Future Prospects for Energy Technologies: Insights from Expert Elicitations

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Introduction

Technological innovation in the energy sector contributes to several societal goals, including mitigating climate change and local air pollution and increasing energy access and energy security (Anadón et al. 2016b). As argued in a number of studies that use past data to analyze the potential role for research, development, and demonstration (RD&D) to lower the costs of energy technologies,[1] public investment in RD&D has played and will continue to play a

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The authors would like to thank the editor and the managing editor for their extensive support and three anonymous referees for excellent comments that helped to improve the article significantly. We would also like to thank all the research groups that provided their original expert elicitation data for the analysis (see table 1). This article builds on a previous contribution commissioned by the United Nations Environment Program and produced through the Green Growth Knowledge Platform (GGKP) Research Committee on Technology and Innovation. The original analysis, which includes detailed data, can be accessed at http://www.greengrowthknowledge.org/resource/future-energy-technologies-overview-expert-elicitations. V. Bosetti would like to acknowledge funding from the ERC (grant agreement 336703 – RISICO). L. D. Anadón, L. Aleluia Reis and E. Verdolini would like to acknowledge funding from the European Union's Horizon 2020 research and innovation programme (grant agreement 730403 – INNOPATHS). The authors alone are responsible for the views expressed in this article, which do not necessarily represent the decisions or policies of the funding bodies.

[1]See appendix A in the online supplementary materials for a full list of references and a detailed discussion of how investments in RD&D affect the costs of energy technology.

Review of Environmental Economics and Policy, pp. 1–22
doi: 10.1093/reep/rex028

key role in technological innovation in energy. However, the design of energy technology RD&D policies is challenging, with one of the foremost challenges being the uncertainty surrounding the outcomes of new research programs.

Expert elicitations provide a structured approach for obtaining expert judgments from scientists, engineers, and other analysts who are knowledgeable about particular issues and variables of interest (e.g., the cost of inverters in photovoltaic [PV] panels). Expert elicitations are an important source of information concerning the future costs, technical performance, and associated uncertainties of technologies. For this reason they have been increasingly used to collect information from experts on a range of energy technologies, including bioelectricity, biofuels, solar, wind, nuclear, and carbon capture and storage (CCS), to inform energy technology policy.

This article, which is part of a symposium on expert elicitation,[2] explores the role of expert elicitations in helping to address uncertainty concerning the future for energy technologies.[3] This information complements other sources of energy technology cost estimates, such as historical data or energy technology models. The article has two main objectives: (1) to describe the basics of expert elicitations, with a focus on energy technologies; and (2) to analyze the results of a subset of the most recent expert elicitations on energy technologies. With this in mind, the next section presents an overview of expert elicitations. We then discuss challenges for the design and use of expert elicitations for energy technologies. This is followed by a discussion of the results of a subset of energy technology expert elicitations and a comparison of the future cost trajectories and cost reduction rates implied by these studies with results that were produced using different data collection methods. Throughout the article we discuss how expert elicitations complement the information obtained through other methods. We conclude with a summary and discussion of future research needs in this area.

The Basics of Expert Elicitations and Applications to Energy Technologies

This section first defines and discusses key features of expert elicitations in general and then describes applications of expert elicitations to energy technologies in particular, including the expert elicitation process and the structure and characteristics of energy technology elicitations.

Definitions and Key Features

As noted in the Introduction, expert elicitation is a methodology for obtaining judgments—specifically, for eliciting subjective probability distributions—from experts about items of interest to decision makers (Hora and von Winterfeldt 1997). Expert elicitation methods were pioneered in the 1960s and 1970s, mainly to support decisions aimed at addressing extreme events.[4] While expert elicitations were first envisioned as a way of collecting existing

[2]The other article is Colson-Cooke (2018), which focuses on the validation of expert elicitations.
[3]This article builds on Bosetti et al. (2012) and Verdolini et al. (2016).
[4]For example, see Howard, Matheson, and North (1972) on mitigating the destructive force of hurricanes by seeding them with silver iodide.

knowledge stored in the heads of experts, it was later argued that the elicitation process helps experts develop probability distributions that represent their knowledge (Morgan and Henrion 1990). Developing such probability distributions is crucial to making informed decisions under uncertainty. However, expert elicitations can only be applied when there are experts that have knowledge that can "support informed judgment and prediction about the issues of interest" (Morgan 2014).

Expert elicitation methodologies complement "backward-looking" methodologies.[5] As noted by Farmer and Lafond (2015), elicitations overcome some of these methods' shortcomings in four key ways. First, expert elicitations draw on the latest information, which may not yet be codified in the literature, and also provide estimates for technologies that are new to the market or have little deployment history, such as CCS or new battery chemistries. Second, expert elicitation methodologies are not tied to the assumption that previous trajectories will continue (Chan et al. 2011); rather, they account for the fact that RD&D is, by its nature, uncertain and that future trends in technology development may be substantially different from historical trends.[6] Third, expert elicitations can distinguish between both technologies and the impacts of funding at different stages of the RD&D cycle (e.g., invention, pilot, diffusion) (National Research Council 2007). Fourth, the nature of the uncertainty represented by expert elicitations is quite different from the uncertainty in forecasts based on historical data; that is, uncertainty in forecasts is typically related to variability in the *data* rather than uncertainty about the *future.*

Applications to Energy Technologies

Numerous energy technology expert elicitation studies have been conducted over the last ten years (see table 1).[7] Insights from these expert elicitations may be used *directly* to inform RD&D programs in individual technologies. More specifically, elicitation results may be used directly when planners have a fixed budget to allocate across different components (e.g., solar cells versus inverters) or variations of a technology (e.g., purely organic versus third-generation solar cells). Moreover, elicitations can provide rich qualitative information, which can inform RD&D planning. For example, in response to specific questions about how to address key scientific and technological bottlenecks in nuclear power, experts emphasized the need to develop ceramic composites and nanomaterials to withstand extreme temperatures and high-radiation fields, as well as the need for improved simulation codes (Anadón et al. 2012).

Elicitation results may also be used *indirectly* as inputs to energy–economy or climate–economy models to inform RD&D allocation decisions across different technologies and to estimate societal outcomes (see Marangoni, deMaere, and Bosetti 2017; Nemet 2009; and Anadón, Baker, and Bosetti 2017). This is useful because the allocation of public RD&D funds across a range of technologies and programs (e.g., solar, nuclear, biofuels, vehicles, etc.) requires information on how technologies interact with each other and with climate policies.

[5]Such backward-looking methodologies include using learning curves and modeling based on historical data to project technology costs.
[6]For example, Goldemberg et al. (2004) document the significant acceleration in cost reduction for sugarcane ethanol in Brazil after 1985. An analysis based on past trends would have been too pessimistic.
[7]More details about these studies are presented in appendix B of the online supplementary materials.

Table 1 Energy technology expert elicitations

Research Group	Publication	Research Group	Publication
Bioelectricity		**Carbon Capture and Storage (CCS)**	
UMass	Baker, Chon, and Keisler (2008b)*	UMass	Baker, Chon, and Keisler (2009b)
Harvard	Anadón et al. (2011) and Anadón, Bunn, and Narayanamurti (2014)*	Harvard	Chan et al. (2011)
FEEM	Fiorese et al. (2014)*	Duke	Chung, Patiño-Echeverri, and Johnson (2011)
		UMass	Jenni, Baker, and Nemet (2013)
Biofuel		FEEM	Ricci et al. (2014)
UMass	Baker and Keisler (2011)*	CMU	Rao et al. (2006)
Harvard	Anadón et al. (2011) and Anadón, Bunn, and Narayanamurti (2014)*	NRC	NRC (2007)
FEEM	Fiorese et al. (2013)*	**Vehicles**	
		UMass	Baker, Chon, and Keisler (2010)
Solar		FEEM	Catenacci et al. (2013)
UMass	Baker, Chon, and Keisler (2009a)*	Harvard	Anadón et al. (2011) and Anadón, Bunn, and Narayanamurti (2014)
Harvard	Anadón et al. (2011) and Anadón, Bunn, and Narayanamurti (2014)*		
FEEM	Bosetti et al. (2012)*	**Other**	
NearZero	Inman (2012)	Harvard – Utility scale storage	Anadón et al. (2011) and Anadón, Bunn, and Narayanamurti (2014)
CMU	Curtright, Morgan, and Keith (2008)*	NRC – IGCC	NRC (2007)
Nuclear		Stanford – Natural gas	Bistline (2013)
UMass	Baker, Chon, and Keisler (2008a)*		
Harvard and FEEM	Anadón et al. (2012)*	GHG MI – Wind	Gillenwater (2013)
		LBNL – Wind	Wiser et al. (2016)
CMU	Abdulla, Azevedo, and Morgan (2013),* GEN III only	UCL – Low carbon energy	Usher and Strachan (2013)

Notes: Appendix B in the online supplementary materials provides more details for each study. *Indicates studies whose results are discussed later in the article. UMass = University of Massachusetts; Harvard = Harvard University; FEEM = Fondazione Eni Enrico Mattei; CMU = Carnegie Mellon University; NRC = National Research Council.

For example, an important input to RD&D portfolio decisions is whether technologies are substitutes (e.g., nuclear and CCS) or complements (e.g., solar and storage) in the economy. Moreover, different technologies might play a different role depending on the stringency of the decarbonization target. Thus it is crucial to integrate results of expert elicitations with models of the economy and the energy system.

The Expert Elicitation Process for Energy Technologies

Expert elicitations are typically codified by researchers in a protocol. The codification of this protocol requires a set of steps (see Jenni and van Luik 2010), which include[8]

1. Define the objective of the study. For energy technology elicitations, the objective may be to inform analysts about the future potential of a technology or to inform RD&D policy decisions.

[8]See appendix B in the online supplementary materials for more detail on these steps.

2. Select an elicitation mode. The mode can be in-person, online, by mail, or a combination of these modes, and may or may not involve interactions between experts.
3. Identify the experts. Experts can vary in their experience, geographic location, and sectoral background (i.e., academia, public, or private), among other attributes.
4. Structure the elicitation. This refers to the development of the elicitation protocol itself (discussed in detail in the next subsection), which typically includes defining the variables of interest—or metrics (e.g., the future cost of solar technologies, the future efficiency of gas turbines)—as well as the target year, the conditioning variables (e.g., whether experts are asked to consider the impact of possible future levels of RD&D spending), and the way in which uncertainty is coded.[9]
5. Perform pilot elicitation survey. Protocols are tested with a subset of experts in the field, using their feedback to improve the clarity of the questions and reduce errors and bias.
6. Perform elicitation. In this step, experts' estimates are collected and processed.
7. Analyze and present results. Elicitation data can be analyzed and reported in several ways, with one of the most important choices (discussed later) being whether to report disaggregated or aggregated data.

Structure and Key Characteristics of Energy Technology Elicitations

We next describe key aspects of the structuring process for expert elicitations: the definition of metrics that experts are asked to estimate, the technologies of interest, the specification of the target year for the estimates, the conditioning variables, and the way in which uncertainty is encoded.

Metrics

Metrics refers to the specific quantity that experts are asked to assess. The definition of this quantity must pass the "clarity test" (Howard 1988), that is, there must be a clear quantity that can be universally agreed upon once the event of interest has taken place. The energy technology expert elicitation studies in table 1 vary in terms of the level of aggregation of the metrics they assess, ranging from very specific technical metrics such as "sorbent concentration" for CCS, to more aggregated characteristics of technologies such as capital cost and efficiency, to highly aggregated cost metrics such as the levelized cost of energy (LCOE)[10] for a specific technology. There are inherent trade-offs in the choice of metric. For example, disaggregated metrics require a great deal of time to assess because, in many cases, a large number of such metrics may be needed to provide decision-relevant insights. Moreover, because aggregated cost metrics have one foot in technological understanding and one foot in economics, they are more directly useful to decision makers. However, the experts that have a deep understanding of the technology may not be the same as the experts that have a deep understanding of economic interactions, making it more challenging for one person to provide good estimates of an aggregate metric.

[9]This step also entails other important tasks, such as developing background materials on the topic, training materials (to reduce experts' error and bias), and visual aids. See appendix B in the online supplementary materials for details.

[10]The LCOE is the average total cost to build and operate a power-generating asset over its lifetime divided by the total energy output of the asset over that lifetime. The LCOE is used to compare the costs of different methods of electricity generation (e.g., solar and nuclear) on a consistent basis.

Technologies and target year

The number and types of (sub)technologies covered also vary significantly across studies, with some assessing a single specific technology category (e.g., small modular reactors), some asking separate questions about different technologies within a technology area (e.g., large-scale generation III/III+, large-scale generation IV, and small modular reactors), some aggregating the technologies by assessing only those technologies that experts believe will be most commercially viable (e.g., enzymatic hydrolysis for biofuels), and some asking experts to assess the future of an entire technology class (e.g., CCS).

The target year is the year for which the parameters are being estimated. In existing energy technology elicitations, this ranges from 2020 to 2050, with some studies asking experts about intermediate time points (e.g., 2030).

Conditioning variables

Conditioning variables are the variables that the experts are asked to consider when providing their judgments. These might include assumptions about future input prices, a characterization of government RD&D efforts to support the specific technology (e.g., an increasing or decreasing level of future government investment), other key energy or environmental policy (e.g., a carbon tax), and/or the future state of the economy (e.g., business-as-usual conditions for economic growth). More specifically, the analysts designing elicitations will identify which conditions to consider explicitly and which to consider implicitly, leaving the experts to make judgments about them.

The most important conditioning variable in the studies listed in table 1 is the public RD&D budget for that technology. These budget levels vary widely across the twenty-one studies that explicitly specify them. The studies used a range of approaches to identify such budgets (e.g., they considered the number of labs that would be able to make use of the funding, asked the individual expert to recommend a funding amount, or asked experts to consider business-as-usual levels). In the five studies that did not specify RD&D budgets, an implicit part of the elicitation was for the expert to think about what future budgets might be and to average over all of the possible futures. Clearly, there is a trade-off between fully specifying external conditions (such as economic growth and trade policies), which requires many more questions to the experts, and leaving them unspecified (i.e., unconditioned), which may put experts in the position of providing guesses rather than truly informed estimates.

Encoding uncertainty

The encoding of uncertainty refers to the way in which the experts are asked about probabilities concerning the metrics of interest. This can be done in two ways. The first option entails eliciting the value of the metric in question, whereby experts are asked to assign values to different percentiles of the distribution over future costs (for instance, they are asked to provide values for the tenth, fiftieth and ninetieth percentiles). In the second option, the probabilities associated with specified endpoints of the metric in question are assessed, whereby the experts are asked to assign a probability that a future metric (say, the capital cost of solar PV) will achieve at least some specified endpoint. Both approaches involve trade-offs (in particular, see the discussion on bias in the next section). Using both methods may provide information on the robustness of the elicited values, but it is time consuming for experts, meaning that fewer values can be assessed.[11] Thus only 18 percent of the studies in table 1 used both percentile and probabilities, while 46 percent used only percentiles and 36 percent used only probabilities.

Challenges for Designing and Using Expert Elicitation for Energy Technologies

This section discusses the three main challenges identified in the literature concerning the use of expert elicitations to support analysis and policy: (1) designing elicitation protocols to minimize experts' biases (which is relevant to the step of structuring the elicitation), (2) identifying and engaging a highly qualified and diverse pool of experts (which is relevant to the step of selecting experts), and (3) choosing a method for aggregating results (which is relevant to the step of presenting the data collected).

Designing Protocols to Minimize Experts' Biases

Although expert elicitations rely on individuals who are experts in the field under investigation, these experts are not necessarily proficient at expressing themselves in terms of probability (Winkler 1967). Experts, like most people, are subject to common biases, such as anchoring, status quo trap, and framing, among others (Tversky and Kahneman 1974; Hammond, Keeney, and Raiffa 1999).[12] The protocols and methodologies for structured expert elicitations were developed to reduce these biases (see Morgan and Henrion 1990; Hora 2007; and O'Hagan et al. 2006), but they cannot eliminate them.

One method for identifying and evaluating the bias in an expert elicitation is to assess if elicited values are well calibrated. As explained in Lichtenstein, Fischhoff, and Phillips (1982: 307), "a judge is calibrated if, over the long run, for all propositions assigned a given probability, the true proportion equals the probability assigned," where the true proportion reflects observations from the data. The literature reveals that people are typically poorly calibrated, that is, they are overconfident, which means they provide estimates of uncertainty that are too narrow (Capen 1976). Overconfidence increases with the difficulty of the judgment task and decreases in the case of repeated tasks with continuous feedback (Lichtenstein and Fischhoff 1977, 1980).[13] In practice, evaluating the calibration of experts is done by first assessing whether the answers given to particular questions (for which the answers are known) are well calibrated. If these answers are well calibrated, then the experts

[11]For example, the FEEM solar study used both methods, but the elicited metric was aggregated (LCOE), while the Harvard solar survey elicited only percentiles but focused on a finer level of detail (i.e., inverter costs, inverter lifetime, module cost, module lifetime).

[12]*Anchoring* occurs when an expert relies too heavily on the first piece of information (the "anchor") she is presented with, so that initial impressions, estimates, or data anchor subsequent thoughts and judgments. The *status quo trap* arises because human beings are predisposed to perpetuating the status quo, displaying traits of self-protection and risk-aversion. The *framing* of a specific question can profoundly influence the choice of answers.

[13]However, Colson and Cooke (2018) discuss how the use of calibration questions might help improve the quality of elicited information.

are also considered to be well-calibrated when providing judgments related to unique events far in the future.

Another common approach to reduce biases such as anchoring and status quo trap is explicitly briefing experts on the existence of such biases. Studies can also be designed to reduce bias. For instance, some of the studies in table 1 asked experts about extreme scenarios first, forcing them to think about unexpected events and stretching their imagination, and thus reducing the tendency to anchor to the status quo. Some studies assessed both percentiles and probabilities, while in a couple of cases the elicitation was repeated using two time horizons.[14] These types of approaches force experts to make sure that their answers are consistent with each other. Finally, most of the studies decomposed the costs into multiple parts, thus reducing the complexity of the metrics evaluated by the experts.

Relying on a Highly Qualified and Diverse Pool of Experts

Selecting a highly qualified and diverse pool of experts helps to avoid the issue of obtaining judgments that are anchored on the current state of technology (Raiffa 1968) because experts in different technology areas, sectors, or regions will likely have different experiences, which will affect their estimates (Tversky and Kahneman 1974). This is confirmed in a set of studies (Anadón et al. 2013; Verdolini et al. 2015; Nemet et al. 2016) that found that for some technologies there are systematic differences in the estimates provided by experts from the public sector, the private sector, and academia, as well as by experts from different geographical regions.[15]

While diversity is important, the number of experts needed for a valid study is not clear because the notion of statistical significance is not entirely appropriate in the case of expert elicitations. First, expert elicitation is meant to provide a representation of the views of the community of experts; it is not a draw from some kind of underlying existing probability distribution. Second, informed experts are necessarily correlated because the existing knowledge about any technology, and especially novel ones, is necessarily limited. In fact, studies have found that there are diminishing marginal returns to additional experts after as few as three or four because the incremental gains in precision quickly diminish when experts are correlated (see, e.g., Clemen and Winkler 1985, 1999, 2007). Thus diversifying experts to reduce correlation should take priority over increasing the number of experts involved in the elicitation.

The number of experts assessed in the studies in table 1 varies from as few as three in a solar study (Baker, Chon, and Keisler 2009a) to as many as 163 in a wind study (Wiser et al. 2016). The average is eighteen experts, with 56 percent of the studies having more than twelve. Just over half of these studies had at least one participant each from academia, government, and

[14]Note that both modes of encoding—percentiles and probabilities—are subject to certain types of bias. For instance, eliciting percentiles is more prone to overconfidence than probabilities, with experts often reporting ranges of elicited costs that are too narrow and do not capture the full range of true uncertainty (Juslin, Wennerholm, and Olsson 1999). On the other hand, probabilities may anchor experts to the predefined endpoints, thus leading to a situation where only a small portion of the probability distribution is assessed, which means that the extreme values of the cost distribution (i.e., the best and worst possible outcomes) are not captured by the elicitation results.

[15]See appendix D in the online supplementary materials for details.

the private sector. Academia was missing from three studies, industry from five, and government from seven. Most studies had specific reasons for selecting the particular set of experts, ranging from those most interested in breakthrough technologies (and thus focused on experts from academia and government) to those primarily interested in the current state of the technology (and thus focused exclusively on experts from industry).

Choosing an Aggregation Method

The issue of how to communicate data on uncertainty to final users is complex (Spiegelhalter, Pearson, and Short 2011). Of particular relevance to the presentation of expert elicitation results is the issue of how, and to what degree, results should be aggregated.[16]

No aggregation of individual experts

Morgan (2014) argues that individual expert distributions should not be aggregated, but rather should be presented to decision makers in a disaggregated form in order to clearly reflect the diversity of the experts' views. This approach has the advantage of allowing decision makers to see firsthand the range of disagreement among experts and to then decide how best to incorporate this into their decision processes. For decisions concerning low-probability events that might have a large impact (e.g., seeding hurricanes with silver iodide to mitigate their destructive force), masking divergent views through an aggregation might prevent a well-informed decision process. However, for many issues, this approach would result in decision makers being flooded with information and left with the daunting task of translating this wealth of views into an action, which makes decisions vulnerable to biases (see, e.g., Bunn 1985).

Aggregating results to a single probability distribution

Another approach is to aggregate results to provide a single probability distribution. Such aggregation can be mathematical (ranging from simple averages to more complex Bayesian models of aggregation) or behavioral (relying on experts reaching consensus through interaction and structured discussion). However, there is no consensus on the best method. Clemen and Winkler (1999) conclude that a *combination* of behavioral and mathematical methods may be prudent; they also argue that while all mathematical methods have pros and cons, the simple linear average performs quite well and is more robust than more complicated methods. Cooke and Goossens (2008) show that *weighting* experts based on their answers to test questions can result in a considerable improvement relative to an unweighted average; however, identifying calibration questions for long-term predictions, such as those required for energy technologies, is not straightforward. Recent work on alternative mathematical aggregation methods, such as by median or quantiles, indicates that these methods have some attractive properties (Hora et al. [2013] investigate medians; Lichtendahl, Grushka-Cockayne, and Winkler [2013] investigate quantiles) and might be considered in place of, or along with, linear averaging. One approach that addresses

[16]See Clemen and Winkler (1999) and Hora et al. (2013) for overviews and Baker and Olaleye (2013) for a specific example for energy RD&D portfolios.

concerns about misrepresenting the level of disagreement is to provide both aggregated and disaggregated data.

Synthesis of expert data

An alternative approach that falls somewhere between the previous two is to synthesize the expert data within a specific decision problem (e.g., policymakers choosing the level of RD&D investment in a particular energy technology) through mathematical or interactive methodologies. The mathematical methods employ nonstandard decision rules intended to reflect decision makers' feelings about facing conflicting information (known as ambiguity aversion).[17] For example, some decision makers may want to consider only the most pessimistic probability distributions over future technology costs derived from the elicitations. The interactive methods explicitly expose decision makers to the heterogeneity of expert estimates, with the aim of generating more robust policy choices.[18] For example, analysts might present the range of implications of a specific investment in energy RD&D for an outcome of interest, such as the cost of electricity. Rather than presenting the policymaker with either too much individual data or a single optimal choice based on an aggregate distribution, the interactive methods illustrate how a set of policy choices responds to the range of probability distributions of relevant parameters and work with decision makers to find policies that best fulfill their objectives given the range of distributions.

Results of Technology Expert Elicitations and Comparisons with the Broader Literature

With this background on expert elicitations, we next turn to an analysis of several energy technology elicitation studies to identify lessons from the current state of knowledge and key unresolved issues. We summarize the forecasted costs of five technologies (biofuels, bioelectricity, CCS, solar, and nuclear; see table 1) from four research groups (UMass, Harvard, FEEM, and CMU; see table 1) and compare the cost estimates from the elicitation studies with historical data and other forecasts of the technology costs.[19] We then discuss what the elicitations imply about the impact of RD&D investments on technology costs. Before discussing our findings, we outline the methodology used in our analysis.

Methodology and Assumptions

To compare the results from the expert elicitations and other data sources, we use two metrics: the *technology cost estimates* themselves and the *average annual changes in technology cost* that are implicit in the cost estimates. The former illustrates how future technology costs

[17]These methods range from Maxmin to more sophisticated methods applying ambiguity aversion using a function similar to a utility function, as in Heal and Millner (2014).

[18]These are known as "bottom-up exploratory" methods, such as robust decision making (Lempert and Collins 2007), decision scaling (Brown et al. 2012), and information gaps (Ben-Haim 2004).

[19]Further details on the data used can be found in appendixes C and E in the online supplementary materials.

Table 2 RD&D scenarios

	RD&D Level (million 2010$)														
	Bioelectricity			Biofuel			CCS			Nuclear			Solar		
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
UMass	15	50	150	13	201	838	13	48	108	40	480	1980	25	140	
Harvard	214	585	5,850	*Combined w/ bioelectricity*			701	2,250	22,500	466	1,883	18,833	143	409	4,090
FEEM	169	254	338	168	252	336				800	1,514	15,140	171	257	342
CMU							BAU	10 BAU		BAU			BAU	10 BAU	

Notes: BAU = business as usual.

compare with estimates of recent (historical) technology costs (i.e., in 2010). The latter shows whether experts believe the future rates of cost change will differ from past rates (calculated from historical data) or from other model forecasts (calculated from different estimates of future costs, such as from energy technology models). It is important to note that the elicited technology costs analyzed here are based on specific scenarios for RD&D funding. In order to compare technology costs across studies, we grouped the publically funded RD&D amounts of the different studies into three funding scenarios: low, medium and high (see table 2). We discuss the two metrics and our methodology in more detail next.

Technology cost estimates

The common metric used to compare technology cost estimates across studies is dollars per kilowatt-hour.[20] This data standardization ensures that the cost units are the same across studies and across technologies. Note, however, that the cost estimates cannot be directly compared across different technologies because they capture different types of costs. In the case of solar, the costs represent the full LCOE, accounting for all costs (other than grid integration);[21] for both bioenergy metrics, the costs represent the levelized nonenergy cost (i.e., excluding fuel costs); for nuclear, the costs represent the levelized capital cost (excluding operations and maintenance, fuel costs, and waste storage); and for CCS, the costs represent the levelized additional capital cost (which would need to account for the energy penalty and be added to the levelized cost of fossil generation to get the full cost of electricity).[22]

The distribution of standardized elicited cost data for each technology, study, and RD&D scenario are indicated as vertical lines in panel A of figure 1. More specifically, the ends of the thin vertical lines show the lowest tenth percentile and the highest ninetieth percentile of elicited costs in each study (i.e., for studies that elicited percentiles, these represent the most and least optimistic estimate among all experts in the study for a given RD&D level); the ends of the thick lines show the median of the tenth and ninetieth percentiles among experts (i.e., the median of

[20]The details of the standardization procedure are provided in appendix C in the online supplementary materials.

[21]Note that this cost was calculated assuming a capacity factor of 12 percent (to be consistent with the implicit assumptions of the FEEM study); the costs would be about 35 percent lower if the capacity factor were 18.5 percent.

[22]Note that in the specific case of the UMass CCS data, we show the tenth, fiftieth and ninetieth percentiles of a distribution that aggregates experts in that particular study.

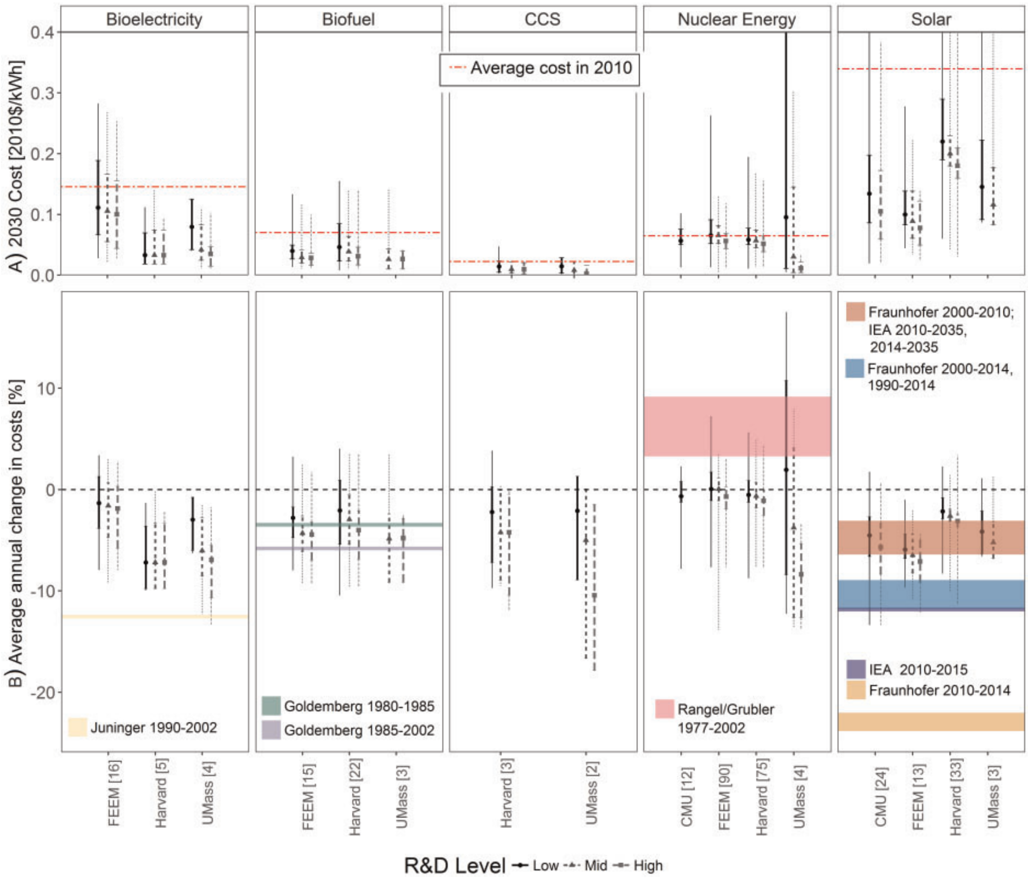

Figure 1 Technology cost estimates from elicitation studies and comparison with historical data and other forecasts.

Notes: Panel A shows 2030 technology cost estimates from selected energy technology expert elicitations compared with current technology costs. Panel B shows the implied average annual rate of cost change compared with cost change rates from past data and other forecast methods. The vertical lines in panel A indicate the distribution of standardized elicited cost data for each technology, study, and RD&D scenario. The vertical lines in panel B indicate the distribution of the average annual change in technology costs based on the expert elicitation data for each study, technology, and RD&D scenario. The horizontal lines and bands in panel B indicate the implied annual rates of cost change from specific studies. Year ranges next to the source of data in panel B indicate the range of data used to deterministically forecast costs in 2030. The square brackets next to the study name on the *x*-axis indicate the number of experts included in each study. See appendix E in the online supplementary materials for more details.

Sources: Panel A: expert elicitation cost data: see table 1. 2010 costs: see table E.1 in the online supplementary materials. Panel B: rate of average cost decrease for expert elicitation data: own calculations. Implied annual rates of cost change from other sources: Goldemberg et al. (2004), Juninger et al. (2006), Grubler (2010), Escobar Rangel and Lévêque (2012), IEA (2014), Fraunhofer Institute for Solar Energy Systems (2015).

the most optimistic and the most pessimistic estimates for a given RD&D scenario in a given study); and the markers in the line (i.e., dot, square, triangle) show the median value of the median estimates in a given study for each RD&D level. The distribution of elicited costs are then compared with representative 2010 costs (horizontal dashed lines in panel A).[23]

[23]See table E.1 in the online supplementary materials for details on sources for the 2010 cost data.

Average annual changes in technology cost

We compare elicited technology costs for 2030 with other forecasts in the literature using the average annual change in technology cost (panel B of figure 1). We calculate this average annual change as the fixed annual reduction in cost that would produce a path from the cost at the starting year to the cost at the ending year of the period under consideration,[24] with the specific starting and ending years depending on the data or elicitation.[25] The vertical lines represent the distribution of the average annual change in technology costs based on the expert elicitation data for each study, technology, and RD&D scenario. The ends of the thin lines show the lowest tenth percentile and the highest ninetieth percentile of the average annual change in technology costs, the ends of the thick lines show the median of the tenth and ninetieth percentiles, and the markers in the line show the median of the medians. The horizontal lines and bands in panel B represent ranges of estimates from historical data sources or other forecasts.[26]

Discussion of Results

We next discuss the key results and implications of our analysis (shown in figure 1), first for energy technology costs, then for average annual changes in technology costs, and finally for the impact of RD&D investments on energy technology costs.

Energy technology costs

Panel A of figure 1 indicates the extent to which experts foresee a decrease in future energy technology costs relative to energy technology costs in 2010. Two results stand out. First, the elicited costs differ substantially across studies within the same technology categories. This is particularly apparent in the case of bioelectricity, but also for nuclear and solar. Three meta-analysis studies—Anadón, Nemet, and Verdolini (2013), Verdolini et al. (2015), and Nemet, Anadón, and Verdolini (2016)—argue that differences in elicitation design (including choice of experts, mode of elicitation, and format of the questions) lead to these differences in estimates.

Second, some of the estimated costs for 2030 provided by experts are higher than the average values for 2010 (horizontal lines). This may be explained partly by the fact that the estimated costs have a wide range, even in 2010; for example, in the Harvard study, the elicited

[24]These values are calculated as the linear average rate of change using the formula:

$$\textit{Average annual percent change} = \left\{ \left[\left(\frac{\text{cost}_{t1}}{\text{cost}_{t0}} \right)^{\frac{1}{t1-t0}} \right] - 1 \right\} \times 100$$

where $t0$ and $t1$ are the starting and final years of the interval considered, and $Cost_{t0}$ and $Cost_{t1}$ are the relevant costs for those two years.

[25]The calculated cost reduction rates are highly dependent on the starting and final years of the interval considered (as shown in Nemet [2009]). Thus we show multiple ranges of estimates when they exist or can be calculated. For the elicitations, the starting year ($t0$) is 2010 and the ending year ($t1$) is 2030. See appendix E in the online supplementary materials for further details concerning the sources and coverage of the data used for the comparisons.

[26]There are two important caveats for interpreting figure 1. First, the historical data used for the comparisons is more appropriate for some technologies than for others. Second, as discussed earlier, the time intervals of the comparisons have different implications.

distributions for solar PV for 2010 varied significantly, due to geographical variability and other factors.[27]

Overall, experts expect there will be a decrease in the cost of most technologies, in the sense that the median costs (round, triangle, or square markers), along with a large part of the future cost distribution (vertical lines), are lower than the 2010 cost (dashed horizontal line) for the different RD&D scenarios. Furthermore, the possibility of technology breakthroughs and failures is reflected in the wide range of most expert estimates (i.e., the vertical lines span large ranges of costs, with the upper end indicating a worst-case estimate and the lower end indicating the best possible outcome). In particular, in the case of nuclear, the median cost is estimated to remain close to the 2010 average cost, with many of the highest cost estimates (ninetieth percentiles) above current costs.

Average annual change in technology cost

Panel B of figure 1 suggests a relationship between past cost trends of energy technologies and experts' beliefs about future costs. Indeed, the vertical lines (which indicate cost decreases from expert elicitations) often cross the horizontal bands (which indicate cost decreases from other sources). For all technologies except nuclear, the medians are well below zero, which means the experts generally believe future costs will decrease (i.e., the future will be similar to past experience). However, the technologies differ in the degree to which the experts see the future as being similar to the past; that is, the extent to which the median estimate of the cost decrease based on elicited data lies in the same range as other estimates of cost decreases. For example, for biofuels, the median rates of change are very similar to what has been seen historically. On the other hand, experts are not particularly optimistic about nuclear, which has had past increases in costs. Nevertheless, they are more optimistic than past data (primarily cost increases) would imply. This may simply reflect experts' optimism, or it may be a sign that experts believe that current research, modeling, and licensing practices make it less likely that costs will continue to increase in the future. Note that the rate of cost change for most of the nuclear elicitations overlaps with the historical data, suggesting that continued increases are expected by some experts. The experts expect a significant slowdown in the rate of change of bioelectricity costs, at least when compared with the experience in Sweden (which provided the historical rates for bioelectricity). The figure indicates that only the UMass experts foresaw a reasonable chance of a continuation of such rapid cost decreases. This means that either the experts in the other studies believe that much of the cost reduction has been achieved or that they were over-confident and did not account for the kind of rapid cost reduction that was recently seen in Sweden.

The results for solar are particularly interesting. The lowest band (based on estimates from Fraunhofer Institute for Solar Energy Systems [2015], relative to the period 2010 to 2014) indicates a recent significant annual cost decrease over a short period of time. However, the experts appear to believe that in the long term the annual rate of decrease will be, on average, similar to what has been seen over longer historical periods and similar to other forecasts (e.g., IEA 2014). There are two possible interpretations for this result.

[27]This broad range of costs in the "present" is consistent with data in IRENA (2014).

First, it is possible that experts in the elicitations missed a fundamental change in the trajectory of costs that started in 2010 and will continue; this is a real possibility since most of the elicitations took place before 2010, when prices started falling rapidly. Second, the experts may have correctly estimated the long-term trajectory of solar, with the short-term rapid reductions in cost indicating not a change in the trajectory, but rather a simple random deviation.

The impact of RD&D investments on energy technology costs

Elicitation results provide insights regarding the impact of RD&D on the full distribution of technology cost as well as insights into the presence of diminishing returns to RD&D investments. While historical evidence from other sources is useful for determining the role of public energy RD&D investments in past cost and performance improvements, elicitations can indicate the importance of energy technology RD&D in the future. Indeed, the use of estimates from expert elicitations can help decision makers understand what they are "buying" with RD&D, thus making them less likely to be surprised by the outcomes of their investments because they are better able to "anticipate the unexpected" (Morgan, Henrion, and Small 1992). With this in mind, we examine what the results of our analysis of expert elicitations tell us about the impact of RD&D investments on energy technology costs.

First, panel A in figure 1 indicates that RD&D affects the entire cost distribution. More specifically, for all technologies except nuclear, a higher level of RD&D leads to lower median costs (see the markers in the vertical lines) and also lowers the extreme cost estimates (see the ends of the vertical lines). This is particularly true for the bad-outcome, high-cost tails (see the top extreme of the vertical lines).[28] Thus higher RD&D is associated with greater rates of cost reduction. Note, however, that there is heterogeneity across technologies. For instance, although for solar increased RD&D is associated with visible cost reductions in all the studies presented, this is less the case for bioelectricity.

The data from the expert elicitations also indicate that higher RD&D investments do not reduce the range of uncertainty (i.e., they do not consistently shorten the length of the vertical lines, which represents the variation in experts' estimates). Indeed, panel A of figure 1 suggests that a higher investment sometimes leads to a wider range and sometimes a narrower range of elicitation values (i.e., to longer or shorter vertical lines).

Finally, the evidence from panel B in figure 1 indicates decreasing returns to scale for RD&D investments— that is, increasing RD&D investments may decrease technology costs, but at a decreasing rate.

These insights are consistent with the findings of other studies. Anadón, Nemet, and Verdolini (2013), Verdolini et al. (2015), and Nemet, Anadón, and Verdolini (2016) show that higher RD&D investments are associated with lower elicited technology costs. In particular, Nemet, Anadón, and Verdolini (2016) show that going from a low to a high RD&D scenario, median costs drop by roughly 4 percent for solar, 2 percent for bioenergy, and 1 percent for nuclear and biofuel.[29] This variation may reflect different technological maturity and perceived cost-reduction options. However, one must be extremely careful in making

[28] See also appendix F in the online supplementary materials for further details.

[29] Note, however, that this result is based on the use of categorical variables for R&D levels and does not allow a comparison of the impact of one additional dollar on the costs of different technologies.

such comparisons across technologies because the dollar amount of RD&D expenditures in the low, medium and high scenarios differs significantly across technologies (see table 2). Anadón, Nemet, and Verdolini (2013), Verdolini et al. (2015), and Nemet, Anadón, and Verdolini (2016) also show that increased RD&D does not necessarily increase the probability of achieving lower costs in the future. Anadón et al. (2016a) explicitly consider the impact of additional RD&D expenditures on the probability distributions for performance and cost and find that elicitations predict decreasing returns to investment and that the current U.S. funding levels for most of the technologies fall into a range with predicted decreasing marginal returns. Note, however, that decreasing returns do not imply that investment is not justified.

Finally, it is also important to note that the impact of RD&D on median cost is small relative to the range of uncertainty (i.e., the length of the vertical lines) in panel A of figure 1, suggesting that while experts believe that RD&D will play a role in reducing technology costs in the future, it is not the only component that matters. Many other factors (e.g., material costs, economies of scale) play important roles in the evolution of technology costs.

Summary of Results

We have argued that expert elicitations provide insights about the future costs of energy technologies, especially regarding uncertainty, which complement other sources of information and analytical approaches (such as engineering models, historical data, and other types of forecasts). Comparing elicitation forecasts with past data allows us to determine whether experts expect the evolution of technical change to continue on a historical path or whether they believe the future will be different from the past. Comparing elicited costs with costs recorded in a time period after the elicitations have taken place (e.g., when comparing solar costs elicited in 2007 by UMass with the 2010–2014 data from Fraunhofer Institute for Solar Energy Systems [2015]) provides a sort of ex post validation exercise, indicating whether experts' forecasts were too conservative or too optimistic. Comparing elicited costs with other forecasts made at a similar time indicates how perceptions emerging from expert elicitations differ from those emerging from other methodologies, in particular learning or experience curves.

In summary, our discussion of the results from several energy technology expert elicitations and figure 1 reveal some key insights concerning the future costs of energy technologies and the associated uncertainty. First, and most simply, experts largely believe that increased public RD&D investments will result in reductions in future technology costs by 2030, although possibly with diminishing marginal returns. Second, implicit median annual rates in cost reduction collected through expert elicitations partly reflect historical trends, but the information collected is much richer, thus allowing the design of more robust policies. Third, for all technologies, experts see the possibility of breakthroughs that would make the technology cost competitive, envisioning sustained annual rates of cost reduction on the order of 10 percent per year. Moreover, such breakthroughs appear more likely under higher RD&D. Fourth, the range of uncertainty and disagreement among the technologies and teams seems to imply that there are benefits to a portfolio approach to technology RD&D rather than picking a small number of winners (Anadón et al. 2016a). Finally, overall, our results highlight that one of the values of expert elicitation relative to other sources of cost estimates lies in its ability to provide information about the *full distribution of costs* rather than providing one single, deterministic estimate. Integrating this information into decision making often leads to near-term decisions that are significantly different from those identified by simply doing sensitivity analysis across all possible individual outcomes (see the discussion and examples in Wallace [2000]). For example, if policymakers understand that the uncertainty around the cost of a particular technology is large, they may decide to devote additional financial resources to exploring a wide range of novel technological paths rather than simply investing in the development of the current technology. Such a decision is less likely to emerge if policymakers are relying on deterministic estimates that mask the uncertainty about the technology.

Conclusions and Future Research Needs

In the spirit of Convery and Wagner (2015), this article has provided an up-to-date summary of what we know and what we do not know about the future of technological progress in energy and how it is influenced by public RD&D efforts. These insights are key to both the design of energy RD&D portfolios and the development of better projections of the costs of future climate-mitigation scenarios. We presented an overview of expert elicitation and reviewed the evidence emerging from expert elicitation studies on the future of energy technologies. We have argued that the data on future energy costs provided by expert elicitations complements data on the evolution of technological costs and the past performance of RD&D programs. As shown in figure 1, elicitation data provide insights about the range of future possibilities. Importantly, this includes the impact of prospective policies and improvements enabled by new scientific developments. The comparison of elicitation data with past data indicates whether experts believe that the future evolution of technology costs will be different from the past. Incorporating uncertainty may lead to near-term decisions that are significantly different from decisions made with point estimates. While scientists and economists are often more comfortable with point estimates derived from past data, we have shown here that uncertainty about the future is much wider than can be derived from past data, and that surprises, both happy and unhappy, are real possibilities that need to be accounted for. The presence of multiple studies covering similar technologies highlights the complexity of representing uncertainty. Including insights from energy technology expert elicitations allows for more transparent and informed decision making that incorporates technical uncertainty into the design and assessment of energy and climate change mitigation policies.

This examination of expert elicitation also reveals some important gaps in the literature, which provide a guide to future research in this area. First, although many elicitation studies ask experts to consider current or increased RD&D investments, very few considered drastic reductions to current RD&D spending.[30] In times of tight governmental budgets, it is important to assess what would happen if RD&D programs were scaled down. Second, it is important to extend expert elicitations to include experts from emerging economies in order to obtain a more comprehensive picture of how technologies might progress in those countries. Third, some technology areas, such as utility-scale energy storage, wind, vehicles, gas turbines, geothermal, and energy efficiency technologies, have been the subject of few, or no, publicly available expert elicitations. Thus the ability to analyze these technologies and how

[30]The exceptions are National Research Council (2007), Jenni, Baker, and Nemet (2013), Fiorese et al. (2014), and Ricci et al. (2014).

they fit into energy RD&D portfolios is more limited. Fourth, only a few expert elicitations included specific questions on the diffusion of energy technologies; future work might address how governments should allocate public resources between public RD&D and deployment (see, for instance, Anadón et al. 2012). Fifth, there is potential to incorporate data from expert elicitations into more complex analyses (e.g., the impact of increased funding on the joint reduction of uncertainty, the definition of robust energy RD&D portfolios that account for multiple societal objectives). Finally, to further improve the science of expert elicitations, the elicitation data compiled for this article could be used in future analyses that compare these cost estimates with actual technology cost trajectories.

Overall, the recent emergence of data on future energy costs through expert elicitations provides the opportunity and, we would argue, the obligation to more rigorously and transparently introduce considerations of uncertainty around technical change into discussions about energy policies and climate change mitigation. We believe this is essential given the magnitude of the uncertainties involved and their impact on costs. The elicited probabilistic information summarized in this article sheds light on where technological progress is most likely and how it may be influenced by public RD&D efforts.

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Abstract

Expert elicitation is a structured approach for obtaining judgments from experts about items of interest to decision makers. This method has been increasingly applied in the energy domain to collect information on the future cost, technical performance, and associated uncertainty of specific energy technologies. This article has two main objectives: (1) to introduce the basics of expert elicitations, including their design and implementation, highlighting their advantages and disadvantages and their potential to inform policymaking and energy system decisions; and (2) to discuss and compare the results of a subset of the most recent expert elicitations on energy technologies, with a focus on future cost trajectories and implied cost reduction rates. We argue that the data on future energy costs provided by expert elicitations allows for more transparent and robust analyses that incorporate technical uncertainty, which can then be used to support the design and assessment of energy and climate change mitigation policies. (*JEL*: O3, Q4, Q55)