# NOTA DI LAVORO

45.2015

## Future Costs of Key Low-Carbon Energy Technologies: Harmonization and Aggregation of Energy Technology Expert Elicitation Data

**Erin Baker**, University of Massachusetts Amherst, Amherst, MA, United States
**Valentina Bosetti**, Fondazione Eni Enrico Mattei and Bocconi University, Italy
**Laura Diaz Anadon**, Harvard University, Cambridge, MA, United States
**Max Henrion**, Lumina Decision Systems, Los Gatos, CA, United States
**Lara Aleluia Reis**, Fondazione Eni Enrico Mattei, Milano, Italy

Climate Change and Sustainable Development
Series Editor: Carlo Carraro

# Future Costs of Key Low-Carbon Energy Technologies: Harmonization and Aggregation of Energy Technology Expert Elicitation Data

By Erin Baker, University of Massachusetts Amherst, Amherst, MA, United States
Valentina Bosetti, Fondazione Eni Enrico Mattei and Bocconi University, Italy
Laura Diaz Anadon, Harvard University, Cambridge, MA, United States
Max Henrion, Lumina Decision Systems, Los Gatos, CA, United States
Lara Aleluia Reis, Fondazione Eni Enrico Mattei, Italy

## Summary

In this paper we standardize, compare, and aggregate results from thirteen surveys of technology experts, performed over a period of five years using a range of different methodologies, but all aiming at eliciting expert judgment on the future cost of five key energy technologies and how future costs might be influenced by public R&D investments. To enable researchers and policy makers to use the wealth of collective knowledge obtained through these expert elicitations we develop and present a set of assumptions to harmonize them. We also aggregate expert estimates within each study and across studies to facilitate the comparison. The analysis showed that, as expected, technology costs are expected to go down by 2030 with increasing levels of R&D investments, but that there is not a high level of agreement between individual experts or between studies regarding the technology areas that would benefit the most from R&D investments. This indicates that further study of prospective cost data may be useful to further inform R&D investments. We also found that the contributions of additional studies to the variance of costs in one technology area differed by technology area, suggesting that (barring new information about the downsides of particular forms of elicitations) there may be value in not only including a diverse and relatively large group of experts, but also in using different methods to collect estimates.

**Keywords:** Expert Elicitation, Energy Technology Cost, R&D Investments
**JEL Classification:** O30, O32, Q40, Q55

*This is a pre-print version of the article "Future costs of key low-carbon energy technologies: Harmonization and aggregation of energy technology expert elicitation data, Energy Policy, Volume 80, May 2015, Pages 219-232, ISSN 0301-4215, http://dx.doi.org/10.1016/j.enpol.2014.10.008.*

*Address for correspondence*

Erin Baker
Department of Mechanical and Industrial Engineering
University of Massachusetts Amherst
Amherst, MA
United States
Email: edbaker@ecs.umass.edu

The opinions expressed in this paper do not necessarily reflect the position of
Fondazione Eni Enrico Mattei
Corso Magenta, 63, 20123 Milano (I), web site: www.feem.it, e-mail: working.papers@feem.it

**Future Costs of Key Low-Carbon Energy Technologies: Harmonization and Aggregation of Energy Technology Expert Elicitation Data**

Erin Baker[2],Valentina Bosetti[3,4] Laura Diaz Anadon[1],Max Henrion,[5] Lara Aleluia Reis[3]

[1] Harvard Kennedy School, Harvard University, Cambridge, MA, United States
[2] Department of Mechanical and Industrial Engineering, University of Massachusetts Amherst, Amherst, MA, United States
[3] Fondazione Eni Enrico Mattei, Milano, Italy
[4] Department of Economics, Bocconi University, Milano, Italy
[5] Lumina Decision Systems, Los Gatos, CA, United States

Abstract.

In this paper we standardize, compare, and aggregate results from thirteen surveys of technology experts, performed over a period of five years using a range of different methodologies, but all aiming at eliciting expert judgment on the future cost of five key energy technologies and how future costs might be influenced by public R&D investments. To enable researchers and policy makers to use the wealth of collective knowledge obtained through these expert elicitations we develop and present a set of assumptions to harmonize them. We also aggregate expert estimates within each study and across studies to facilitate the comparison. The analysis showed that, as expected, technology costs are expected to go down by 2030 with increasing levels of R&D investments, but that there is not a high level of agreement between individual experts or between studies regarding the technology areas that would benefit the most from R&D investments. This indicates that further study of prospective cost data may be useful to further inform R&D investments. We also found that the contributions of additional studies to the variance of costs in one technology area differed by technology area, suggesting that (barring new information about the downsides of particular forms of elicitations) there may be value in not only including a diverse and relatively large group of experts, but also in using different methods to collect estimates.

**Keywords**: Expert Elicitation, Energy Technology Cost, R&D investments

## 1. **Introduction**

The economic practicality of paths towards a sustainable future depends crucially on the future costs of low-carbon energy technologies. The recently published 5th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), in its summary for policy makers, points to the fact that: "Estimates of the aggregate economic costs of mitigation vary widely and are highly sensitive to model design and assumptions as well as the specification of scenarios, including the characterization of technologies and the timing of mitigation" [IPCC 5th AR, WG III, mitigation2014.org]. Indeed, total discounted mitigation costs (2015–2100) may increase up to 138% when some technologies are limited in their availability. It is expected that costs for most of these technologies will continue to fall, driven by various factors including research and development, economies of scale, and experience effects. However, the specific trajectories that costs may take in the future are highly uncertain. In the absence of a clairvoyant who can eliminate these uncertainties, policy decisions should be informed by credible forecasts of technology costs that incorporate explicit estimates of the uncertainties. Effective policy decisions should be based on analysis of a comprehensive set of possible scenarios, with a probabilistic treatment of the uncertainties.

The 2010 InterAcademy Council review of the climate change assessment of the IPCC had only one substantive (rather than process-oriented) topic in its recommendations — the treatment of uncertainty:

*"To inform policy decisions properly, it is important for uncertainties to be characterized and communicated clearly and coherently. … Quantitative probabilities (subjective or objective) should be assigned only to well-defined outcomes and only when there is adequate evidence in the literature and when authors have sufficient confidence in the results. … Where practical, formal expert elicitation procedures should be used to obtain subjective probabilities for key results."* (Council, 2010)

Similarly, the National Research Council (NRC, 2007) recommends that the U.S. Department of Energy use probabilistic assessment based on expert elicitations of R&D programs in making funding decisions.

On December 2-3, 2010, the Department of Energy's Office of Policy and International Affairs sponsored a two-day workshop on energy RD&D portfolio analysis. This workshop concluded that (1) the large and growing elicitation data sources need to be integrated with each other and with other relevant data on technology supply, and (2) that the integrated data needs to be communicated in ways that are useful to a variety of users, including both government decision makers and researchers who require expert technology supply information for their research. (Clarke & Baker, 2011)

This paper outlines the results of three major expert elicitation efforts carried out independently by researchers at UMass Amherst (Baker & Keisler, 2011; Baker, et al., 2009b; Baker, et al., 2009a; Baker, et al., 2008), Harvard (Anadon, et al., 2011; Anadon, et al., 2012; Anadón, et al., 2014a; Chan, et al., 2011), and FEEM (Bosetti, et al., 2012; Catenacci, et al., 2013; Fiorese, et al., 2013). Each of the three groups covered many of the most promising future clean energy technologies [IPCC 5th AR, WG III, mitigation2014.org]: liquid biofuels, electricity from biomass, carbon capture (CCS), nuclear power, and solar photovoltaic (PV) power. The surveys varied considerably in terms of quantities elicited, projected dates, funding assumptions, types of questions, and modes of survey administration. These differences make the comparison challenging, but also allow us to span a variety of different assumptions and

detect whether there are robust insights to be drawn by these exercises taken together.

In Section 2, we review the methodology of the elicitations themselves, of the harmonization, and of the aggregation across experts and teams. In Section 3, we present results from the harmonized and aggregated elicitations, including a discussion of the sources of uncertainty and disagreement. In Section 4, we conclude with a discussion of applications for policy and future energy technology expert elicitations.

## 2. **Methodology**

There are four main challenges to comparing and combining the estimates of cost and performance elicited using different surveys. First, the surveys elicited different metrics, with different levels of aggregation. For example, the Harvard and UMass solar surveys asked questions about capital cost and efficiency, while FEEM asked directly for the Levelized Cost Of Electricity (LCOE). Second, the surveys elicited probability distributions in different ways: the UMass survey elicited the probability that a quantity would reach specific values, while the others elicited the 10th, 50th, and 90th percentiles for each quantity. Third, the surveys differed on time scale: Harvard and FEEM asked for estimates for cost and performance in 2030, while UMass asked about 2050. Fourth, they differed greatly in the level of public R&D investments, upon which the probability estimates were conditional. In the remainder of this section we describe the design of the expert elicitations, the harmonization, and the aggregation processes.

### 2.1. **Elicitation Methodology**

A total of 165 individual surveys or interviews with experts were completed by the three teams, each survey covering one (or two in the case of the Harvard bioenergy elicitation, which covered biofuels and electricity from biomass) of the technology areas. Some experts participated in multiple surveys, and the surveys of some experts were omitted due to missing data. Thus, there were between 114-119 distinct participating experts. (Due the anonymity of the individual surveys, we cannot narrow this number further). The complete list of experts is reported in the appendix.

The UMass and Harvard elicitations included U.S. experts and the FEEM elicitations included mainly experts from the European Union. The Harvard and FEEM experts spanned academia, public institutions, and the private sector, while the UMass elicitations excluded industry experts since UMass was focused on radical breakthroughs to be realized over a longer (2050) timeframe.

The elicitations used a range of methods: Some were conducted face to face, some were conducted via mail or email in a written form (in most cases with additional interactions between researchers and experts over the phone), some were conducted online (again, with access to researchers when needed), and some of the online surveys were followed up by a group workshop. Below is a summary of the methods used by the three research teams for each of the five technologies.

- FEEM: biofuels (face to face), bioelectricity (face to face), nuclear (mail and group workshop),

solar (face to face).

- Harvard: biofuels (mail); bioelectricity (mail and phone); nuclear (online and group workshop); solar PV (online); and CCS (mail and face to face).
- UMass: biofuels (face to face, mail); bioelectricity (face to face, mail, phone); nuclear (face to face and mail); solar (face to face with mail follow-up); and CCS (face to face and mail).

For more details the reader is referred to the papers describing the different expert elicitations. In the case of the online and mail surveys, the elicitation protocols included phone conversations and/or e-mail exchanges between experts and researchers as needed.

As discussed in the detailed papers and reports on the different elicitations, all three teams took precautions to correct biases inherent to expert estimates. In the UMass studies (Baker & Keisler, 2011; Baker, et al., 2009b; Baker, et al., 2009a; Baker, et al., 2008; Clarke & Baker, 2011) experts reviewed a primer on expert elicitation discussing possible biases. As the experts gave their probabilities (or after completing the survey in the case of mail surveys), the analysts used a series of probes aimed at debiasing, including asking about disconfirming evidence, asking backcasting type questions, and reminding the experts of overconfidence, especially when probabilities were very near 0 or 1. All experts were provided with a written summary of their responses, both verbal and quantitative, with the possibility of revising their responses.

In the Harvard mail and online elicitations (Chan, et al., 2011; Anadon, et al., 2012; Anadón, et al., 2014a) experts were provided extensive background information including (1) a summary of the purpose of the elicitations; (2) information about government R&D programs, current costs and future cost projections in the literature; (3) a short tutorial on bias and overconfidence including visual aids; and (4) an explanation of percentiles, also including visual aids. In addition, the elicitations themselves included interactive tools, both in the mail and online elicitations. On average, experts invested between 2 to 5 hours in completing the elicitations, plus additional time interacting with the researchers in some cases. All experts were provided with a written summary of the responses of all experts, with the ability to change theirs, and nuclear experts participating in a group following the individual elicitation workshop were given the possibility of revising their responses in private after each workshop session.

The FEEM studies [Anadon et al, 2012, Bosetti et al, 2012, Fiorese et al, 2013, Fiorese et al, 2014,] also included a preparatory document including information on technology costs and R&D funding and on biases. Each individual interview also included a first stage for training the experts in the elicitation process and discussing biases and heuristics. The interviews themselves included probing questions aimed at helping experts avoid overconfidence. Moreover, the questions were asked in multiple ways and then compared, allowing the expert to revise answers when needed. The average elicitation lasted more than three and a half hours.

The teams elicited different metrics for the different technologies. The top rows in Table 1 summarize the metrics that were elicited for each study, while the last two rows report the metrics used in this work to aggregate across surveys and the required assumptions.

**Table 1: Key survey characteristics and assumptions for the harmonization**

| Group | Biofuels | Bioelectricity | CCS | Nuclear | Solar | |
|---|---|---|---|---|---|---|
| **UMass metrics elicited** | Capital cost per gge[1] capacity, efficiency, other | Various technical endpoints, cost | Various technical endpoints, cost | Various technical endpoints, cost | Manufacturing cost per $m^2$, efficiency, lifetime | |
| **FEEM metrics elicited** | Cost per gge | Cost per kWh | N/A | Overnight capital cost ($/kW), fixed O&M cost, variable O&M cost, fuel cost, thermal burnup | LCOE | |
| **Harvard metrics elicited** | Cost per gge, yield (gge/dry ton of feedstock), plant life, feedstock costs | Cost per kWh, yield (gge/dry ton of feedstock), plant life | Overnight capital cost ($/kW) generating efficiency (HHV), capacity factor, book life for fossil plants with and without CCS | Overnight capital cost ($/kW), fixed O&M cost, variable O&M cost, fuel cost, thermal burnup | Module capital cost per $W_p$, module efficiency, inverter cost, inverter efficiency, inverter lifetime, O&M costs, other electronic components, etc. | |
| **Common Metrics Harmonized** | Non-energy cost per gge; efficiency | Non-energy cost per kwh; efficiency | Additional capital cost per kW; Energy penalty | Overnight capital cost | LCOE | |
| **Key Assumptions** | Assumptions on efficiency, share of non-energy cost. Assumption on time horizon transformation | Assumptions on efficiency, share of non-energy cost. Assumption on time horizon transformation | Calculating the additional cost of CCS over a coal plant without CCS Assumption on time horizon transformation | Assumption on time horizon transformation. | Capacity Factor | 12% |
| | | | | | Discount rate | 10% |
| | | | | | Lifetime* | 20 |
| | | | | | BOS $/$m^2$ | 75 UMass; 250 Harvard |
| | | | | | Assumption on time horizon transformation. | |

[1] gge are gallons of gasoline equivalent.

* For the Harvard elicitations module lifetime was provided by each expert, and thus not always equal to 20 years

Each study asked experts to assess uncertain future costs and performance of energy technologies conditional on the level of R&D funding by governments with the goal of examining the effect of government R&D on the costs of reducing carbon emissions. The studies defined R&D funding levels in

different ways (see Table 2). The FEEM surveys focused on the implications of European public R&D expenditures, hence "Low" R&D refers to an average of yearly expenditure over a five year period, per data collected by the OECD (IEA, 2013); "Mid" and "High" scenarios represent an increment of one and a half and twice the current levels; the UMass and Harvard studies considered the impact of U.S. public R&D investments. Harvard's "Mid" funding level is an average of the experts' recommended funding level for research, development and demonstration; low is ½ this amount, and high is 10 times this amount. Harvard experts were asked to break down their recommended level of investment by specific technology area or research pathway and by the stage of technology development. The UMass funding levels were defined in conjunction with a subset of the experts in a bottom-up manner, with experts thinking about how many labs could reasonably do research on specific technologies. The UMass funding amounts do not include demonstration plants while the Harvard funding amounts do.

**Table 2: Definition of R&D levels in each of the three studies (in millions of $2010/year).**

| **UMass** | Low | Mid | High |
|---|---|---|---|
| Solar | 25 | 140 | NA |
| Nuclear | 40 | 480 | 1980 |
| CCS | 13 | 48 | 108 |
| Biofuels | 13 | 201 | 838 |
| Bio electricity | 15 | 50 | 150 |
| **Harvard** | | | |
| Solar | 205 | 409 | 4091 |
| Nuclear | 942 | 1883 | 18833 |
| CCS | 1125 | 2250 | 22500 |
| Biofuels** | 293 | 585 | 5850 |
| Bio electricity** | 293 | 585 | 5850 |
| **FEEM** | | | |
| Solar | 171 | 257 | 342 |
| Nuclear* | 753 | 1514 | 15140 |
| CCS | NA | NA | NA |
| Biofuels | 168 | 252 | 336 |
| Bioelectricity | 169 | 254 | 338 |

Funding Levels $M/yr

* The Nuclear survey is an exception for the FEEM surveys as it was carried out together with Harvard, hence the nuclear mid and high R&D levels represent the average R&D investment across all the experts corresponding to that R&D level.

** Harvard combined Biofuels and Bio-electricity in one elicitation. The amount shown is the total R&D amount for both areas.

There are a number of challenges in evaluating the effect of government R&D funding on future technology costs, including the role of international and private sector spillovers, and the relationship

between deployment policies and cost reductions through economies of scale and induced R&D. It is hard for any analyst, including the experts participating in each study, to disentangle these effects. Moreover, just as there is some evidence of insensitivity to scale in contingent valuation studies (Carson, 2001), it is possible that the experts were not well-calibrated to the specific funding amounts—and would have given similar answers when considering a doubling of investment from $20 million to $40 million as they would from $200 million to $400 million. Therefore, in order to avoid over-specificity due to this list of challenges, we compare the results for low, medium, and high funding amounts in each study, against each other.

FEEM and Harvard asked their experts to provide $10^{th}$, $50^{th}$, and $90^{th}$ percentiles for each quantity to be assessed as a probability distribution. The UMass survey asked experts to assess the probability of two to four specified cost values.

## 2.2. **Fitting probability distributions to elicitation data**

For the FEEM and Harvard surveys, we examined three approaches to fitting probability distributions to the elicited 10th, 50th, and 90th percentiles (x10, x50, x90): Triangular, shifted Weibull, and a piecewise cubic fit to the cumulative distribution. The triangular and Weibull distributions each have three parameters. A triangular can fit x10, x50, x90 only if the skewness ratio (x50-x10)/(x90-x50) < 1.618. Similarly a Weibull can fit the three percentiles only if the skewness ratio is less than 1.569. Since only 58% and 57%, respectively, of the expert assessments have skewness ratios below these limits, we used the piecewise cubic method, which fits a cubic polynomial between successive percentiles, x0, x10, x50, x90, x100, on the cumulative distribution. We specify the minimum and maximum (x0 and x100) such that the ratios satisfy the following conditions:

$$x0/x10 = x10/x50$$
$$x100/x90 = x90/x50$$

We limit the minimum, x0, to be positive. Figure 1 shows an example of a fitted distribution. For the UMass surveys, we first aggregated across experts using simple averaging of the probabilities. After aggregation across experts, a piecewise cubic was used to fit the selected points. This required additional assumptions in some cases about the zero and $100^{th}$ percentiles.

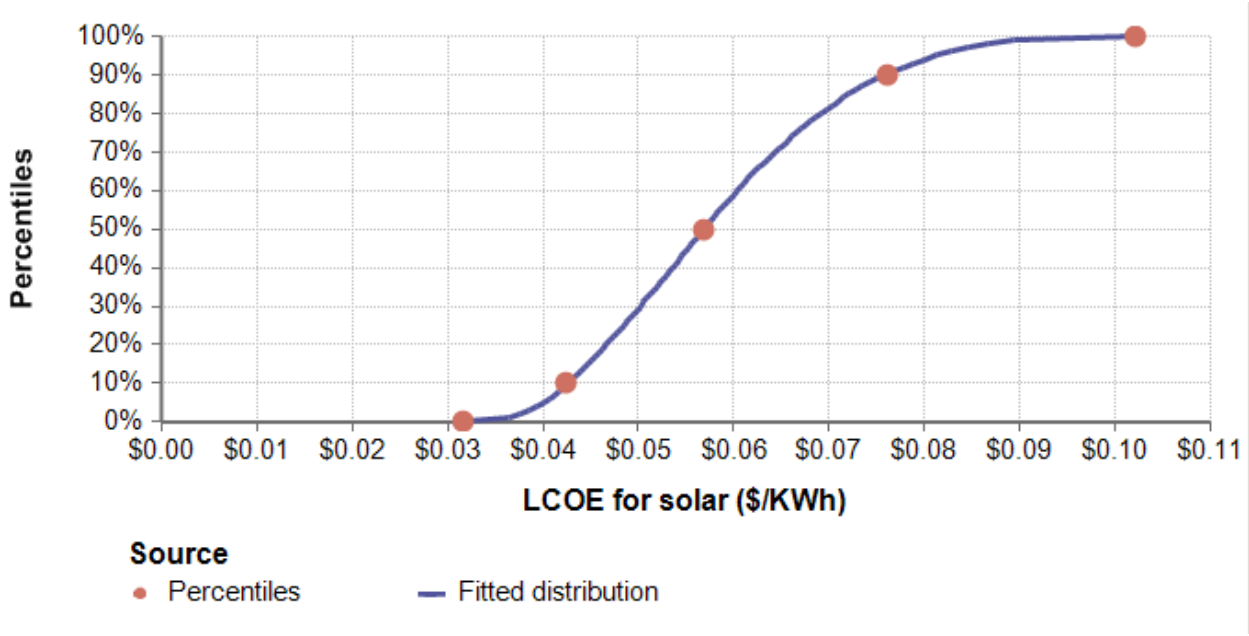


Fig 1 An example of a fitted distribution for one expert for solar LCOE. The 10th, 50th, and 90th percentiles estimated by the expert are shown as red dots. The 0 and 100th percentiles have been extrapolated as described above and are also shown with red dots. The blue line shows the cumulative distribution fitted to those percentiles using a piecewise cubic curve.

### 2.3. **Harmonization Methodology**

In order to compare and aggregate the elicited distributions, we harmonized them, making assumptions to have comparable currencies and currency years, endpoint years, and common metrics. Key assumptions used to convert to common metrics are included in the bottom rows of Table 1. The fifth row of Table 1 shows the metrics that were chosen as the goal of the harmonization for each technology. Typically, the most aggregated metric elicited in each survey represented the binding constraint in defining the common metric. For this reason in most cases we used the FEEM surveys to define the common metric. An exception is the metrics for the bioenergy technologies. In this case we use two metrics, allowing us to disentangle biomass cost from the conversion technology cost. We did this in order to connect these results with Integrated Assessment Models (IAMs) which take these distributions as inputs. Most IAMs treat the biomass cost as endogenous, and so must separate the energy and non-energy costs for the bioenergy technologies.

The sixth row summarizes assumptions. In order to divide bioenergy costs into energy and non-energy portions for the FEEM and Harvard studies, we assume that the fraction of non-energy costs provided by experts at the mean is the same across the distribution. In the case of solar technologies, experts participating in the FEEM study provided their estimates in terms of LCOE under the assumptions of a 12% capacity factor. Thus, to make the UMass and Harvard costs comparable, their more disaggregated costs were converted into an LCOE metric using a 12% capacity factor, even though most of the Harvard and UMass experts would have provided LCOE estimates using a higher capacity factor if that had been the metric that they were asked about. In order to illustrate the impact of capacity factor on LCOE,

Table 3 applies the TEaM assumptions to estimate the LCOE of a module cost of $0.75/Wp, estimated to be the 2013 cost of modules manufactured in China [ (Baker, et al., 2013)]. The two rows use two different assumptions about Balance Of Systems (BOS) costs, consistent with assumptions by UMass (the lower cost) and the average from Harvard experts (the higher cost). These values can be compared to the range of values in Figure 4.

**Table 3 Example calculation of converting current solar costs into the TEaM aggregated metric with different BOS cost assumptions in terms of $/m$^2$ (as in Table 2).**

| Study | Module cost 2014 ($/Wp) | BOS ($/Wp) | Lifetime | LCOE TEaM using BOS cost assumption |
|---|---|---|---|---|
| UMass | 0.75 | 0.73 | 20 | $0.17 |
| Harvard | 0.75 | 1.67 | 20 | $0.28 |

Finally, we needed to make no major assumptions to harmonize the nuclear overnight capital cost estimates, since all teams asked about the same metric. In Section 2.4.1 we discuss how we aggregated multiple different nuclear technologies into one category.

As previously mentioned, all UMass estimates were elicited for 2050. In order to make them more comparable to estimates in 2030, which was the timeframe used in the FEEM and Harvard studies, we backcasted the UMass 2050 estimates to 2030 assuming a constant learning rate (cost reduction percentage) per year -- similar to Moore's Law for electronics. Nagy et al. (2013) looked at a large amount of data for many different technologies, and found that estimated costs that used only time as a parameter (like Moore's law) performed nearly as well as the traditional experience curve. Equation (1) shows the cost curve used in the calculations.

$$c_t = c_\tau e^{-m(t-\tau)} \quad (1)$$

Where $c_t$ is the cost at time t, *m* is a parameter of this model calculated from *B*, the learning rate, and *g*, the growth rate of production:

$$m = Bg \quad (2)$$

Thus, we use this method to estimate the values for 2030, namely:

$$c_{2030} = c_{2050} e^{-m(2030-2050)} \quad (3)$$

To estimate the parameter *m*, we combine learning parameters *B* from the literature, with the growth parameter *g* from (Nagy, et al., 2013). Table 4 summarizes the parameters used.

**Table 4: Parameters for backcasting UMass elicitation results.**

| Technology | G | B | m |
|---|---|---|---|
| Solar | 0.09 | 0.32 | 0.0302 |
| Nuclear | 0.025 | 0.086 | 0.0022 |
| Liquid Biofuels | 0.06 | 0.36 | 0.0215 |
| Bio-electricity | 0.046 | 0.34 | 0.0156 |
| CCS | 0.075 | 0.16 | 0.0120 |

## 2.4. **Aggregation Methodology**

In their surveys of methods for aggregating probability distributions obtained from different experts (Clemen & Winkler, 1999; Clemen & Winkle, 2007) distinguish (i) mathematical approaches and (ii) behavioral approaches. Behavioral approaches are qualitative and involve the direct repeated interaction between experts in order to reach consensus on a single “group" estimate. Given the size and the coverage of the elicitations included the present paper, behavioral approaches would be prohibitively expensive.

Mathematical approaches use the individual probability distribution functions to construct a single probability distribution in two basic ways: either through axiomatically-justified mathematical formulas of aggregation, or, where possible, through Bayesian statistical methods that pay particular attention to issues of dependence and bias. Bayesian approaches to combine expert judgments treat each expert's judgment as data to be used in updating a prior distribution. They require assessment of a prior on the quantity of interest, usually specified as diffuse. Of greater challenge, they require specification of a likelihood function: a distribution of expert judgments conditional on the value of the uncertain quantity of interest—in other words, they require assessing the dependence among experts. Moreover, Bayesian methods typically assign zero probability in the combined distribution to any value to which any expert assigns zero. Experts are often overconfident and assign zero to ranges to which others might assign positive probability. Based on a comparison of results, simple averages typically perform almost as well as the theoretically superior, and technically much more complex, Bayesian methods. (Clemen, et al., 1996).

For this reason we resort to the simplest and most widely-used mathematical aggregation method of a weighted average or linear opinion pool. The aggregate distribution is the weighted average of the probability density (or cumulative probability) over the expert distributions. This method is sometimes called "Laplacean mixing" (Laplace, 1812). In the present context we follow this approach and, for simplicity, we use equal weighting of the experts assessing each quantity in each study.

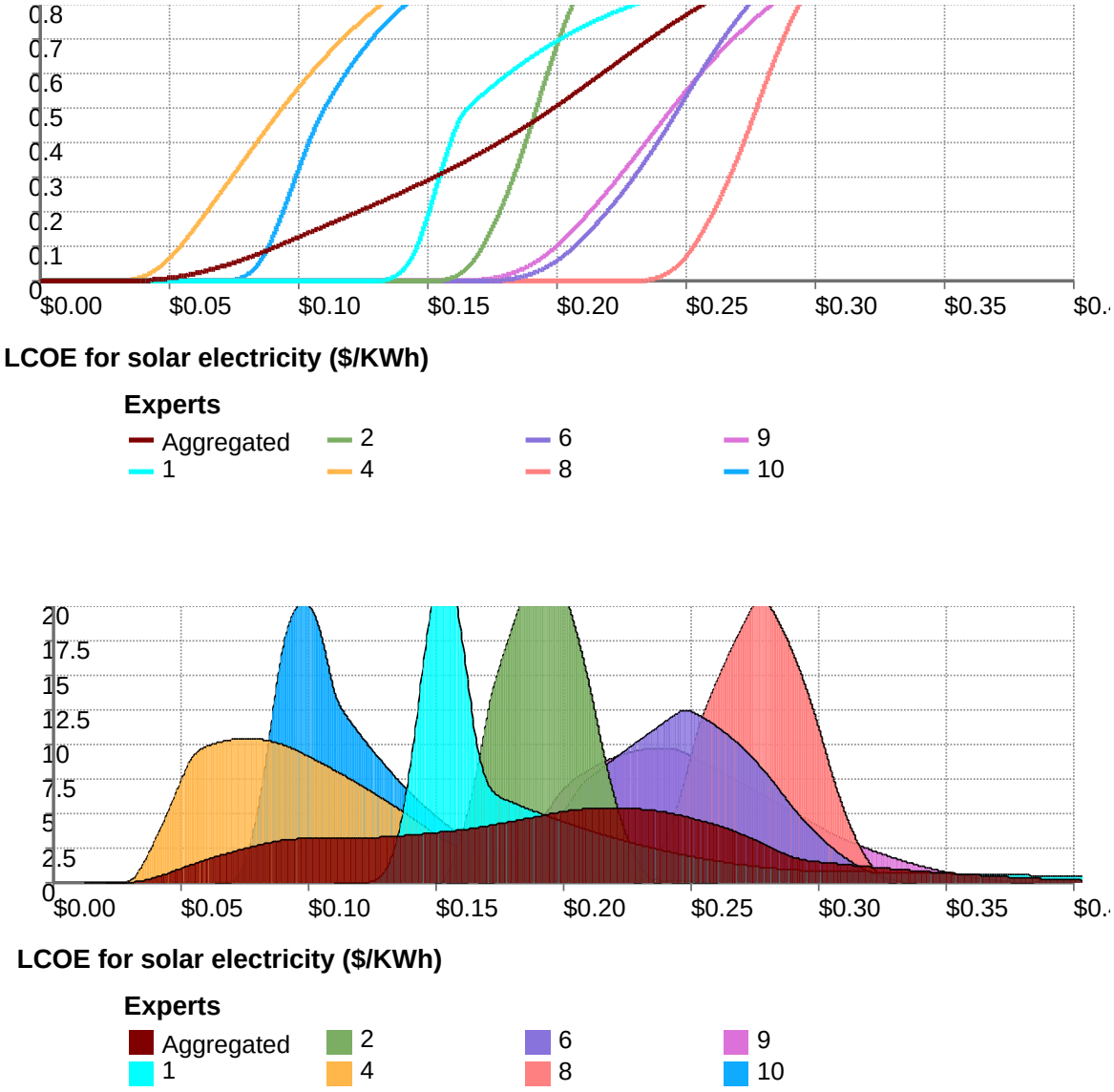


**Figure 2: Cumulative probability distributions (top) and probability density functions (bottom) for levelized cost of energy for solar in 2030 for low R&D spending for the aggregate and for each of the seven experts from the Harvard study. Cumulative distributions are piecewise cubic fit to 0, 10th, 50th, 90th, and 100th percentiles.**

Visualizing the location of the distributions of different experts in relation to each other shows that many distributions have little or no overlap (Figure 2). Therefore the distributions from simple Laplacean mixing are often irregular with multiple modes (see Figure 3 for a typical example). It is conceivable that, for a certain quantity, multiple modes may in fact reflect multiple schools of thought: For example, for nuclear power, some experts may believe that small modular reactors produced in large quantities are likely to lead to dramatically reduced cost; while other experts may not expect this to happen, and

so expect the cost of nuclear power to remain high. Aggregating opinions of experts from both schools of thought might lead to a bimodal distribution that reflects the bimodal distributions of opinions.

However, this situation is uncommon. It is more likely that the multimodal distributions result from some or most experts being overconfident, that is, providing distributions that are too narrow given the inherent uncertainty. Accordingly, we smooth the distributions so that they are nearer "bell-shaped" with a single mode with tails on each side. We do this by fitting a piecewise cubic to the 0, 10$^{th}$, 50$^{th}$, 90$^{th}$, and 100$^{th}$ percentiles from the Laplacean mixing distribution (Figure 3).

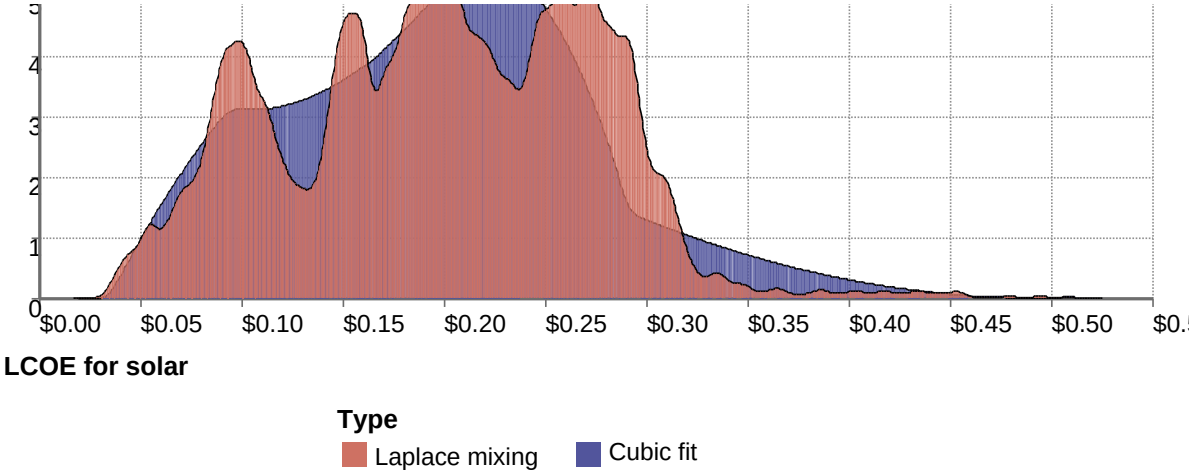


**Figure 3: Comparison between Laplacean mixing and fitted piecewise cubic distributions for aggregating over experts for levelize cost of energy for solar in 2030 for low R&D spending from the Harvard study.**

We also present results for a combined distribution aggregated across the three teams. We again use Laplacean mixing with equal weights for each team and apply piecewise cubic smoothing.

### 2.4.1. Aggregating various nuclear technologies into a single metric

For nuclear power, the Harvard and FEEM studies both elicited estimates for three technologies: Nuclear large-scale generation III+ systems, Nuclear large-scale generation IV systems, and Nuclear Factory built (or small modular reactors). We assume that the market and/or future power system planners will select whichever technology has the lowest cost. Thus, for each study, we combined these estimates over the technologies selecting the lowest cost technology from a Monte Carlo sample from the cost of each technology, assuming an 80% rank correlation between the costs of each technology. UMass elicited estimates for independent projects involving different nuclear technologies (including advanced light water reactors, High temperature gas cooled reactors, and Feeder reactors), and similarly assumed that only the lowest cost technology would be chosen when preparing the aggregated distribution.

## 3. **Results**

Here we present results on 2030 costs of the different technologies aggregated across experts for the individual teams and for the combination of the different teams. We discuss the implied effectiveness of R&D, reporting results for different R&D funding levels. Finally, we unpack the information that gets lost when showing aggregate figures of probability distributions or uncertainty ranges: we discuss in detail the key sources driving the uncertainty surrounding these aggregate distributions in terms of the uncertainty that comes from disagreement between experts about the mean versus the expert-specific uncertainty.

### 3.1. **Distributions of Cost and Efficiency Metrics**

In order to evaluate the expected impact of public R&D investments on the 2030 cost and performance of the five technologies covered by the teams, in Figure 4 we plot the distribution of cost for five cost metrics (Levelized Cost of Electricity for solar ($/kWh); non-energy cost for bio-electricity ($/kWh) and for biofuels ($/gallon of gasoline equivalent); additional capital cost for CCS ($/kW) and overnight capital cost for nuclear ($/kW)) and of performance for three efficiency metrics (conversion efficiency for bio-electricity and biofuels, energy penalty for CCS) for three different funding scenarios: Low in red, Mid in green, and High in blue. To allow for an easy visual comparison of the impact of R&D within studies, for each of the 8 metrics presented, we plot the results for the impact of the three different R&D levels next to each other. This representation also allows a relatively straightforward comparison of the differences across studies. The box plots show the $5^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, and $95^{th}$ percentiles for each of the distributions. The empty spaces reflect the fact that not all studies asked questions about all parameters. Only half of the metrics investigated—Solar LCOE, Bio-electricity non-energy cost, Biofuels non-energy cost, and Nuclear capital cost—were estimated by all three studies. Note that these studies were done in 2008-2010, so the experts were predicting future costs based on the current costs at that time.

Across all studies, metrics, and budget levels, increasing levels of public R&D investment are associated with cost decreases and efficiency improvements, as shown by the upwards movement of the box plots for efficiencies and the downwards movement of the box plots for the cost categories and energy penalty as R&D levels increase.

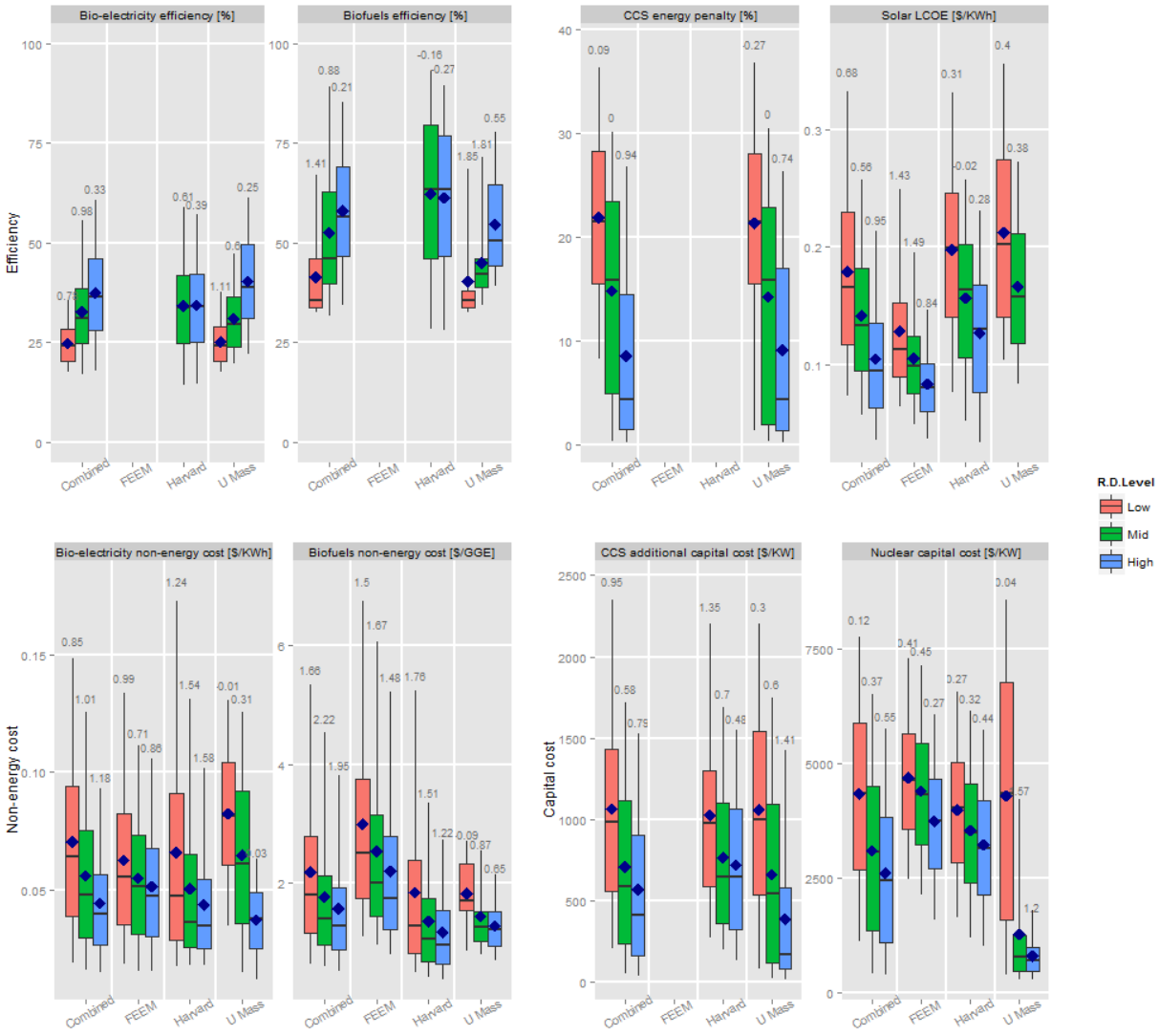


**Figure 4: 2030 costs and efficiency elicitation results across studies and R&D levels. We show the combined distribution of the three studies using equal weights ("Combined"), the FEEM aggregate, the Harvard aggregate, and the UMass aggregate and technologies by R&D level (Low, Mid, and High). The box plots show the 5th, 25th, 50th, 75th, and 95th percentiles for each of the distributions, the diamond the mean value, and the black number the skewness of the distribution.**

The experts seem to agree that R&D investments are expected to have a major impact on Solar LCOE by 2030. At the median, LCOE is expected to be reduced by 20% from low to medium funding, and by another 20% by increasing investments from the medium to the high funding levels. Note that the solar results are particularly difficult to compare across the three teams, since the harmonization required applying common exogenous assumptions about insolation and discount rates, among other factors, to the Harvard and UMass component data to make them comparable to the FEEM data. As mentioned above and illustrated in Table 2, FEEM used a somewhat pessimistic assumption of a 12% capacity value. Moreover, the price of solar has decreased rapidly since the time that these studies were done. Current estimated solar prices of about $0.75/Wp would translate into an LCOE of between $0.17 and $0.28,

depending on assumptions about BOS. The lower estimate is about equal to the median 2030 cost estimated by the combined teams at low R&D investment. This implies that the very rapid reduction in solar costs over the last few years were a surprise, and the experts have perhaps underestimated the possibility of cost reduction over the next 20 years.

Bio-electricity non-energy costs show a relatively consistent range of outcomes across the three studies, ranging from 0.025 to 0.125 $/kWh for the interquartile range. The Biofuels non-energy cost shows distributions that are significantly skewed upwards (with skewness coefficients that generally range from 0.8 to 2.12, with one exception), indicating a large probability of high cost outcomes, when compared to the distributions of the other metrics.

CCS additional capital costs exhibit a less pronounced upper tail, but still show wide uncertainty. We see similar outcomes between the two teams with data for the Low R&D scenario, but very different ones for the High R&D scenario. While Harvard experts expected that, at the median, R&D would reduce additional CCS capital cost by about $200/kW, UMass experts expected costs to come down by $800/kW.

Nuclear capital cost shows a wide range of perspectives for the future of nuclear power in 2030. The aggregated distributions of the FEEM and Harvard studies suggest that nuclear capital costs will be around $5,000/kW, similar to the estimate in the MIT 2009 Update to the Future of Nuclear study (Ansolabehere, et al., 2009).

## 3.2. **Returns to R&D**[1]

In (Anadon, et al., 2014c), we report on the returns to R&D. Specifically, Figure 5 shows the percentage increase (for efficiency) or decrease (for cost and energy penalty) in each metric as we move from low to mid funding, or mid to high funding. We found that most of the technologies had similar returns in the 20% range (with CCS the exception); and that no technology fared well in all three studies (i.e., across the elicitation studies conducted by FEEM, Harvard and UMass).

[1] This section draws heavily from Anadon et al 2014

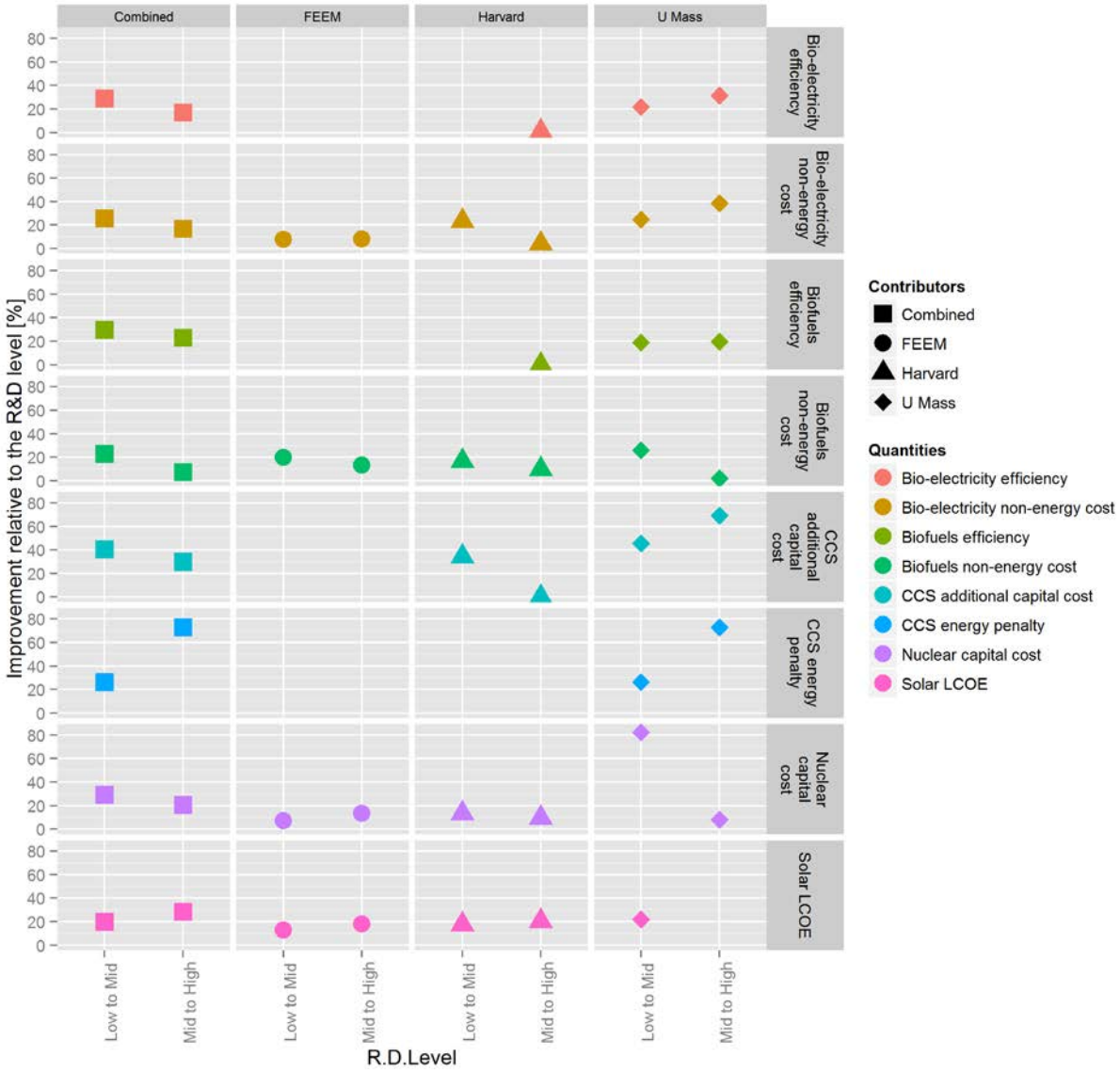


**Figure 5: The marginal returns on the aggregated median of each study, when compared to the next lower R&D level (change from low to mid and from mid to high R&D levels).**

Thirteen of the 24 panels with two points in Figure 5 clearly show decreasing marginal returns to scale, with a lower return for the Mid-to-High investment than the Low-to-Mid. In almost all the other cases in which the Mid-to-High return is higher, the additional investment to get from Mid to High is also very large. Thus, marginal return per dollar of R&D investment is in fact decreasing in all cases, except for CCS energy penalty as assessed by UMass. Thus, we see that the results imply that experts have a model of decreasing marginal returns to additional R&D dollars.

Such a model may be explained by two different underlying beliefs. One is a "fishing-out" model (Jones, 1995). This implies that there is only a certain amount of innovation available in any one category, and

so with large enough investments the ideas start to get fished out and returns decrease. Another is a model of decreasing returns within a period, but a recharging between periods (Nordhaus, 2002). The increase in R&D amounts in most of the studies were presented as increasing amounts over a fixed amount of time, rather than an extension of the period of research. Thus, while the experts may have been envisioning a fishing-out model, it is also possible that they were identifying decreasing returns within a period. It would be very interesting in future research to test whether explicitly asking experts to think about having additional time to devote to a particular research project has a different effect on experts than adding funding over a set period of time.

Table 5 shows each team's ranking of the technologies, with technologies listed by the highest median return for each technology in either the low to mid or the mid to high funding increase. Clearly there is very little agreement between the teams on which technologies have the best prospects for significant improvements in response to R&D.

Table 5: Rankings of the technologies in terms of prospects for advancement

| Combined | FEEM | Harvard | UMass |
|---|---|---|---|
| CCS | Solar | CCS | Nuclear |
| Nuclear | Bio-fuels | Bio-electricity | CCS |
| Solar | Nuclear | Solar | Bio-electricity |
| Bio-electricity | Bio-electricity | Biofuels | Biofuels |
| Bio-fuels | | Nuclear | Solar |

### 3.3. **Sources of uncertainty**

In an expert elicitation with multiple experts (and in this case also with multiple studies), there are multiple sources of uncertainty. Each individual expert incorporates uncertainty into his estimate. Differences between experts then add additional uncertainty. Finally, in this case, the differences between the studies adds a final dimension of uncertainty.

Uncertainty within each expert's estimate reflects each individual expert's assessment of how much is known about the particular question (in this case future costs and performance contingent on public R&D investments). However, it is important to note that experts tend to be systematically over-confident: they assess distributions which are too narrow and lead to numerous surprises (Lin & Bier, 2008). Uncertainty between experts reflects disagreement between the experts, which in turn reflects different knowledge sets (and to some degree, different biases). Averaging different experts counterbalances the over-confidence seen in individual experts. In fact, a distribution that is derived from averaging across well-calibrated experts (that is, experts who are not over-confident) will be under-confident, or too diffuse (Hora, 2004). Given, however, that individuals are almost always over-confident, this is a correction. Finally, disagreement between studies leads to yet more uncertainty. This may reflect different biases that may be related to the different metrics elicited, question wording, and modes of data collection (Anadon, et al., 2014b); or it may reflect that the different studies worked with

significantly different sets of experts.

Here we decompose the uncertainty into two of these factors. Figure 5 illustrates the contribution of variance allocated between the individual-experts and the between-experts in the FEEM and Harvard studies. (We did not calculate these values for the UMass study as the individual probabilities were first aggregated and then continuous distributions were estimated.) Equation (4) decomposes the overall variance of a distribution into two parts, where $w_i$ is the weight given to each individual expert i, $\sigma_i$ is the standard deviation of each individual expert's distribution, $\mu_i$ is the mean of individual i's distribution and $\mu_x$ is the mean of the aggregated distribution. We interpret the first term as representing the individual experts' variances and the second term as the between-expert variance. (See Jenni et al.2013 for a similar method).

$$\sigma^2{}_x = \sum_i w_i \sigma^2{}_i + \sum_i w_i \times (\mu_i - \mu_x)^2 \qquad (4)$$

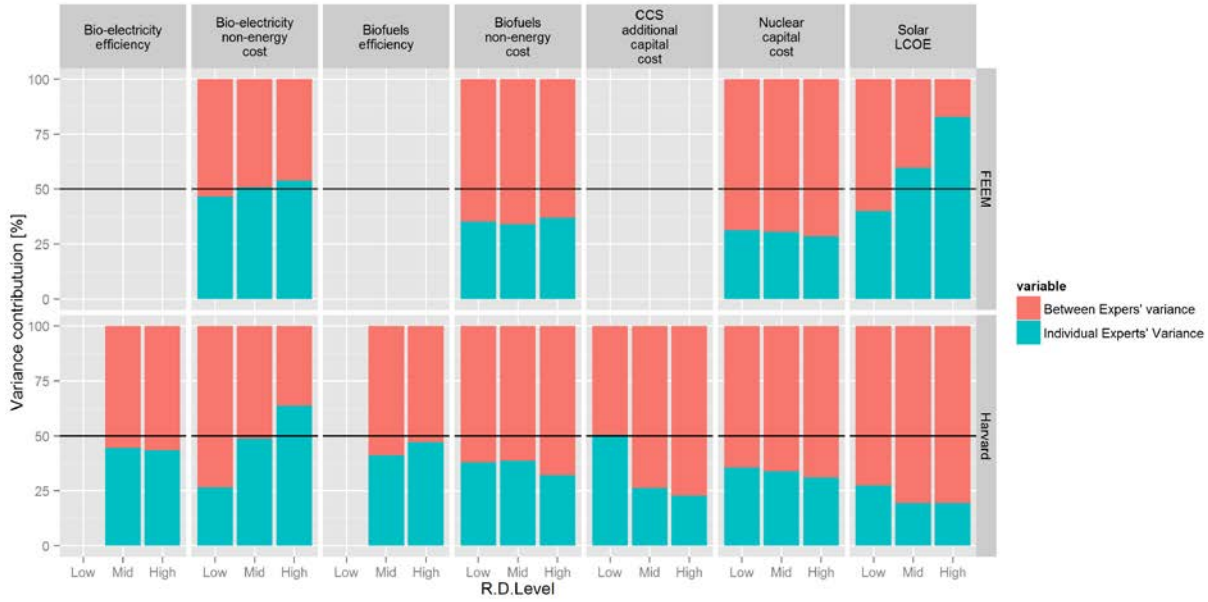


**Figure 5: Contribution of the variance of individual experts vs. the variance among experts to the variance in the individual aggregated studies.**

As shown in Figure 5, we find that both factors—intra-expert and inter-expert uncertainty (or disagreement)--are significant contributors. In most of the studies, more than half of the variance is attributed to the between-expert variance; this is particularly strong in the Harvard study for solar power when compared to the FEEM study. This may indicate that individual experts are over-confident (a typical finding in the literature [ (Henrion & Granger Morgan, 1990); Lin and Bier, 2008]). A large number of studies have shown that experts are not well-calibrated, with between 20% to 45% of correct values falling outside of assessed 98% intervals (rather than the expected 2%). Overconfidence can also be judged by the degree to which experts overlap. A lack of overlapping in distributions indicates that non overlapping experts (at least all but one of them) are overconfident; we see this in many cases in our data. The large between-expert variance also may imply that information about the technologies is

not well-diffused through the community (Jenni, et al., 2013). Particularly striking is the different between FEEM and Harvard in the solar studies. One interpretation is that European experts are much closer to consensus than US experts. On the other hand, this difference may also be driven by the fact that the Harvard LCOE costs were calculated using disaggregated cost components provided by experts: it may be that the European experts anchored more strongly on available estimates for LCOE, whereas few similar available estimates exist for the metrics assessed in Harvard study.

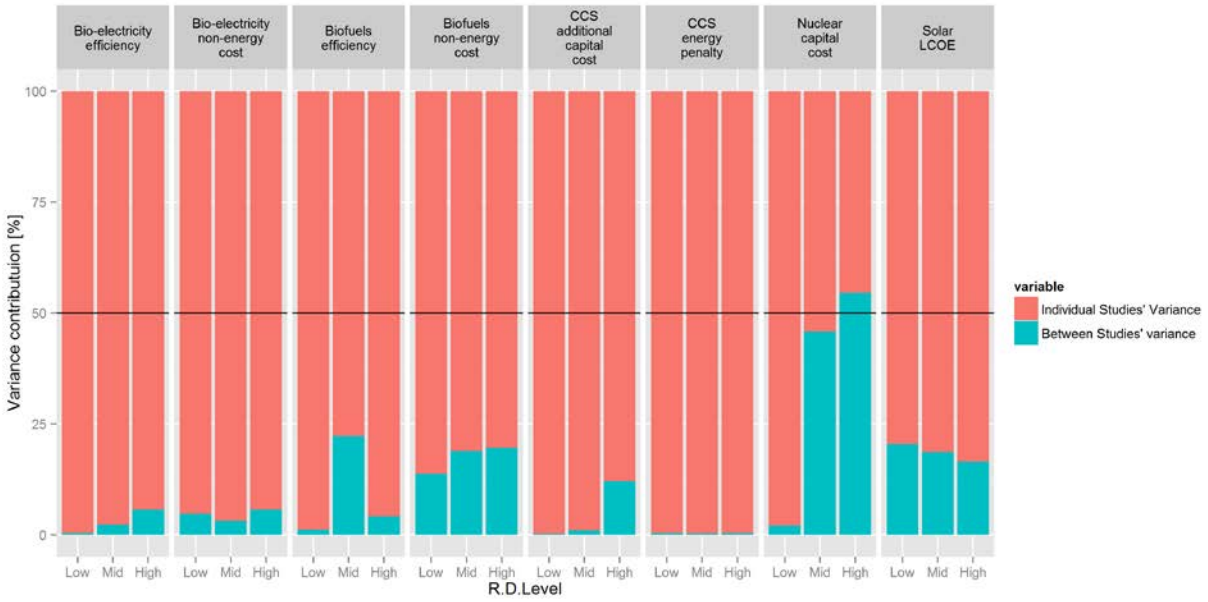


**Figure 6: Contribution of the variance of individual Studies vs. the variance among studies to the variance in the combined distribution.**

In a similar way, Figure 6 illustrates the relative contribution of within-study variance and between-study variance. The two variances are calculated according to equation (4), where, in this case, i is the individual study and x is the combined distribution. Here we see that while there is a great deal of disagreement between studies when looking at the median values of the cost and performance, most of the variance in the combined distribution comes from the uncertainty expressed in the individual studies.

## 4. **Conclusions**

Given that significant amounts of funding are being invested in R&D in energy and low-carbon technologies by some public agencies, and that many stakeholders have requested an increase in these investments, it is crucial to obtain estimates of the possible returns to society of such activities, both economic and environmental. This paper summarizes the result of a multi-team study, comparing a number of expert elicitations in five important technology areas performed independently. The starting point for this study was a set of existing expert elicitations. For this study, we harmonized the results over R&D funding amounts, metrics, and timing. We then aggregated the results, first across experts within each expert elicitation study, and then across the various elicitation studies covering each

technology. We present results for each team and for the aggregation over teams, and indicate the amount of variation that occurs between experts and teams.

It was very challenging to harmonize and compare the disparate elicitations, yet this is crucial for researchers and policy makers to get an understanding of the current state of knowledge. An important suggestion for future elicitation studies is for all such studies to make assumptions very explicit in order to ease future comparisons. Moreover, a central database for collecting and comparing energy technology probability distributions would provide great benefits to future researchers. Along this vein, the results of these surveys are available on-line at http://megajoule.org/.

Balancing out the great challenges of harmonizing this data, there is considerable value in this process and the outcomes. In particular, we see a considerable amount of disagreement between the studies, both on the absolute values of the metrics elicited and on the possible returns from higher investments in R&D. For example, we see that when comparing technologies in terms of the median return to R&D, each team has a different ordering for the technologies. A policy maker who stopped at one study may be overconfident about the relative value of additional R&D investment in one technology area when compared to another area, given the current state of information. This study suggests that our understanding of what R&D can buy us is at an early stage for most of these technologies. Moreover, in providing a combined data set along with the underlying team data sets, we allow researchers and policy makers to make near-term decisions based on the best available information, with a clear understanding of the amount of disagreement and uncertainty underlying it.

Typical of expert elicitation studies, we see a considerable amount of overconfidence among the individual experts, illustrated by the many non-overlapping distributions as well as the large amount of variance allocated to the difference between experts (as opposed to the variance being reported by each expert). Future studies may want to include some additional techniques for reducing over confidence, such as presenting experts with past surprises for related quantities, such as periods during which a technology costs increased or dropped rapidly — e.g. cost of photovoltaic modules increased from 2004 to 2008, and then dipped by a factor of about 4 from 2008 to 2012; incorporating information about past learning curves; and having experts participate in group discussions before the elicitations to ensure that the current state of knowledge among the participating experts is well disseminated among them.

On the other hand, this study shows that the process of eliciting and combining multiple experts results in less overconfidence in each of the study's aggregated distributions. This is illustrated by the fact that the overall variance in the combined distribution is due almost entirely to the variance in the underlying team distributions, rather than to disagreement among the teams. What this means is that, even though the individual team elicitations disagree in terms of medians and means, in most technology areas each of the studies does a pretty good job of covering a wide range: a draw from the distribution in one study is not highly likely to be a surprise in the distribution of another study. On the other hand, we still see a significant amount of between-study variance in one technology (nuclear). Given that it is hard to know where these widespread disagreements will take place, there is still value in multi-team studies like this,

not only for understanding disagreements between experts over the central values, but also for establishing well calibrated probability distributions.

One result coming out of the data is that the experts have a model, implicit or explicit, of decreasing returns to scale in R&D investment. This brings up a couple of interesting questions for future work. First, are the experts reporting decreasing returns to scale because this is such a common model for investment, or do the decreasing returns accurately reflect their views of the particular technology they are analyzing? The second question is whether the experts are assessing decreasing returns consistent with a fishing-out model or consistent with a recharge model.

One particular challenge of using expert judgment to inform energy technology R&D decisions is the very large number of technologies that can potentially be part of a portfolio. Expert elicitation studies are very resource intensive. One question that this study brings up related to this is whether it would be better to have very detailed, resource-intensive interviews with a small number of experts for each technology; or whether it would be better to have much lower cost elicitations (such as automated online surveys) with a large number of experts. The fact that between-study variance was low for many (but not all) technology areas may indicate that it does not strongly matter in terms of getting a reasonable probability range, so that the deciding factor may be the overall cost. However, this study was not designed to test this question and it only provides some very general indications.

**Acknowledgment**

Baker's research was partially supported by NSF under award number SES-0745161. Bosetti acknowledges funding from the European Research Council under the European Community's Seventh Framework Programme (FP7/2007-2013) / ERC grant agreement n◦ 240895 - project ICARUS "Innovation for Climate Change Mitigation: a Study of energy R&D, its Uncertain Effectiveness and Spillovers". - Anadon acknowledges funding from the Science, Technology, and Public Policy program at the Harvard Kennedy School and grants from the Doris Duke Charitable Foundation and BP to the Energy Technology Innovation Policy research group. This paper was partially supported by the GEMINA project, funded by the Italian Ministry for the Environment, Land and Sea (MATTM); and by the Energy Modeling Forum at Stanford University. The authors would like to thank Gabriel Chan and Stephen Elliott for contributions in data processing at Harvard in the CCS and solar data, respectively.

# Bibliography


Anadon, L. et al., 2012. Expert judgments about RD&D and the future of nuclear energy. *Environ. Sci. Technol.,* Volume 46, pp. 11497-504.

Anadón, L., Chan, G. & Lee, A., 2014a. *Transforming U.S. Energy Innovation.* Cambridge, U.K., and New York, NY, USA: Cambridge University Press.

Anadon, L. D., Baker, E., Bosetti, V. & Aleluia Reis, L., 2014c. Too early to pick winners: disagreement across. *Submitted to PLOS ONE.*

Anadon, L. D. et al., 2011. *Transforming U.S. Energy Innovation,* Cambridge, MA: Belfer Center for Science and International Affairs. Harvard Kennedy School.

Anadon, L., Lu, J., Nemet, G. & Verdolini, E., 2014b. The impact of R&D, expert selection, and elicitation design on expert estimates about the future cost of photovoltaic technologies. *Submitted to Energy Policy.*

Ansolabehere, S. et al., 2009. *Update of the MIT 2003 Future of nuclear power,* 77 Massachusetts Avenue, Cambridge MA: Massachusetts Institute of Technology.

Baker, E., Chon, H. & Keisler, J., 2009a. Carbon capture and storage: combining economic analysis with expert elicitations to inform climate policy. *Climatic Change,* Volume 96, pp. 379-408.

Baker, E., Chon, H. & Keisler, J., 2009b. Advanced solar R&D: Combining economic analysis with expert elicitations to inform climate policy. *Energy Economics,* Volume 31, pp. S37-S49.

Baker, E., Chon, H. & Keisler, J. M., 2008. Advanced Nuclear Power: Combining Economic Analysis with Expert Elicitations to Inform Climate Policy. 08 August.

Baker, E., Fowlie, M., Lemoine, D. & S., R. S., 2013. The Economics of Solar Electricity. *Annu. Rev. Resour. Econ.,* Volume 5, pp. 387-426.

Baker, E. & Keisler, J., 2011. Cellulosic biofuels Expert views on prospects for advancement. *Energy,* Volume 36, pp. 595-605.

Bosetti, V., Catenacci, M., Fiorese, G. & Verdolini, E., 2012. The future prospect of PV and CSP solar technologies: An expert elicitation survey. *Energy Policy,* Volume 49, pp. 308-317.

Carson, R. a. F. N. a. M. N., 2001. Contingent Valuation: Controversies and Evidence. *Environmental and Resource Economics,* Volume 19, pp. 173-210.

Catenacci, M. V. E., Bosetti, V. & Fiorese, G., 2013. Going electric: Expert survey on the future of battery technologies for electric vehicles. *Energy Policy,* Volume 61, p. 403–413.

Chan, G., Anadón, L., Chan, M. & Lee, A., 2011. Expert elicitation of cost, performance, and RD&D budgets for coal power with CCS. *Energy Procedia,* p. 2685–2692.

Clarke, L. & Baker, E., 2011. *Workshop Report: RD&D Portfolio Analysis Tools and Methodologies,* s.l.: Joint Global Change Research Institute Report.

Clemen, R. T., Jones, S. K. & Winkler, R. L., 1996. Aggregating forecasts: An empirical evaluation of some Bayesian methods. In: K. C. &. J. G. D. Berry, ed. *Bayesian Statistics and Econometrics: Essays in Honor of Arnold Zellner.* New York: Wiley, pp. 3-13.

Clemen, R. & Winkle, R., 2007. Aggregating probability distributions. In: W. a. M. R. a. W. D. v. Edwards, ed. *Advances in Decision Analysis.* Cambridge , UK: Cambridge University Press, pp. 154-176.

Clemen, R. & Winkler, R., 1999. Combining Probability Distributions from Experts in Risk Analysis. *Risk Analysis,* Volume 19, pp. 187-203.

Council, I., 2010. *Climate change assessments: Review of the processes and procedures of the IPCC,* Alkmaar, The Netherlands: InterAcademy Council.
Fiorese, G., Catenacci, M., Verdolini, E. & Bosetti, V., 2013. Advanced biofuels: Future perspectives from an expert elicitation survey. *Energy Policy,* Volume 56, p. 293–311.
Henrion, M. & Granger Morgan, M., 1990. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis.* New York: Cambridge University Press.
Hora, S., 2004. Probability Judgments for Continuous Quantities: Linear Combinations and Calibration. *Management Science,* pp. 597-604.
IEA, 2013. *RD&D Budget.* s.l., IEA Energy Technology RD&D Statistics database.
Jenni, K., Baker, E. & Nemet, G., 2013. Expert Elicitations of Energy Penalties for Carbon Capture. *International Journal of Greenhouse Gas Control,* Volume 12, pp. 136-145.
Jones, C. I., 1995. R & D-Based Models of Economic Growth. *Journal of Political Economy,* Volume 103, pp. 759-784.
Laplace, P. S., 1812. *Théorie analytique des probabilités.* Paris: Veuve Courcier.
Lin, S.-W. & Bier, V., 2008. A study of expert overconfidence. *Reliability Engineering and System Safety,* Volume 93, p. 711–721.
Nagy, B., Farmer, J., Bui, Q. & Trancik, J., 2013. Statistical Basis for Predicting Technological Progress. *PLoS ONE,* Volume 8, p. e52669.
Nordhaus, W., 2002. Modeling induced innovation in climate change policy. In: A. Grubler, N. Nakicenovic & W. Nordhaus, eds. *Technological change and the environment.* Grubler, A.; Nakicenovic, N.; Nordhaus, W.D. ed. Washington DC: RFF Press, pp. 182-209.
NRC, 2007. *Prospective evaluation of applied energy research and development at DOE (phase two),* s.l.: National Academies Press (National Research Council).

**Appendix**

**A1. List of experts for each study by technology**

| **Harvard – Bioenergy (bioelectricity and biofuels)** | |
|---|---|
| Name | Affitiation |
| David Austgen | Shell |
| Joe Binder | UC Berkeley |
| Harvey Blanch | UC Berkeley |
| André Boehman | Penn State University |
| Robert Brown | Iowa State University |
| Randy Cortright | Virent |
| Eric Larson | Princeton |
| Lee Lynd | Dartmouth |
| Tom Richard | Penn State University |
| Phillip Steele | Mississippi State University |
| Bob Wallace | Penn State University |
| Bryan Willson | Solix |

| **Harvard - nuclear** | |
|---|---|
| Name | Affitiation |
| John F. Ahearne | NRC, NAS nuclear power, Sigma XI |
| Joonhong Ahn | University of California at Berkeley |
| Edward D. Arthur | Advanced Reactor Concepts |
| Sydney J. Ball | Oak Ridge National Laboratory |
| Ashok S. Bhatagnar | Tennessee Valley Authority |
| Bob Budnitz | Lawrence Berkeley National Laboratory |
| Douglas M. Chapin | MPR Associates |
| Michael Corradini | University of Wisconsin |
| B. John Garrick | U.S. Nuclear Waste Technical Review Board |
| Michael Warren Golay | Massachusetts Institute of Technology |
| Eugene S. Grecheck | Dominion Energy, Inc. |
| Pavel Hejzlar | TerraPower USA |
| J. Stephen Herring | Idaho National Laboratory |
| Thomas Herman Isaacs | Stanford University and Lawrence Livermore National Laboratory |
| Kazuyoshi Kataoka | Toshiba |
| Andrew C. Klein | Oregon State University |
| Milton Levenson | Retired (previously at ORNL, Bechtel, and EPRI) |
| Regis A. Matzie | RAMatzie Nuclear Technology Consulting, LLC (previously at Westinghouse) |
| Andrew Orrell | Sandia National Laboratory |

| | |
|---|---|
| Kenneth Lee Peddicord | Texas A&M University |
| Per F. Peterson | University of California at Berkeley |
| Paul Pickard | Sandia National Laboratory |
| Burton Richter | Stanford University |
| Geoffrey Rothwell | Stanford University |
| Pradip Saha | Wilmington, North Carolina |
| Craig F. Smith | Livermore/Monterey Naval Post Graduate School |
| Finis H. Southworth | Areva |
| Temitope A. Taiwo | Argonne National Laboratory |
| Neil Emmanuel Todreas | Massachusetts Institute of Technology |
| Edward G. Wallace | Pebble Bed Modular Reactor (Pty) Ltd. |

| **Harvard - CCS** | |
|---|---|
| Name | Affitiation |
| Janos Beer | Massachusetts Institute of Technology |
| Jay Braitsch | U.S. Department of Energy |
| Joe Chaisson | Clean Air Task Force |
| Doug Cortez | Hensley Energy Consulting LLC |
| James Dooley | Pacific Northwest National Laboratory |
| | Joint Global Climate Research Institute |
| Jeffrey Eppink | Enegis, LLC |
| Manoj Guha | Energy & Environmental Service International |
| Reginald Mitchell | Stanford University |
| Stephen Moorman | Babcock & Wilcox |
| Gary Rochelle | University of Texas at Austin |
| Joseph Smith | Idaho National Laboratory |
| Gary Stiegel | National Energy Technology Laboratory |
| Jost Wendt | University of Utah |

| **Harvard - PV** | |
|---|---|
| Name | Affitiation |
| Allen Barnett | University of Delaware |
| Sarah Kurtz | NREL |
| Bill Marion | NREL |
| Robert McConnell | Amonix, Inc. |
| Danielle Merfeld | GE Global research |
| John Paul Morgan | Morgan Solar |
| Sam Newman | Rocky Mountain Institute |
| Paul R. Sharps | Emcore Photovoltaics |
| Sam Weaver | Cool Energy |
| John Wohlgemuth | NREL |

| **U Mass - Biofuels** | |
|---|---|
| Name | Affitiation |
| Richard Bain | National Renewable Energy Lab |
| Robert Brown | Iowa State University |
| Bruce Dale | Michigan State University |
| George Huber | University of Massachusetts, Amherst |
| Chris Somerville and Harvey Blanch | University of California, Berkeley |
| Phillip Steele | Mississippi State University |

| **U Mass - Nuclear** | |
|---|---|
| Name | Affitiation |
| Robert Budnitz | Lawrence Berkeley National Laboratory |
| Darryl P. Butt | Boise State |
| Per Petersen | U.C. Berkeley |
| Neil Todreas | MIT |

| **U Mass - CCS** | |
|---|---|
| Name | Affitiation |
| Richard Doctor | Argonne National Laboratory |
| Barry Hooper | Cooperative Research Centre for Greenhouse Gas Technologies |
| Wei Liu | Pacific Northwest National Lab |
| Gary Rochelle | The University of Texas at Austin |

| **U Mass - PV** | |
|---|---|
| Name | Affitiation |
| Nate Lewis | The California Institute of Technology |
| Mike McGehee | Stanford University |
| Dhandapani Venkataraman (DV) | University of Massachusetts, Amherst |

| **U Mass - Bio-eletricity** | |
|---|---|
| Name | Affitiation |
| Bruce Folkdahl | University of North Dakota |
| Richard Bain | NREL |
| Dave O'connor | EPRI |
| Evan Hughes | EPRI |

| **FEEM - PV** |
|---|

| Name | Affiliation |
|---|---|
| Rob Bland | McKinsey |
| Luisa F. Cabeza | University of Lleida |
| Roberta Campesato | Centro Elettrotecnico Sperimentale Italiano |
| Carlos del Canizo Nadal | Universidad Politecnica de Madrid |
| Aldo Di Carlo | UniRoma2 |
| Ferrazza Francesca | Ente Nazionale Idrocarburi |
| Paolo Frankl | International Energy Agency |
| Arnulf Jäger-Waldau | European Commission DG JRC |
| Roland Langfeld | Schott AG. |
| Ole Langniss | FICHTNER GmbH & Co. KG |
| Antonio Luque | Universidad Politecnica de Madrid |
| Paolo Martini | Archimede Solar Energy |
| Christoph Richter | German Aerospace Center |
| Wim Sinke | Energy Research Centre |
| Rolf Wüstenhagen | University of St. Gallen |
| Paul Wyers | Energy Research Centre |

| **FEEM – Bio-electricity** | |
|---|---|
| Name | Affiliation |
| Alessandro Agostini | JRC - Joint Research Centre |
| Göran Berndes | Chalmers University of Technology |
| Rolf Björheden | Skogforsk - the Forestry Research Institute of Sweden |
| Stefano Capaccioli | ETA - Florence Renewable Energies |
| Ylenia Curci | Global Bioenergy Partnership |
| Bernhard Drosg | BOKU - University of Natural Resources and Life Science |
| Berit Erlach | TU Berlin - Technische Universität Berlin |
| André P.C. Faaij | Utrecht University |
| Mario Gaia | Turboden s.r.l. |
| Rainer Janssen | WIP - Renewable Energies |
| Jaap Koppejan | Procede Biomass BV |
| Esa Kurkela | VTT - Technical Research Centre of Finland |
| Sylvain Leduc | IIASA - International Institute for Applied Systems Analysis |
| Guido Magneschi | DNV KEMA |
| Stephen McPhail | ENEA - Agenzia nazionale per le nuove tecnologie, l'energia e lo sviluppo economico sostenibile |

| | |
|---|---|
| Fabio Monforti-Ferrario | JRC - Joint Research Centre |

| **FEEM - Biofuels** | |
|---|---|
| Name | Affiliation |
| David Chiaramonti | Università degli Studi di Firenze |
| Jean-Francois Dallemand | Joint Research Centre (Ispra) |
| Ed De Jong | Avantium Chemicals BV |
| Herman den Uil | Energy Research Centre of the Netherlands (ECN) |
| Robert Edwards | Joint Research Centre (Ispra) |
| Hans Hellsmark | Chalmers University of Technology |
| Carole Hohwiller | Commissariat à l'énergie atomique et aux énergies alternatives (CEA) |
| Ingvar Landalv | CHEMREC |
| Marc Londo | Energy Research Centre of the Netherlands (ECN) |
| Fabio Monforti-Ferrario | Joint Research Centre (Ispra) |
| Giacomo Rispoli | Eni S.p.A. |
| Nilay Shah | Imperial College London |
| Raphael Slade | Imperial College London |
| Philippe Shild | European Commission |
| Henrik Thunman | Chalmers University of Technology |

| | **FEEM - Nuclear** |
|---|---|
| Name | Affiliation |
| Markku Anttila | VTT (Technical Research Centre of Finland) |
| Fosco Bianchi | Italian National Agency for New Technologies, Energy and sustainable economic development (ENEA) |
| Luigi Bruzzi | University of Bologna |
| Franco Casali | Italian National agency for new technologies, Energy and sustainable economic development ENEA; IAEA; University of Bologna |
| Jean-Marc Cavedon | Paul Scherrer Institut |
| Didier De Bruyn | SCK CEN, the Belgian Nuclear Research Centre |
| Marc Deffrennes | European Commission, DG TREN, Euratom |
| Allan Duncan | Euratom, UK Atomic Energy Authority, HM Inspectorate of Pollution |
| Dominique Finon | Centre national de la Recherche Scientifique (CNRS), Centre International de Recherche sur l'Environnement et le Developpement (CIRED) |

| | |
|---|---|
| Konstantin Foskolos | Paul Scherrer Institut |
| Michael Fuetterer | Joint Research Centre - European Commission |
| Kevin Hesketh | UK National Nuclear Laboratory |
| Christian Kirchsteiger | European Commission, Directorate-general Energy |
| Peter Liska | Nuclear Power Plants Research Institute<br>Institute of Safety Research |
| Bruno Merk | Forschungszentrum Dresden-Rossendorf |
| Julio Martins Montalvão e Silva | Instituto Tecnologico e Nuclear |
| Stefano Monti | Italian National agency for new technologies, Energy and sustainable economic development (ENEA) |
| Francois Perchet | World Nuclear University |
| Enn Realo | Radiation Safety Department, Environmental Board, Estonia; University of Tartu |
| Hans-Holger Rogner | International Atomic Energy Agency (IAEA) |
| David Shropshire | Joint Research Centre - European Commission |
| Simos Simopoulos | National Technical University of Athens; Greek Atomic Energy Commission, NTUA |
| Renzo Tavoni | Italian National agency for new technologies, Energy and sustainable economic development (ENEA) |
| Andrej Trkov | Institute Jozef Stefan |
| Harri Tuomisto | Fortum Nuclear Services Oy |
| Ioan Ursu | Horia Hulubei National Institute of Physics and Nuclear Engineering (IFIN-HH) |
| Bob van der Zwann | Energy Research Centre of the Netherlands (ECN) |
| Georges Van Goethem | European Commission, DG Research, Euratom |
| Simon Webster | European Commission, DG Energy, Euratom |
| William Nuttall | University of Cambridge |

## NOTE DI LAVORO DELLA FONDAZIONE ENI ENRICO MATTEI

**Fondazione Eni Enrico Mattei Working Paper Series**

**Our Note di Lavoro are available on the Internet at the following addresses:**

http://www.feem.it/getpage.aspx?id=73&sez=Publications&padre=20&tab=1
http://papers.ssrn.com/sol3/JELJOUR_Results.cfm?form_name=journalbrowse&journal_id=266659
http://ideas.repec.org/s/fem/femwpa.html
http://www.econis.eu/LNG=EN/FAM?PPN=505954494
http://ageconsearch.umn.edu/handle/35978
http://www.bepress.com/feem/

## NOTE DI LAVORO PUBLISHED IN 2015

| | | |
|---|---|---|
| ERM | 1.2015 | Elena Verdolini, Laura Diaz Anadon, Jiaqi Lu and Gregory F. Nemet: The Effects of Expert Selection, Elicitation Design, and R&D Assumptions on Experts' Estimates of the Future Costs of Photovoltaics |
| CCSD | 2.2015 | James Lennox and Ramiro Parrado: Capital-embodied Technologies in CGE Models |
| CCSD | 3.2015 | Claire Gavard and Djamel Kirat: Flexibility in the Market for International Carbon Credits and Price Dynamics Difference with European Allowances |
| CCSD | 4.2015 | Claire Gavard: Carbon Price and Wind Power Support in Denmark |
| CCSD | 5.2015 | Gunnar Luderer, Christoph Bertram, Katherine Calvin, Enrica De Cian and Elmar Kriegler: Implications of Weak Near-term Climate Policies on Long-term Mitigation Pathways |
| CCSD | 6.2015 | Francisco J. André and Luis M. de Castro: Incentives for Price Manipulation in Emission Permit Markets with Stackelberg Competition |
| CCSD | 7.2015 | C. Dionisio Pérez Blanco and Thomas Thaler: Water Flows in the Economy. An Input-output Framework to Assess Water Productivity in the Castile and León Region (Spain) |
| CCSD | 8.2015 | Carlos M. Gómez and C. Dionisio Pérez-Blanco: Simple Myths and Basic Maths about Greening Irrigation |
| CCSD | 9.2015 | Elorri Igos, Benedetto Rugani, Sameer Rege, Enrico Benetto, Laurent Drouet, Dan Zachary and Tom Haas: Integrated Environmental Assessment of Future Energy Scenarios Based on Economic Equilibrium Models |
| ERM | 10.2015 | Beatriz Martínez and Hipòlit Torró: European Natural Gas Seasonal Effects on Futures Hedging |
| CCSD | 11.2015 | Inge van den Bijgaart: The Unilateral Implementation of a Sustainable Growth Path with Directed Technical Change |
| CCSD | 12.2015 | Emanuele Massetti, Robert Mendelsohn and Shun Chonabayashi: Using Degree Days to Value Farmland |
| CCSD | 13.2015 | Stergios Athanassoglou: Revisiting Worst-case DEA for Composite Indicators |
| CCSD | 14.2015 | Francesco Silvestri and Stefano Ghinoi : Municipal Waste Selection and Disposal: Evidences from Lombardy |
| CCSD | 15.2015 | Loïc Berger: The Impact of Ambiguity Prudence on Insurance and Prevention |
| CCSD | 16.2015 | Vladimir Otrachshenko and Francesco Bosello: Identifying the Link Between Coastal Tourism and Marine Ecosystems in the Baltic, North Sea, and Mediterranean Countries |
| ERM | 17.2015 | Charles F. Mason, Lucija A. Muehlenbachs and Sheila M. Olmstead: The Economics of Shale Gas Development |
| ERM | 18.2015 | Anna Alberini and Charles Towe: Information v. Energy Efficiency Incentives: Evidence from Residential Electricity Consumption in Maryland |
| CCSD | 19.2015 | ZhongXiang Zhang: Crossing the River by Feeling the Stones: The Case of Carbon Trading in China |
| CCSD | 20.2015 | Petterson Molina Vale: The Conservation versus Production Trade-off: Does Livestock Intensification Increase Deforestation? The Case of the Brazilian Amazon |
| CCSD | 21.2015 | Valentina Bosetti, Melanie Heugues and Alessandro Tavoni: Luring Others into Climate Action: Coalition Formation Games with Threshold and Spillover Effects |
| CCSD | 22.2015 | Francesco Bosello, Elisa Delpiazzo, and Fabio Eboli: Macro-economic Impact Assessment of Future Changes in European Marine Ecosystem Services |
| CCSD | 23.2015 | Maryse Labriet, Laurent Drouet, Marc Vielle, Richard Loulou, Amit Kanudia and Alain Haurie: Assessment of the Effectiveness of Global Climate Policies Using Coupled Bottom-up and Top-down Models |
| CCSD | 24.2015 | Wei Jin and ZhongXiang Zhang: On the Mechanism of International Technology Diffusion for Energy Technological Progress |
| CCSD | 25.2015 | Benjamin Michallet, Giuseppe Lucio Gaeta and François Facchini: Greening Up or Not? The Determinants Political Parties' Environmental Concern: An Empirical Analysis Based on European Data (1970-2008) |
| CCSD | 26.2015 | Daniel Bodansky, Seth Hoedl, Gilbert Metcalf and Robert Stavins: Facilitating Linkage of Heterogeneous Regional, National, and Sub-National Climate Policies Through a Future International Agreement |
| CCSD | 27.2015 | Giannis Vardas and Anastasios Xepapadeas: Time Scale Externalities and the Management of Renewable Resources |
| CCSD | 28.2015 | Todd D. Gerarden, Richard G. Newell, Robert N. Stavins and Robert C. Stowe: An Assessment of the Energy-Efficiency Gap and Its Implications for Climate Change Policy |
| CCSD | 29.2015 | Cristina Cattaneo and Emanuele Massetti: Migration and Climate Change in Rural Africa |
| ERM | 30.2015 | Simone Tagliapietra: The Future of Renewable Energy in the Mediterranean. Translating Potential into Reality |
| CCSD | 31.2015 | Jan Siegmeier, Linus Mattauch, Max Franks, David Klenert, Anselm Schultes and Ottmar Edenhofer: A Public Finance Perspective on Climate Policy: Six Interactions That May Enhance Welfare |
| CCSD | 32.2015 | Reyer Gerlagh, Inge van den Bijgaart, Hans Nijland and Thomas Michielsen: Fiscal Policy and CO2 Emissions of New Passenger Cars in the EU |
| CCSD | 33.2015 | Marie-Laure Nauleau, Louis-Gaëtan Giraudet and Philippe Quirion: Energy Efficiency Policy with Price-quality Discrimination |

| | | |
|---|---|---|
| CCSD | 34.2015 | Eftichios S. Sartzetakis, Anastasios Xepapadeas and Athanasios Yannacopoulos: Regulating the Environmental Consequences of Preferences for Social Status within an Evolutionary Framework |
| CCSD | 35.2015 | Todd D. Gerarden, Richard G. Newell and Robert N. Stavins: Assessing the Energy-efficiency Gap |
| CCSD | 36.2015 | Lorenza Campagnolo and Fabio Eboli: Implications of the 2030 EU Resource Efficiency Target on Sustainable Development |
| CCSD | 37.2015 | Max Franks, Ottmar Edenhofer and Kai Lessmann: Why Finance Ministers Favor Carbon Taxes, Even if They Do not Take Climate Change into Account |
| CCSD | 38.2015 | ZhongXiang Zhang: Carbon Emissions Trading in China: The Evolution from Pilots to a Nationwide Scheme |
| CCSD | 39.2015 | David García-León: Weather and Income: Lessons from the Main European Regions |
| CCSD | 40.2015 | Jaroslav Mysiak and C. D. Pérez-Blanco: Partnerships for Affordable and Equitable Disaster Insurance |
| CCSD | 41.2015 | S. Surminski, J.C.J.H. Aerts, W.J.W. Botzen, P. Hudson, J. Mysiak and C. D. Pérez-Blanco: Reflections on the Current Debate on How to Link Flood Insurance and Disaster Risk Reduction in the European Union |
| CCSD | 42.2015 | Erin Baker, Olaitan Olaleye and Lara Aleluia Reis: Decision Frameworks and the Investment in R&D |
| CCSD | 43.2015 | C. D. Pérez-Blanco and C. M. Gómez: Revealing the Willingness to Pay for Income Insurance in Agriculture |
| CCSD | 44.2015 | Banchongsan Charoensook: On the Interaction between Player Heterogeneity and Partner Heterogeneity in Two-way Flow Strict Nash Networks |
| CCSD | 45.2015 | Erin Baker, Valentina Bosetti, Laura Diaz Anadon, Max Henrion and Lara Aleluia Reis: Future Costs of Key Low-Carbon Energy Technologies: Harmonization and Aggregation of Energy Technology Expert Elicitation Data |