm control on the various components of the analysis and ensuring a rigorous validation of the whole process, through methods such as repeated elicitations of experts, controlled comparison of elicitation methods, open source code for integrated assessment models and frameworks, randomized control trials, and open data sets. Nonetheless, we hope this Review has shown that expert knowledge reflecting uncertainty can be profitably integrated with sophisticated modelling methods to inform energy technology R&D policy.

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TABLES

Table 1: Summary of energy technology expert elicitation studies. Authors' own analysis, expanding the work reviewed in Verdolini et al.[19].

Technology Category	Name of the home institution of the research group doing the study*	Number of studies	Studies without explicit questions about R&D	Publication year(s)§	Geographic regions of experts included	Target year for technological change (number of studies with that target year)	Studies with that target year
Bio-electricity	FEEM[82], Harvard[22] UMass[59]	3		2007-11	EU/US	2030 2050	Refs 83, 22 Ref. 84
Biofuels	FEEM[83], Harvard[22], UMass[84]	3		2008-11	EU/US	2030 2050	Refs 85, 22 Ref. 86
Carbon Capture & Storage	CMU[85], ERG&Duke[86], FEEM&UMass[31], Harvard[87], NRC[88], UMass (x2)[44,48]	7	Ref. [44]	2006-12	EU/US	2015 2025 2030 2050	Ref. [85] Refs. 31, 48, 90, Refs 88, 89 Ref. 44
Nuclear	CMU[89], FEEM&Harvard[90], UMass[91]	3	Ref. [89]	2007-11	EU/US	2030 2050	Refs 91 Ref. [91]
Solar	CMU[92], FEEM[93], Harvard[22], NearZero[94], UMass[45]	5	Ref. [94]	2007-11	EU/US	2030 2030/2050 2050 Unspecified	Refs 22, 94 Ref. 93*** Ref. 45 Ref. 95
Vehicles, batteries	FEEM[95], Harvard[22], UMass[46]	3		2008-12	EU/US	2030 2050	Refs 96, 22 Ref. 46
Utility scale storage	Harvard[22]	1		2011	US	2030	Ref. 22
Integrated gasification combined cycle (IGCC)	NRC[88]	1		2006	US	2025	Ref. 89
Natural Gas	Stanford[96]	1		2012	US	2025	Ref. 97
Wind	Princeton[97] LBNL[98]	2	Refs [97], [98]	2010-15	EU/US	2011 (1) 2020/2030/2050	Ref. 98 Ref. 99***
Low carbon electricity**	UCL[16]	1	Ref. [16]	2010	EU	2030	Ref. 16

* CMU: Carnegie Mellon University, Department of Engineering & Public Policy; Duke: Duke University, Nicholas School of the Environment; ERG: Eastern Research Group, Ltd; FEEM: Fondazione Eni Enrico Mattei; Harvard: Harvard University, Harvard Kennedy School; LBNL: Lawrence Berkeley National Lab; NearZero: Near Zero: nearzero.org; NRC: National Research Council; Princeton: Princeton University, Woodrow Wilson School of Public and International Affairs; Stanford University, Department of Management Science & Engineering; UCL: University College London, Energy Institute; UMass: University of Massachusetts Amherst. §. Elicitations were typically conducted between 0.5 and 2 years before publication.
** In this study by UCL researchers experts were asked about the levelized cost of electricity for any low-carbon technology that could contribute to a 20% share in the UK electricity market by 2030. Experts provided costs and identified that the following low-carbon technologies may be able to achieve this: on-shore and off-shore wind, nuclear and gas or coal with carbon capture and storage (CCS), with one individual mentioning that solar could technically also contribute this quantity of electricity in the UK.
*** These two studies provided cost estimates from elicitations for more than one end year.

Table 2: Studies relying on technological uncertainty from expert elicitations. Studies are organized by decision method and type and number of technologies. Note that the only studies that can provide results on optimal R&D investments are in the last two columns. BE: Electricity from Biomass; BF: Liquid biofuels; CCS: Carbon capture and storage; F: fossil fuel; NG: natural gas; S: solar technologies; W: wind. Note:* Santen & Anadon (2016)[17] optimized R&D funding for one technology (solar PV) and deployment for four technologies: solar PV, wind, gas and coal and used continuous variables for solar R&D and solar costs.

Technology	Sensitivity	Uncertainty analysis	1-stage DMUU	Multi-stage DMUU
Individual Technologies				
Biofuels (BF)			Ziokowska 2013[68]	
Batteries for vehicles (V)		Baker, Chon, Keisler (2010)[46]		
Carbon Capture and Storage (CCS)	Ricci et al (2014)[31]	Baker, Chon, Keisler (2009)[44]; Nemet et al (2013)[48]; Nemet et al (2015)[99]		
Nuclear	Iyer et al (2014)[32]	Baker, Chon, Keisler [91]		
Solar (S)		Baker, Chon, Keisler (2009)[45]; Nemet & Baker (2009)[100]		Santen & Anadon (2016)[17] *
Wind (W)		Gillenwater (2013)[39]		
Multiple Technologies				
CCS; Natural Gas (NG); Nuclear(N)				Bistline & Weyant (2013)[101]
CCS; Nuclear; S	McJeon et al (2011)[102]	Lemoine and McJeon (2013)[43]	Barron, Djimadoumbaye, and Baker (2014)[54]	Baker & Solak (2011, 2014)[45,55]
BF; S; V				Marangoni et al. (2017)[56]
CCS; N; S; V				McJeon (2012) [53]
CCS; NG; N; S				Bistline (2016)[58]
BioEnergy(BE); BF; CCS; N; S	Barron and McJeon (2015)[33]; Bosetti et al (2015)[36]	Olaleye & Baker (2015)[34]	Baker, Bosetti, Salo (2016)[103]	Baker et al (2015)[8]; Barron (2015)[60]
BE; BF; CCS; N; S; V				Olaleye (2016)[42];
BE;BF;CCS;F;W;S		Pugh et al (2011) [30]		
BE; BF; CCS; N; S; V; Storage		Webster et al (2013)[104] Anadon, Chan & Lee (2014)[22]; Chan & Anadon (2016)[41]	Chan & Anadon(2016)[41]; Anadon, Chan & Lee (2014)[22]	

Table 3: Details of the papers used to produce the Figures.

Study	Elicitations	IAM	Objective	DMUU Framework	Timeframe and Climate Targets	R&D Budgets	Number of technologies
Baker et al. (2015)[8]	UMass, Harvard, FEEM[59]	GCAM	minimizes cost of climate stabilization plus damages plus R&D cost	1-stage, using dynamic programming. [paper also includes 2-stage, results not in figures]	To 2050 or 2100 depending on elicitation (uncertainty resolved in 2030)	Each technology can be invested in at low, mid, or high, as follows (NPV in US$ Billion) Solar,1.7,4.0,33.0; Nuclear 6.2,19.2,178.3; CCS 5.3, 17.1,168.2; Bio-fuels,1.6,3.7,20.3; Bio-electricity 1.6,3.0,16.9	5
McJeon (2012)[53]	UMass[59]	GCAM	minimizes cost of climate stabilization under R&D budget	2-stage, using dynamic programming	To 2100	NPV R&D budgets in US$ Billion are 0.6, 0.72, 1.	3
Marangoni et al. (2017)[56]	FEEM[59]	WITCH	maximizes welfare under budget constraint and climate constraint (moderate pledges, 2.8°C in 2100)	2-stage, using ADP	To 2150, (moderate pledges, 2.8°C in 2100)	Annual R&D budgets for all technologies in $billions are 9 (halved R&D budget) and 19 (unconstrained). When only results on solar R&D budgets are presented (Fig. 4) these are US $ Billion 1.6 (halved R&D budget) and 2.4 (unconstrained scenario)	4
Chan & Anadon (2016[41])**	Harvard[105]	MARKAL - U.S.	maximizes consumer and producer surplus*	1-stage, using LHS	To 2050	Annual energy R&D budget constraints in US$ Billion are 3 (consistent with BAU), 5, 7, 10, normalized to the value of the lowest R&D	6 R&D programs (they influence 25 individual technologies)
Barron et al (2014)[54]	UMass[59]	GCAM/DICE	minimizes abatement costs (including R&D expenditures) plus damages	2-stage	To 2185 (uncertainty resolved in 2050)	NPV R&D budgets in US$ Billion are 0.2, 1.5, 5	3
Baker & Solak (2011)[55]	UMass[59]	GCAM	minimizes abatement costs (including R&D expenditures) plus damages	2-stage	To 2185 (uncertainty resolved in 2050)	NPV R&D budgets are in US$billions 0.2, 1.5, 5;	3
Olaleye (2016)[42]	UMass[59]	GCAM/DICE	maximizes welfare	2-stage, stochastic	To 2185 (uncertainty resolved in 2050)	NPV R&D budgets in US$ Billions 0.3, 1.5, 4.9, 10.2, 29.5	6
Bistline (2016)[58]	Stanford, UMass, Harvard[59]	Purpose built model	minimizes energy system costs (accounting for a $30/tCO2-eq carbon tax) subject to budget constraints	3-stage	To 2050, with uncertainties resolving in 2025	Annual R&D budgets in US$ Billion are 0.25, 0.5, 1.4	4
Nemet and Baker (2009)[47]	UMass[59]	Purpose built model	18 scenarios with different levels of R&D, subsidy, and carbon tax	Sensitivity Analysis	To 2050 (results reported here only to 2040)	Results shown in Figure 4 reflect low and high R&D (15 and 80 US$ Million per year) and no carbon tax	1
Santen & Anadon (2016)[17]	Harvard[59]	Purpose built electricity expansion including DMUU	minimizes total system cost	4-stages, using ADP	To 2050 (although results reported here only show 2010-2040)	Solar PV R&D budgets optimized for different stages under no carbon policy and stringent carbon policy	R&D in PV (1) and PV competes with wind, coal & gas in deployment

NPV: Net Present Value.
* The study also optimizes other objective functions but they are not used in this Review.
** An earlier less detailed version was published in Anadon Chan and Lee (2014)[22].

FIGURES

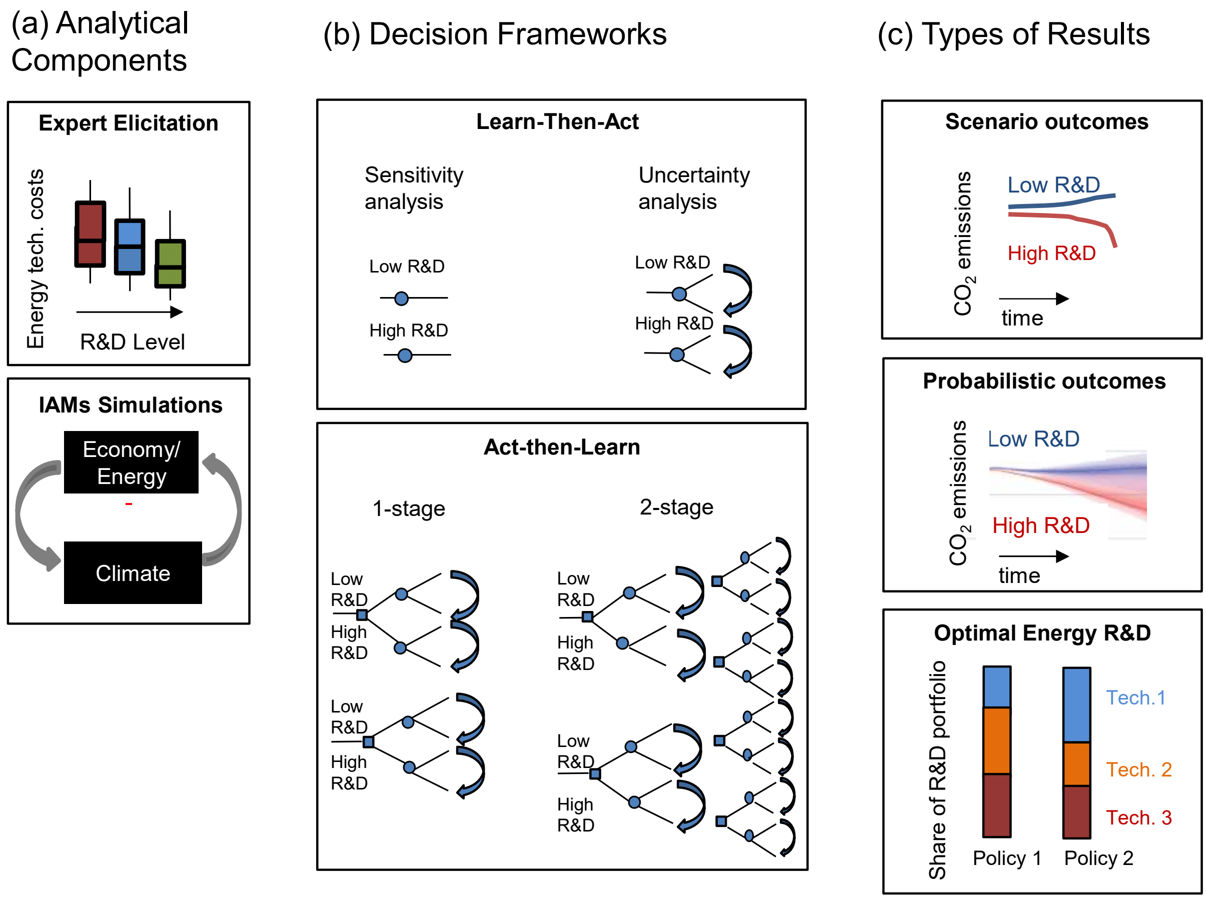

Figure 1: Analytic Approach to Support Energy R&D Decisions Using Expert Elicitations. (a) Analytical components in this Review are expert elicitations and IAMs, illustrated here by the two different schematic diagrams. (b) Two main types of decision making under uncertainty (DMUU) frameworks to support policy are illustrated here: Learn-then-Act frameworks, in which we include sensitivity and uncertainty analysis; and Act-then-Learn-then-Act (Act-Learn-Act) frameworks, where we include 1-stage and multi-stage DMUU. (c) Illustrated here are the types of outputs that emerge from the different types of analysis: deterministic scenarios of future CO_2 emissions under different R&D levels, probabilistic outcomes of future CO_2 emissions under different R&D levels, and optimal energy R&D portfolios for 3 technologies under two different climate policies in terms of the level of stringency. More details can be found in the text..

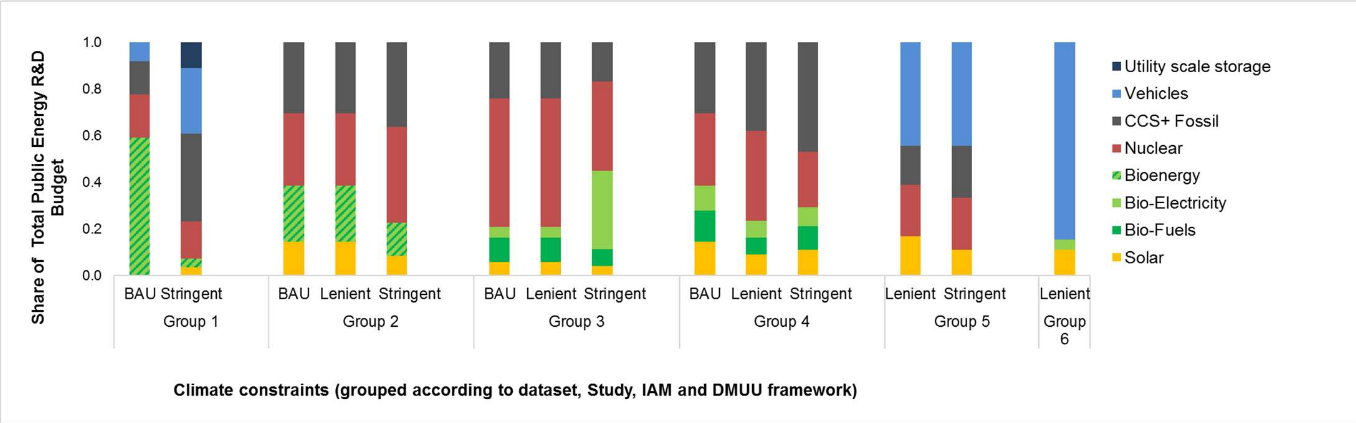

Figure 2: Optimal R&D portfolios under different climate stabilization levels. This figure shows the fraction of the R&D portfolio devoted to different technology areas for different climate stabilization levels, as determined by different approaches. In the color key, bioenergy refers to an R&D program in which biofuels and bio-electricity R&D were not differentiated, even if technologies were. Note that many technologies such as wind were not included in these modelling approaches using elicitation data. Group 1[41] uses elicitations from Harvard[22,59,106], the MARKAL IAM, 1-stage DMUU, and maximizes consumer and producer surplus under a US$5 billion total R&D constraint under no carbon policy (BAU) and a strict carbon policy (Stringent) of 83% reduction of energy CO_2 emissions by 2050 compared to 2005 levels. Groups 2, 3 and 4 use harmonized elicitations [59] conducted by Harvard, UMass and FEEM, respectively, the GCAM IAM, and minimize the cost of climate stabilization at 450 and 550 ppm plus damages and R&D cost[8]. Group 5 uses the elicitation from UMass [59], the GCAM IAM, 2- stage DMUU, and minimizes the cost of achieving climate constraints of 450 and 550 ppm[53]. Group 6 uses FEEM elicitations[59], WITCH IAM, 2-stage DMUU, and minimizes costs of achieving a 2.8°C global average temperature by [56]. Note that the definitions of "lenient" and "stringent" are not identical in the different studies. BAU, business as usual.

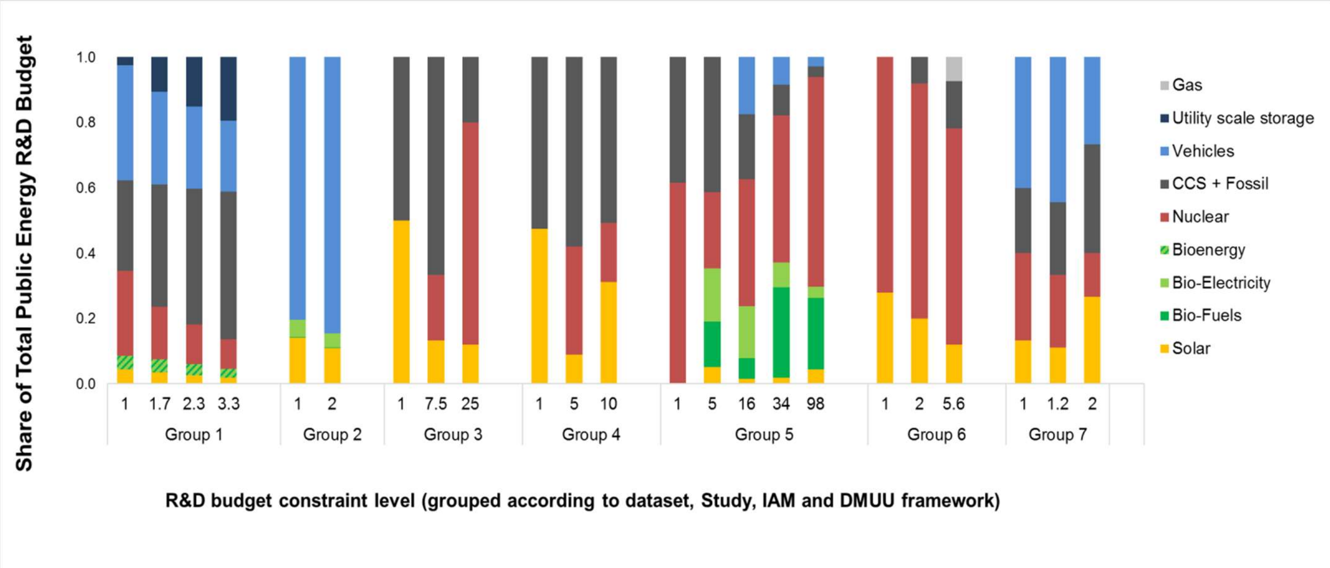

Figure 3: Optimal R&D portfolios under different total energy R&D budget constraints. This figure shows the fraction of the R&D portfolio devoted to different technology areas for different budget constraints, as determined by different approaches. The R&D budget constraint level is normalized by the lowest R&D budget constraint for each group: for each Group an R&D level of 1 represents the lowest budget considered in that study, with the subsequent budget levels shown as multiples of that value. *Group 1*[41] uses elicitations from Harvard[22,59,105,106]. *Group 2*[56] uses elicitation from FEEM[59], *Groups 3*[54]**,** *4*[52]**,** and *5*[42] use elicitations from UMass[59] in different frameworks. *Group 6*[58] uses elicitations from Harvard[22,59,106], UMass[59] and Stanford[96]. *Group 7*[53] uses elicitations from UMass[59], Note that many technologies such as wind were not included in these modelling approaches using elicitation data. Climate constraints are the most stringent available in each of the studies, see Table 3 for details. Not all studies included all technologies. Table 3 includes additional details.

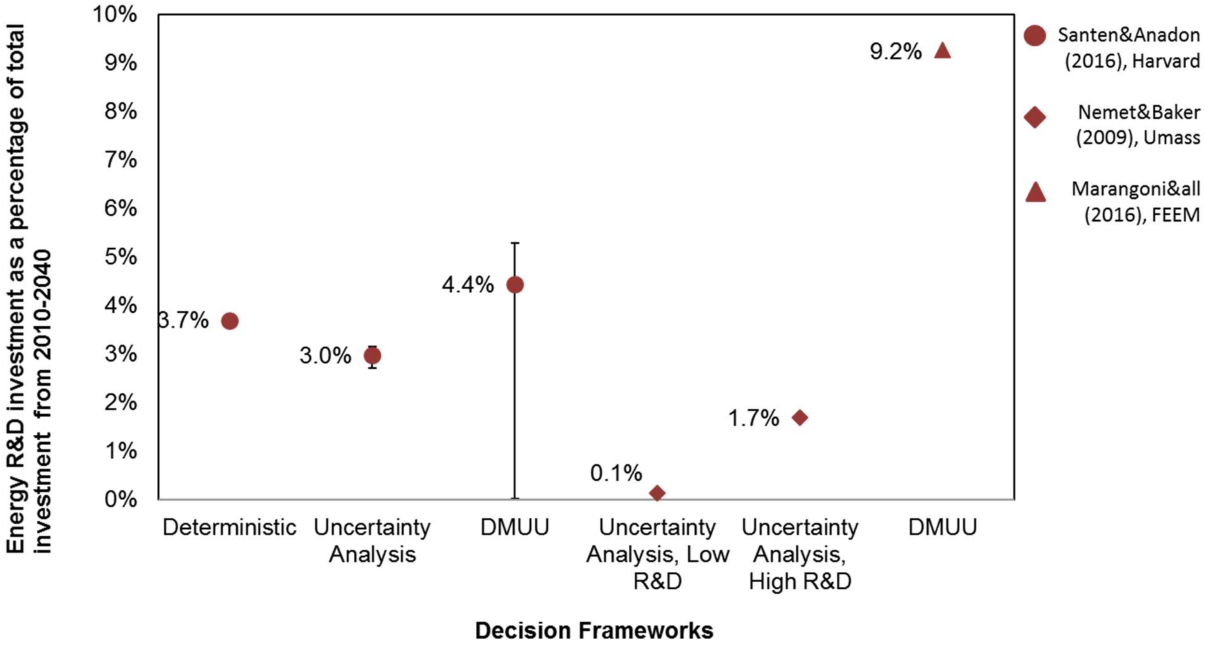

Figure 4: Public investment in energy R&D as a percentage of the total investment energy technologies. Total investments are estimated as the sum of public energy R&D investment and investment in energy technology capacity deployment. Energy investment is defined here as energy R&D plus deployment capital investment and subsidies between 2010 and 2040. Results from Santen & Anadon (2016)[17] include the percentage of R&D to total electricity capacity investment using three decision frameworks (no uncertainty, uncertainty analysis, and DMUU with 5 decision stages) Including continuous variables for R&D investments and for R&D-dependent solar technology costs. Nemet and Baker (2009)[47] optimize deployment for a given level of R&D. Marangoni et al. (2017)[56] optimize under two-stage DMUU. The results shown here are scaled down to reflect only the contribution of the United States. The uncertainty ranges for Santen & Anadon (2016)[17] include the range of future period decisions, which are conditional upon realizations of the past; the marker represents the median of these values.

BOXES

Box 1: Energy-Economic and Integrated Assessment Models

Energy economic models (EEMs) are typically bottom-up models that represent the energy sector with a fine level of detail on individual technologies. They may represent a particular geographic area or region (although EEMs covering the whole globe exist) and they are typically used to estimate how changes in input parameters representing resources prices, technologies characteristics, climate or energy policies, and energy demand all shape energy use, investments in the energy system, and the energy system's impacts on environmental or economic metrics. Technologies are deployed on a least cost basis, given assumptions about the rate at which the lowest cost options can penetrate the market. Energy-economic models also do not require assumptions about the economic cost of environmental impacts (e.g., climate damages) or impacts that the energy sectors may have on other sectors, such as trade. These simplifications come at the cost of not representing interactions between the energy sector and other sectors in the economy that may be affected by fuel and power prices; i.e. energy-economic models do not allow modelers to calculate the impact on GDP of various factors. An example of a widely used energy-economic model by policy makers and analysts in academia and the NGO community is MARKAL[107].

Integrated assessment models[108] are models that integrate different scientific domains in a unique framework in order to model the implications and feedbacks between systems (a common example being the energy system, the climate system and the earth system). IAMs may represent the energy sector at different levels of detail (typically lower than energy system models) but they also represent the interaction between this sector and other economics sectors (e.g. the oil extraction) or even other systems (e.g. forests). IAMs, similarly to EEMs provide to the climate modelling community emissions scenarios of greenhouse gases, and to the impacts community projections of socioeconomic states. IAMs are used to study the implication of climate policies on the energy systems, given assumptions about technologies cost, penetration potentials and conditional on other socio-economic assumptions. A subset of IAMs models the feedback effects of climate impacts on the economy, thus studying the optimal level of admissible climate change, given the balance of mitigation costs and benefits from avoided climate change. As large uncertainties affect this feedback link, several criticisms have been made of IAMs employed to perform this type of analysis[109]. However, most of the analyses presented in this Review abstract from the climate damage feedback and assume a given climate policy, rather than endogenously calculating it. Some prevalent IAMs include DICE[110], GCAM[111] or WITCH[94]. Note that in the main text we refer to both energy-economic models and integrated assessment models as IAMs.

Both categories of models face the challenge of calibrating the dynamic evolution of a large array of technological parameters and of the penetration of different technologies, which is affected by model structure. Therefore, coupling these types of models with expert judgments as input for these key parametric assumptions about technology costs and performance and their associated uncertainties is an important step towards more informative, robust and transparent investigations. Insights robust to differences in model structure can only be addressed through multi-model comparisons. Further investigations in the area of technology diffusion also based on historical evidence can also play an important role.

Box 2: Overview of Energy Elicitations, Challenges and Gaps

Table 2 provides an overview of the energy technology expert elicitations to date. Studies are organized by the research institution that was home to the research, whether or not studies had explicit questions about the future of technologies contingent on public R&D, the year of publication, the geographic coverage, and the year that was the focus of questions about the future of technologies. We then discuss the challenges associated with expert elicitations and research gaps in the area of energy technology expert elicitations that will improve the robustness and scope of the insights of future analysis.

In spite of the fact that expert elicitations overcome some of the challenges of using learning curves or deterministic estimates to forecast future energy technology costs and characteristics, expert elicitations (which are time and resource intensive[7]) have other limitations. First, expert elicitations are subject to a number of biases, such as availability, anchoring, and overconfidence[112] and thus should only be used when there is no other good source of information. In the case of energy technology expert elicitations, we argue that this condition is met: while past aggregate data can give insights on overall effectiveness of public R&D, it has so far not provided probabilistic information about the impact of R&D on particular technologies or programs. This problem is particularly acute when the technology of interest is novel and there is little historical data; more traditional methods, based on historical data, might be fine with more mature technologies. Indeed, Wiser et al.[98] find strong agreement between experience curves and expert forecasts for onshore wind, but not for much-newer offshore wind. In addition, expert elicitations should only be used when there are knowledgeable experts that can provide insights about questions that involve "matters of fact"[7] Some technologies may be too early in their development for experts to reasonably project costs.

Another challenge is that expert elicitation studies may be particularly difficult to compare with each other. The studies listed in Table 2 include different questions asked through different survey modes to different types of experts. For example, the studies vary considerably in their level of disaggregation, ranging from studies that question experts on the levelized cost of electricity for an entire technology category (e.g., for CCS in the NRC study[88]), to those that ask for a probability distribution over specific technical parameters (e.g., for sorbent concentrations in Amine based CCS systems as in the CMU study[85])

Third, it is often difficult to validate forecasts from expert elicitations with realized data. Energy technology expert elicitations look into the future, with endpoints typically between 2022 and 2050. Nevertheless, there is some evidence that some technologies have evolved on the faster end of what experts predicted. For example, the prices in solar PV electricity in Barbose et al.[113] are lower than all but the most optimistic experts in the meta-analysis of solar elicitations by Verdolini et al[23]. A similar preliminary finding on the faster rate of decrease of solar PV in particular periods is shown in Verdolini et al.[19]

). Even once sufficient time has passed, it is difficult to evaluate the accuracy of elicitations that are conditional on things like R&D investments since the conditions may have changed. For the same reason, it is difficult to provide feedback to experts about their projections to help them adjust and improve their forecast. This is obviously an issue affecting all distant future elicitations.

Fourth, there is continuing controversy on the best way to use multiple, conflicting expert judgments (see for example a discussion on whether it is best to aggregate—average in some fashion—elicitations or not in refs. [38,114]). Whether or not multiple expert judgments are combined (and how) can impact the ultimate results. The studies reviewed here used multiple methods, ranging from simple linear averaging[41], to scenarios selecting optimistic, median, and pessimistic experts[22].

Finally, there are gaps in the technologies that have been covered by elicitation studies. The bulk of the attention has gone to the electricity sector, with biofuels being the notable exception. To the best of our knowledge, no elicitations have been published on residential or industrial efficiency technologies. And, within the electricity sector, the supply-side has gotten much more attention than the demand-side, with the three studies on electric or hybrid vehicles as the main exception. Even within the supply side some technologies have received less attention than others. For example, there are two studies on wind[97,98], two on non-CCS fossil technology[88,96], one on advanced storage[22], and none in nuclear fusion, geoengineering, biopower with CCS, or storage potentials. In addition, available expert elicitation studies include experts from the US and the EU, which means that wider regional coverage, including developing countries and especially China and India, is a really important gap.

References

Most significant references (12 in total) with explanation of relevance in Italics:

Jaffe, A. B., Newell, R. G. & Stavins, R. N. A tale of two market failures: Technology and environmental policy. Ecol. Econ.54,164 174 (2005).
This paper discusses some of the key reasons why public investment in energy R&D is very important.

NRC. Prospective Evaluation of Applied Energy Research and Development at DOE (phase two). (2007).
This report by the U.S. National Research Council makes the case that public energy R&D decisions need to be informed by methods that account for the inherent uncertainty in the results of such investments.

Morgan, M. G. Use (and abuse) of expert elicitation in support of decision making for public policy. *Proc. Natl. Acad. Sci.* **111,** 7176–7184 (2014).
This paper provides an overview of the key practices and issues in the use of expert elicitations to inform policy, with examples that include environment and energy applications.

Anadon, L. D., Baker, E., Bosetti, V. & Reis, L. A. Expert views - and disagreements - about the potential of energy technology R&D. *Clim. Change* **136,** 677–691 (2016).
This paper brings together three sets of expert elicitations covering five important energy technologies and presents insights that include aggregated and disaggregated results and the impact of R&D on expected costs

Clarke, L. et al. in Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernment al Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. (2014)
This section of the IPCC report covers the wide range of literature considering the impact of technology costs on mitigation without focusing on the role of public energy R&D.

Kriegler, E. et al. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change 123, 353–367 (2014).
This paper presents a large effort to estimate the value of investing in R&D to improve energy technologies without a direct focus on uncertainty or on optimizing R&D investments across a range of areas.

Bosetti, V. *et al.* Sensitivity to energy technology costs: A multi-model comparison analysis. *Energy Policy* **80,** 244–263 (2015).
This paper conducts a structured sensitivity analysis informed by expert elicitations over energy technology costs across three important energy-economic models shedding light on the impact of model structure on mitigation costs.

Chan, G. & Anadon, L. D. *Improving Decision Making for Public R&D Investment in Energy: Utilizing Expert Elicitation in Parametric Models*. University of Cambridge, Cambridge Working Paper in Economics 1682 (2016).
This paper combines expert elicitations and Latin-Hypercube Sampling to optimize public R&D investments in 6 energy technology areas affecting costs in a total of 25 technologies, identifying areas with the largest returns.

Bistline, J. E. & Weyant, J. P. Electric sector investments under technological and policy-related uncertainties: a stochastic programming approach. *Clim. Change* **121,** 143–160 (2013).
This work uses a stochastic dynamic programming approach without relying on expert elicitations, and thus gives a sense of the literature on this question that does not include such method for parameterizing uncertainty.

Santen, N. R. & Anadon, L. D. Balancing solar PV deployment and RD&D: A comprehensive framework for managing innovation uncertainty in electricity technology investment planning. *Renew. Sustain. Energy Rev.* **60,** 560–569 (2016).
This paper explores the role of the uncertainty framework (including approximate dynamic programming) on the balance between investments in solar R&D versus solar deployment given uncertainty around the future costs of solar PV.

Baker, E., Olaleye, O. & Aleluia Reis, L. Decision frameworks and the investment in R&D. *Energy Policy* **80,** 275–285 (2015).
This paper isolates the impact of decision frameworks on R&D decisions using distributions over future technology costs from a combined set of expert elicitations.

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