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Summary

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Keywords: R&D Investments, Energy Technology, Expert Elicitation, Risk and Reward, Low-carbon Innovation

JEL Classification: Q40

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Too early to pick winners: disagreement across experts implies the need to diversify R&D investment

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Abstract. Mitigating climate change will require innovation in energy technologies. Policy makers are faced with the question of how to promote this innovation, and whether to focus on a few technologies or to spread their bets. We present results on the extent to which public R&D might shape the future cost of energy technologies by 2030. We bring together three major expert elicitation efforts carried out by researchers at UMass Amherst, Harvard, and FEEM, covering nuclear, solar, Carbon Capture and Storage (CCS), bioelectricity, and biofuels. The results show experts believe that there will be decreasing returns to R&D and report median cost reductions around 20% for most of the technologies at the R&D budgets considered. Although the returns to solar and CCS R&D show some promise, the lack of consensus across studies, and the larger magnitude of the R&D investment involved in these technolopgies, calls for caution when defining what technologies would benefit the most from additional public R&D. Indeed, the wide divergence of opinions suggests that it is still too early to pick winners and that a broad portfolio of investments may be the best option.

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1. Introduction

Mitigating climate change will require innovation in energy technologies. There is agreement that both government policies to limit carbon dioxide emissions and R&D investments will be necessary (Jaffe, et al. 2005, Goulder & Schneider 1999) to spur the innovation needed to mitigate climate change at reasonable cost (Hoffert, et al. 2002). Policy makers are faced with the question of how to promote this innovation, and whether to focus on a few technologies or to spread their bets. A key difficulty in making decisions about public R&D investments is the uncertainty about the impacts of those investments. In addition, budgetary constraints in governments create real tensions between focusing on making significant progress in a small number of technologies as opposed to experimenting with a wider set of options. Knowledge on how to foster technological change in the right direction is still sparse. Moreover, questions on how best to support R&D investment decisions when multiple areas compete for funds are common to fields other than energy, including health, agriculture, and defense.

In the field of energy, the U.S. National Research Council (NRC 2007) has explicitly recommended that the U.S. Department of Energy uses probabilistic assessment based on expert elicitations of R&D programs in making funding decisions. A number of studies of expert judgments on single technologies have been published in many places in the literature by a range of researchers (Rao, et al. 2006, Curtright, et al. 2008, Chung, et al. 2011, Zubaryeva, et al. 2012, Abdulla, et al. 2013, Jenni, et al. 2013, Usher & Strachan 2013, Zubaryeva & Thiel 2013). However, due to widely differing assumptions and methods it has been very difficult for decision makers to get a sense of what conclusions can be drawn from the sum of these studies (Clarke & Baker 2011). This study is the first attempt to collect, harmonize, and analyze the insights that can be derived from a large number of expert judgment studies performed by different research teams on different energy technologies. We examine to what degree the international community is coming to consensus around the prospects of key energy technologies that have been highlighted as crucial for climate mitigation (IPCC 2011) and the role that public R&D can play. This rigorous and transparent methodology for analyzing the results of multiple elicitations side by side may be used to inform decisions in other fields where scattered knowledge on the impact of R&D investments exists.

In order to do so we bring together three major expert elicitation efforts carried out by researchers at UMass Amherst, Harvard, and FEEM, (Baker & Keisler 2011, Baker & Chon 2009, Baker, et al. 2009, Baker, et al. 2008, Anadon, et al. 2014, Anadon, et al. 2012, Chan, et al. 2011, Fiorese, et al. 2014, Fiorese, et al. 2013, Bosetti, et al. 2012), covering nuclear, solar, Carbon Capture and Storage (CCS), bioelectricity, and biofuels, and aimed at evaluating the impact that public R&D investments in the United States and the European Union could have on the cost of these technologies. All the above mentioned studies were carried out by means of expert elicitations, a structured process for eliciting subjective probabilities from experts (Henrion & Granger Morgan 1990).

It should be noted that the three studies were not designed to be combined or compared. This is both the motivation for, and a challenge to, the present analysis. The UMass Amherst, FEEM, and Harvard studies were funded, respectively, by the US Government, the EU 7^{th} Framework Program, and Doris Duke Charitable Foundation, respectively. Each study could be taken alone and used to inform R&D decision making. However, using a single study would not represent the best information available, given that we do not have an understanding of whether any of the studies or data points within the studies provides more predictive information or a better representation of uncertainty. Thus, we develop and implement a methodology aimed at supporting decision makers that represents the extent of this uncertainty. We note that this study is not intended to be a meta-analysis evaluating the impact that the expert selection process or other factors in the study design might have had on the median estimates or the uncertainty range (see (Anadon, et al. 2013) and (**?**) for this approach), but rather a presentation of the current state of information in as clear, transparent, and comparable way as possible, given the challenges.

The differences between the surveys allow us to consider a variety of assumptions and detect whether there are robust insights or common patterns on the relative effectiveness and riskiness of R&D programs in these different technologies to be drawn by these exercises taken together. We set out to answer the following question: is there consensus regarding the technologies that would be most affected by R&D investment; or, at least in terms of potential cost reductions, is the best strategy to keep options open by investing widely and gathering more information on the potential evolution of costs?

Each expert elicitation survey covers one technology area and provides information on multiple experts' views from multiple sectors (academia, industry, and other public institutes) on the prospects for future costs conditional on specific R&D funding levels. Funding levels are grouped into three broad categories, Low (which is consistent with a business-as-usual (BAU) scenario for FEEM, an increase of 50% to 200% over BAU for Harvard, small investments, independent from the BAU, into specific technologies for UMass), Medium (ranging between an additional 50% to a 16-fold increase over low) and High (ranging between an additional 30% to a 10-fold increase over medium). While both Harvard and FEEM included demonstration expenditures, UMass asked questions about smaller R&D scenarios that did not include demonstration expenditures. Given these different approaches, the absolute values of the funding levels vary across studies; moreover, each expert thinks about the impact of additional spending in a rather different way. All studies provided significant materials to minimize biases, but it is not possible to define what of these different approaches would work better. The intention of this work is to summarize the full spectrum of information available in these three groups of studies. Our analysis is based on a total of 114 experts' views (see appendix for a complete list) collected through expert elicitation (in person, via mail, or on-line) in a time span of three years (2009-2011). The appendix reports common and heterogeneous assumptions of different surveys on R&D scenarios, funding amounts, elicited metrics and protocols, and how the surveys were harmonized to produce common metrics at common target dates.

2. Materials and Methods

The number of experts included in each study varied from 3, for the UMass solar study, to 31, for the FEEM nuclear study. The average number of experts per study was just under 13, a slightly larger than a typical Expert Elicitation study [USEPA 2009]. All 14 studies had experts from academia; 11 studies had experts from government or NGOs; and 10 studies had experts from industry. Studies varied, with UMass having over 60% from academia and only 10% from industry; FEEM had over 50% from government and NGOs, the remainder divided evenly between academia and industry; Harvard had 40% from government, and with 35%, had the largest percentage from industry.

See Table 2 for a summary by technology.

Technologies	Government	Academia	Industry
Solar	32%	36%	32%
CCS	41%	29%	29%
Biomass	36%	45%	19%
Nuclear	51%	25%	25%

Both Harvard and FEEM surveys collected information on self-reported expertise. However, we note that there is no evidence that weighting by self-reported expertise significantly changes or improves reporting (Bolger & Rowe 2014). Moreover, while some meta-analyses have found differences in assessments based on background (Anadon et al. 2013, **?**), these differences are not consistent across studies of different technologies (e.g., in the two citations provided, private sector experts were consistently more optimistic than academics in the future of solar technologies but more pessimistic than academics for nuclear), nor is there any evidence on which category of expert are more likely to be more accurate. Thus, this variation in background is another strong reason for presenting a wide view of the data.

Experts had given their consent, either in written (Anadon & Chan 2014, Anadon et al. 2012, Chan et al. 2011, Fiorese et al. 2014, Fiorese et al. 2013, Bosetti et al. 2012) or verbal (Baker & Keisler 2011, Baker & Chon 2009, Baker et al. 2009, Baker et al. 2008) form, and have agreed on having their names published. However, the data is reported anonymously thus it is never possible to link data with individual experts. A total of 165 surveys/interviews with experts were completed by the three teams. The details on the methods used by the three teams are presented in the separate papers. Some experts participated in multiple surveys, and some survey results were not used in this study due to missing data. This resulted in 114 distinct participating experts. The complete list of experts is reported in the appendix.

As discussed in the appendix, a harmonization and aggregation protocol was developed to allow the expert estimates from different elicitations to be compared alongside each other. This protocol involved converting data into comparable currencies, as well as converting data to have consistent metrics and years. After the three studies were harmonized, we aggregated them using a linear opinion poll with equal weights. Thus, the "combined" results represent a pooling of the three studies which we always present in parallel to the individual study data for the sake of transparency.

3. Results and Discussion

We first look at returns to R&D, with a formulation that accounts for possible negative returns. We define $R_{i,j}$ as the returns to R&D for technology metric i when R&D funding increases from $j-1$ to j

$$R_{i,j} = \frac{M_{i,j-1} - M_{i,j}}{M_{i,j-1}} \tag{1}$$

j represents the funding level of Low, Medium, or High, and $j-1$ is the next lower funding level; $M_{i,j}$ is the value of the metric for technology i, for funding level j. For example, $M_{Solar,medium}$ would give the value of a specific measurement of the Levelized Cost Of Electricity (LCOE) for solar, say the median, at *Medium funding*.

In order to calculate the returns from increasing R&D funding levels, shown in Figure 1, it is necessary to make an assumption about the correlation of outcomes resulting from different funding levels. We focus on the results under one extreme assumption: the outcomes from different funding levels are perfectly correlated. This assumption would hold if (1) higher funding levels always fund the same projects as lower funding levels, plus additional projects; and (2) the additional projects are perfectly correlated with the initial projects. The first argument explicitly holds for the UMass studies. It does not explicitly hold for FEEM and Harvard, where the experts may have been thinking about different projects at different levels of funding. The second assumption seems unlikely to hold, but may be an approximation if we believe that there are underlying factors that impact success in an entire technology category. In the appendix we consider the implications of a second, extreme assumption that the outcomes from different funding levels are independent and find that the central insights remain the same.

Figure 1 shows the distribution of the relative returns to R&D, $R_{i,j}$, moving from the low-to-mid R&D (left) and from the mid-to-high R&D (right) for cost metrics for five technologies (LCOE for solar (\$/kWh); non-energy cost for bio-electricity (\$/kWh) and biofuels (\$/gge), which considers both thermochemical and biochemical conversion pathways; additional capital cost for CCS in coal power plants (\$/kW); and overnight capital cost for large-scale nuclear power (\$/kW), which includes both Gen. III/III+ and Gen. IV systems). For each of the 5 metrics presented, we plot the results of sampling from each of the aggregate distributions derived using data from the FEEM,

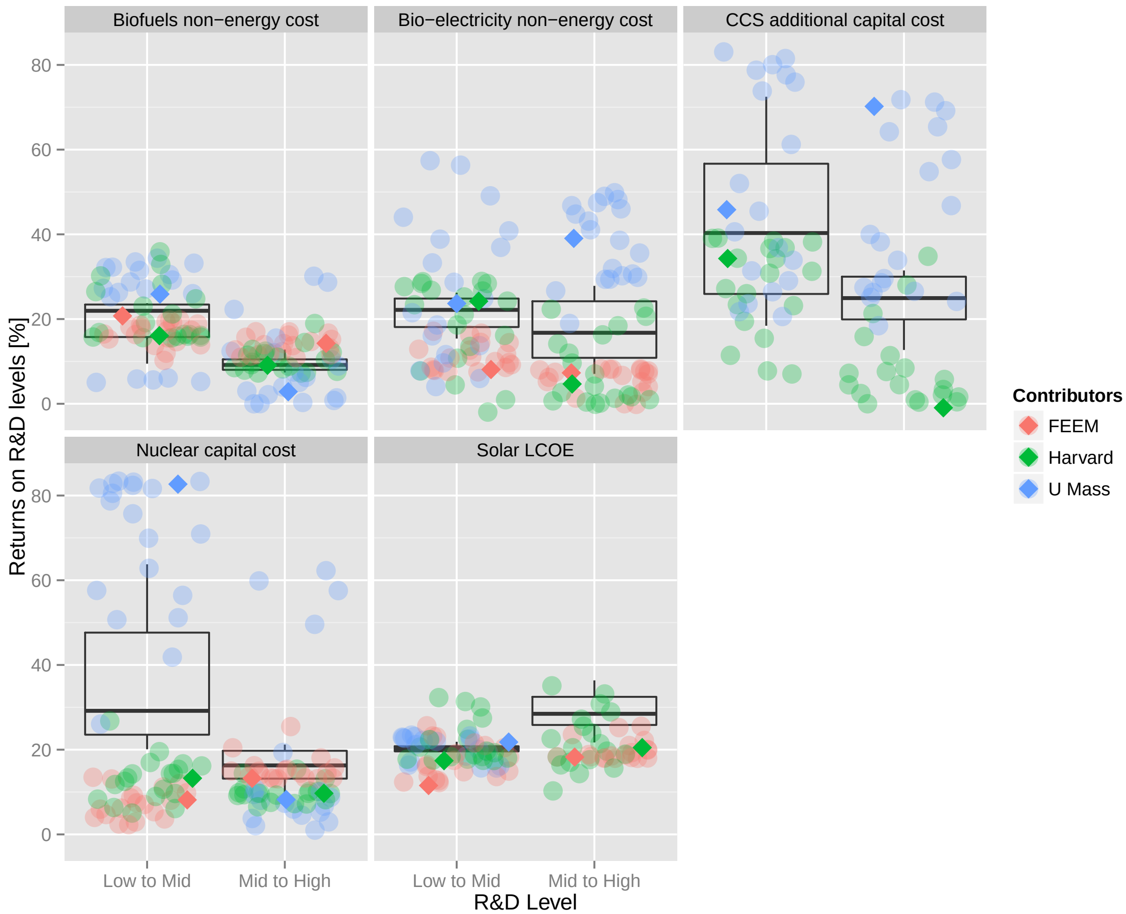

Figure 1. Returns to increasing public R&D funding from low-to-mid R&D levels and from mid-to-high R&D levels, assuming improvements from increments of R&D are perfectly correlated. The box plot represents the 5^{th}, 25^{th}, 50^{th}, 75^{th} and 95^{th} percentiles of the distribution aggregated across teams (the combined analysis) the dots represent samples (in increments of 5 percentage points from the 5th to the 95^{th} percentile) from the FEEM (red), Harvard (green), and UMass (blue) studies. The solid diamond-shaped points refer to the median returns.

Harvard and UMass surveys. The solid diamonds depict the 50^{th} percentile for each of the three studies. We also include the box plot of the combined distribution, which weights equally the results of the three studies. Here we summarize the findings.

Prospects for technologies in the combined analysis: The median returns to R&D tend to be somewhat similar across the technologies, with all technologies except CCS having median returns around 20% for the low-to-mid R&D scenario (low-to-mid). CCS has a median return of 40% for low-to-mid, and has the highest return for that level of funding in both studies that considered it. In the low-to-mid category, Nuclear follows CCS as the highest return, while in the mid-to-high category, solar and CCS have the highest return.

Agreement among studies: Figure 1 also highlights the differences between the aggregate distributions of the potential returns among studies. UMass estimates, marked by the blue circles, are generally more optimistic than FEEM and Harvard, with the exception of solar. We also note a greater agreement among the three studies for the returns on the cost of biofuels and solar PV. This could be due to the fact that there is more recent experience building PV panels and biorefineries than building CCS, nuclear and novel bioelectricity plants.

Focusing on the median returns, we find that different technologies do better under different teams, with each of the 5 technologies showing up in 1^{st} or 2^{nd} place in one of the teams, and only CCS showing up twice in the top 2, as shown in Table A4 of Appendix. We note that while biofuels is one of the technologies with the largest returns for FEEM, it is among the lowest returns for the other two teams. This may be related to the prominent investment in biofuels in the U.S. by the DOE and BP that was already taking place at the time of the elicitations, which did not have an analogue in the EU (Anadon & Chan 2014, Fiorese et al. 2013). This may have led U.S. experts to predict a smaller impact for any additional funding. The teams also result in different ranges, with UMass having the largest range among the returns, and FEEM the lowest.

In general, we stress that the disagreement about the impact of R&D on the future cost of technologies in the different studies may result from different factors. First, the technologies themselves may be at an early stage so that there has not yet been enough time for the creation and circulation of a common knowledge pool. It is possible that different experts have a different experiences with and knowledge of various aspects of the technology, which could result in information being compartmentalized and not widely available. Second, some of the estimates obtained might be more reliable than others, but the science of expert elicitations at this point does not allow us to discriminate among the existing data points. This disagreement can be addressed by more technology R&D and by more research into the study of expert elicitations. Certainly this analysis calls for retrospective research evaluating the extent to which different elicitations were more or less predictive.

Agreement among experts. For the FEEM and Harvard studies we decompose uncertainty into two parts: the contribution to the aggregated variance of individual uncertainty and between-expert uncertainty. Table 1 shows that for most of the studies over half of the uncertainty is due to disagreements between experts.

This may indicate that individual experts are over-confident and/or that information about the technologies is not well-diffused through the community. Particularly striking is the difference between FEEM and Harvard in the solar studies. It appears that European experts are much closer to consensus, at least under the assumption of larger than current R&D investments, than US experts.

Table 1. Contribution (in % of variance) of between-expert uncertainty to the aggregate variance (see S4 for more details).

	R&D Level		
	Low	Mid	High
	Bio-electricity non-energy cost		
FEEM	53.5	49.2	46.1
Harvard	73.3	51.3	36.3
	Biofuels non-energy cost		
FEEM	64.8	65.9	63.1
Harvard	62.1	61.3	67.9
	CCS additional capital cost		
FEEM	NA	NA	NA
Harvard	49.6	73.7	77.2
	Nuclear capital cost		
FEEM	68.7	69.5	71.5
Harvard	64.4	66.1	68.8
	Solar LCOE		
FEEM	60	40.4	17.2
Harvard	72.4	80.6	80.5

Decreasing marginal returns to R&D investment. One of the proposed models in the literature of endogenous growth theory (Jones 1995) is that of decreasing returns to R&D, following a fishing-out model. By plotting returns versus R&D efforts we see the emergence of decreasing marginal returns in almost all of the technologies across the surveys (see Figure 2) along with the wide dispersion of additional R&D investment covered by the three elicitation teams.

Uncertainty of Returns. One way to think about uncertainty over the outcome of R&D programs is to consider the range of possible outcomes, especially in the context of the median outcome. When looked at this way in Figure 1, solar is the least risky, since there is very little variation in the aggregate returns within each and between the three elicitation teams. However, another, more rigorous way, to consider uncertainty is through the idea of stochastic dominance.

Figure 3 shows the Cumulative Distribution Functions (CDFs) for the returns distributions in Figure 1. From these we can see stochastic dominance relations. A distribution First Order Stochastically Dominates (FOSD) another if all decision makers (who prefer more to less) prefer it; visually, a distribution FOSD another if its CDF lies entirely to the right. A distribution Second Order Stochastically (SOSD) dominates another if all risk averters prefer it; visually, a distribution X SOSD Y if the area below the CDF for X measured from left to right, is less than the area below the CDF

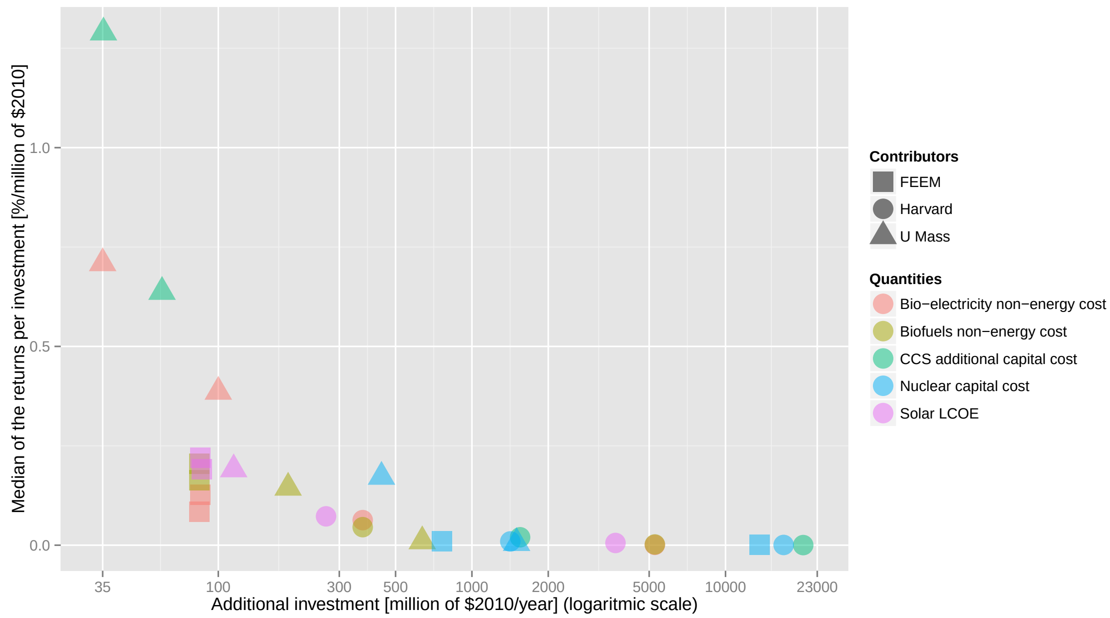

Figure 2. Median return divided by additional R&D investment level for different technologies and teams. The x-axis shows the additional R&D investment in a logarithmic scale [million of $2010/year].

for Y measured from left to right. Using these definitions, the most risky investments are all found in the mid-to-high funding level, including biofuels and nuclear, which are FOSD by all the other distributions, and bio-electricity, which is SOSD by all other distributions. When looking at the combined analysis, the least risky investments are for solar mid-to-high, and nuclear and CCS low-to-mid. These three technologies FOSD all other distributions (excepting a slight crossover for CCS with solar low-to-mid). Note, however, that the sizes of the investments into these three technologies is higher than those into biofuels, bio-electricity, and solar at the low-to-mid level. In addition, nuclear does not dominate in either the FEEM and Harvard results. Thus, the dominance is ambiguous. Solar and CCS are close to second order stochastically dominating in two of the studies each (FEEM and Harvard for solar and Harvard and UMass for CCS), indicating that the prospects for R&D returns in those two technologies may be more robust than for others. Solar, at both investment levels, has very vertical CDFs across the three studies, meaning it has a tight range with little variance. While the medians for most of the returns tend to be fairly close - between 16-30% for most technologies - the upside (the high percentiles) varies significantly — between 21-64% for the same set of technologies. In looking at the individual team panels, we see that all the teams follow the same patterns in riskiness, in terms of stochastic dominance, that they did in the medians, except Harvard bio-electricity, which shows no stochastic dominance over any of the technologies, despite having the 2^{nd} highest median.

In order to best support decision-making, we show both the pooled results of the three studies (in the upper left panel); and the results of each individual study. This is useful in many ways. For near-term decision making, the gold standard is to use the best available information; thus the combined data provides a starting point to support decisions about R&D investments by analyzing the impact of those investments in future costs. However, where there is considerable disagreement or wide uncertainty across the various studies, as in this case, it is important that decision makers focus on near term decisions that maximize option value — that is, near term decisions that increase the flexibility to respond to new information in the future.

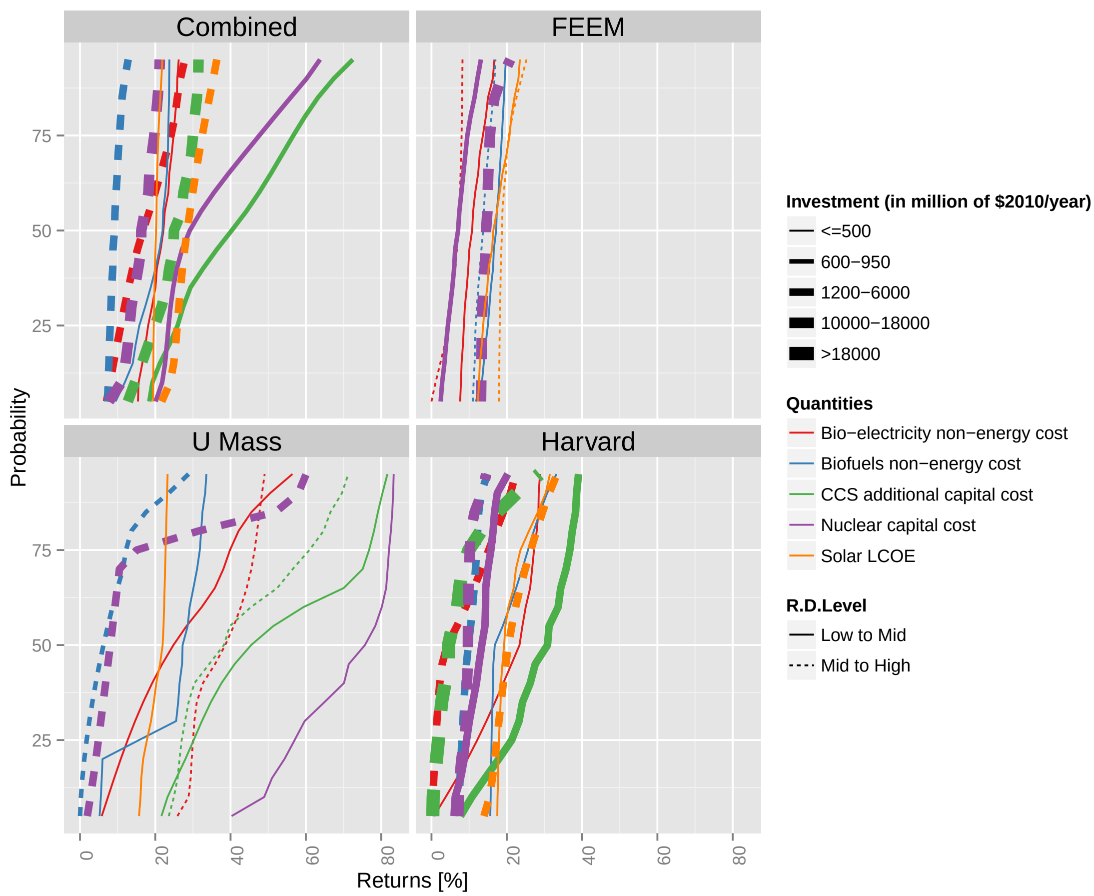

Figure 3. Cumulative distribution functions for the returns distributions in Figure 1 by study, technology, and increase in R&D investment. The thickness of the lines denotes the additional R&D investment level associated with that technology investment. For the combined panel R&D investments are mean investments across studies.

4. Conclusions

We have consolidated what the scientific community across both sides of the Atlantic believe will be the impact of public R&D investments on the 2030 costs of five key energy technologies. Going back to our original question, we find that scientific knowledge on the impact of R&D investments on the future of energy technologies does not justify a strategy of focusing on one or two technologies: no single technology stands out across the studies as having consistently higher returns or being less risky. While this analysis should be complemented by energy economic models to support decision making, the wide range of uncertainty regarding the impact of R&D suggests it is best to focus on the option value of investments, whether into R&D or into expert elicitation, and that it is too early to pick winners. The finding of decreasing marginal returns to investment in any one category further reinforces this conclusion, as increasing funding significantly for only one technology in the short term is expected to result in relatively small benefits. There is, however, some evidence to suggest that experts generally believe that the greatest risks are in large investments in nuclear, biofuel, and bio-electricity technologies; and that solar has relatively low risk at low investment costs.

Our results provide a unique overview, including the largest number of top scientific experts to date, regarding the expected impact of public R&D investments on technological change in key energy technologies. The results from the harmonization of the three separate expert elicitation studies are important, because each of the three studies, taken alone, indicates that some technologies are more promising than others. Yet, when taken together, the results are not as clear. The process outlined in this paper allows us to analyze all the evidence available; the results of this process point to the necessity of maximizing flexibility, rather than focusing on a specific technology. Further research — into the technologies themselves and into methods for assessing the future prospects of the technologies, such as expert elicitations — should be pursued before committing too strongly to one path over another. The reason for this is that different expert elicitations point to different technologies having greater potential for cost reduction.Thus, while harmonizing and combining disparate studies is a considerable challenge, it provides a great deal of value over and above the individual elicitation studies, which are themselves very labor and resource intensive.

It is important to note that in order to make R&D funding decisions to meet particular goals, such as mitigating climate change or improving energy security, policy makers need to combine the information on cost reduction potentials with an analysis of the macroeconomic implications of these technological changes. Small changes in the cost of key technologies may have a disproportional impact on the cost of mitigating climate change (Rogelj, et al. 2013, Kriegler, et al. 2014). Thus, information on the potential for success alone, although a key element of such analysis, is not enough to fully identify a portfolio of investments to contribute towards a particular societal goal. Nevertheless, this analysis using all expert data available across technologies suggests the need to continue a portfolio approach.

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Appendix

Appendix .1. Elicitation and Harmonization Methodology

Surveys characteristics and assumptions to facilitate comparisons across survey results in common units.

In order to compare and aggregate these values, we harmonized them, making assumptions to convert currencies and currency years, endpoint years, and common metrics. Key assumptions used to convert to common metrics are in Table A1. Note in particular that the experts in the FEEM study indicated a 12% capacity factor, thus the other studies used this to harmonize. But, most of the Harvard and UMass experts were thinking about much higher capacity factors, and therefor much lower LCOE than are reported here.

In order to adjust the UMass endpoints from 2050 to 2030, which was the time frame used in the FEEM and Harvard studies, we backcasted the UMass 2050 estimates to 2030

Table A1. Key survey characteristics and assumptions for harmonization.

Group	Biofuels	Bioelectricity	CCS	Nuclear	Solar
UMass metrics elicited	Capital cost per gge (gallon of gasoline equivalent), capacity, efficiency, other	Various technical endpoints and cost	Various technical endpoints and cost	Various technical endpoints and cost	Manufacturing cost per m^2, efficiency lifetime
FEEM metrics elicited	Cost per gge, O&M cost	Cost per kwh, O&M cost	N/A	Overnight capital cost	Manufacturing
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 ($/kW) generating efficiency, (HHV) capacity factor, book life	Overnight capital cost ($/kW) fixed O&M cost, variable O&M cost, fuel cost, thermal burnup	Module capital cost per Wp, module efficiency, module efficiency, module efficiency, inverter cost, inverter efficiency, inverter lifetime
Common Metrics Harmonized	Non-energy cost per gge, efficiency	Non-energy cost per kwh efficiency	Capital cost per KW Energy penalty	Overnight capital cost	LCOE
Key Assumptions	Calculations assume that the fraction of non-energy costs at the mean is the same across the distribution. See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates.	Calculations assume that the fraction of non-energy costs at the mean is the same across the distribution. See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates.	See description below needed about assumptions to turn UMass 2050 estimates to 2030 estimates.	See description below needed about assumptions to turn UMass 2050 estimates to 2030 estimates.	Capacity Factor 12% Discount rate 10% Lifetime* 20 BOS $/m^2 75 UMass 250 Harvard See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates

using Moore's Law and parameters from (Nagy, et al. 2013). (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 performed nearly as well as the traditional experience curve. Thus, we use the following relation based on Moore's Law:

$$c_t = t_t e^{-m(t-\tau)} \tag{A.1}$$

Where m is a parameter of this model calculated from B, the learning rate, and g, the growth rate of production, as follows.

$$m = Bg \tag{A.2}$$

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

$$c_{2030} = c_{2050} e^{-m(2030-2050)} = c_{2050} e^{m(2050-2030)} \tag{A.3}$$

In order to estimate the parameter m, we combine learning parameters B from the literature, with the growth parameter g from (Nagy et al. 2013). Table A2 summarizes the parameters used.

R&D funding levels

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 reducing the costs of reductions in carbon

Table A2. Parameters for backcasting.

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	0.012

Table A3. Definition of R&D levels (bins) in each of the three studies (in million of $2010/year).

UMass	Low	Mid	High
Solar	25	140	NA
Nuclear	40	480	1980
CCS	12.75	48	108
Biofuels	12.5	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 Harvard low, mid and High R&D levels for biofuels and bioelectricity are the same because the elicitation considered the bioenergy program at the U.S. Department of Energy as a whole and a breakdown between RD&D for bioelectricity and biofuels was not provided by the experts. Thus, the investment in biofuels and bioelectricity respectively in the three different R&D levels is a fraction of the number included in the table.

⋆The Harvard numbers for the mid and high R&D scenarios and the FEEM numbers for the nuclear mid and high R&D levels represent the average R&D investment across all the experts corresponding to that R&D level.

emissions from energy production and use. The studies defined R&D funding levels in different ways (see Table A3).

A key question is the relationship between government R&D funding in Europe, US, and other parts of the World, notably China. A further question is the relationship between government and private sector R&D funding—and the effects of government policy, such as feed-in tariffs, renewable tax credits, renewable portfolio standards, government purchasing of renewables, on private sector R&D funding, and manufacturing scale-up. It is hard for any analyst, including the experts selected by each study, to disentangle these effects. Moreover, just as there is some evidence of insensitivity to scale in contingent valuation studies, we felt that our experts may not be well-calibrated to the specific funding amounts. Therefore, in order to avoid a sense of over-specificity, we compare the results for low, medium, and high funding amounts in each study, against each other.

Experts that participated

A total of 165 surveys/interviews with experts were completed by the three teams. Due to missing data some of the survey results were not included in the final probability distributions. Additionally, some experts participated in multiple surveys. This resulted in 114 distinct participating experts. (Due the anonymity of the individual surveys, we cannot narrow this number further). The complete list of experts is reported in Tables A5–A17.

Differences between the expert elicitations among the three teams

The elicitations were conducted in various ways. Some were conducted face to face, some were conducted via mail 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. For more details the reader is referred to the papers describing the elicitation results (referenced in the main text).

- FEEM: biofuels (face to face); bioelectricity (face to face); nuclear (mail and group workshop); solar (face to face).
- Harvard: biofuels (mail); bioelectricity (mail); nuclear (online and group workshop); solar (online); and CCS (mail, 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 followup); and CCS (face to face and mail).

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.

The UMass and Harvard elicitations included US experts and the FEEM elicitations included mainly experts from the European Union. And while Harvard and FEEM experts spanned academia, public institutions, and the private sector, the UMass elicitations did not include industry experts with the rationale that the focus of the UMass elicitations was on radical breakthroughs.

Appendix A.2. Methodology for fitting distributions

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. We examined three approaches to fitting probability distributions to the specified 10^{th}, 50^{th}, and 90^{th} percentiles ($x10$, $x50$, $x90$): Triangular, shifted Weibull, and a piecewise cubic fit to the cumulative distribution, and settled on the piecewise cubic fit. The piecewise cubic fits a cubic polynomial between successive percentiles, $x0$, $x10$, $x50$, $x90$, $x100$, on the cumulative distribution. We specify the minimum ($x0$ or zeroth percentile) and maximum ($x100$ or hundredth percentile) such that the ratios:

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

We also limit the minimum to be positive (including for CCS additional capital cost, which included a small chance of being negative according to the U Mass fitted distributions).

The UMass elicitations asked experts to assess two to four points on the cumulative probability distribution, with specified value and probability. They use a piecewise cubic to fit the selected points. This required additional assumptions in some cases, particularly on high and low values.

Appendix A.3. Methodology for aggregating

There has been considerable research on methods for aggregating probability distributions obtained from different experts (Berry, et al. 1996, Hammitt & Shlyakhter 1999). The simplest and most widely-used aggregation method is 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” after Pierre-Simon Laplace who described it in *Thorie Analytique des Probabilits* (Hammitt & Shlyakhter 1999). For simplicity, we use equal weighting of the experts assessing each quantity in each study.

In order to avoid specious irregularity and multiple modes due to overconfidence of the experts, 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^{th}, 10^{th}, 50^{th}, 90^{th}, and 100^{th} percentiles from the Laplacean mixing distribution.

Between-expert uncertainty to the aggregate variance

In order to calculate the between-expert uncertainty σ^2 we use the equation $\sigma^2 = (\mu_i - \mu_x)^2$, where μ_i is the mean of each expert distribution and μ_x the average of the aggregate distribution.

Appendix A.4. Returns to R&D assuming independence

Each dot in Figure A1 represents equation 1 in the main text for random draws from the two relevant distributions, assuming the distributions are independent. Thus, we see a number of negative returns to R&D.

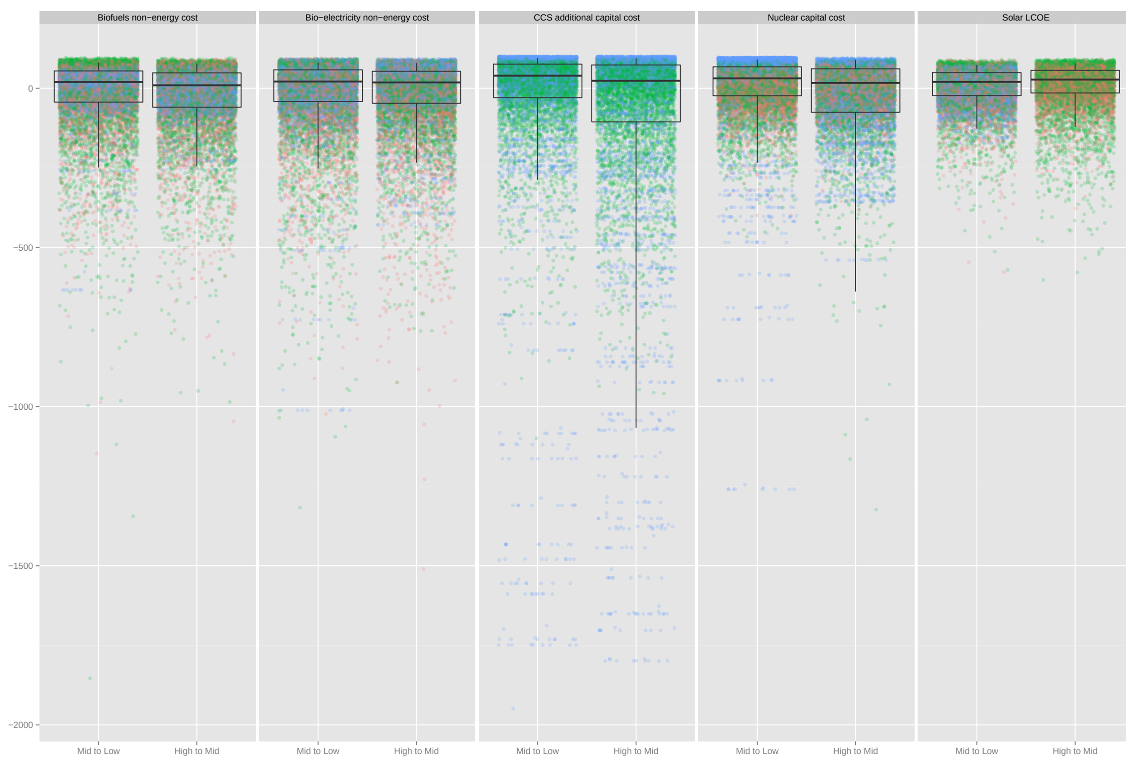

Figure A1. Boxplots of the returns to R&D assuming improvements from increments of R&D assuming independence between R&D funding levels. The boxplots show the 5^{th}, 25^{th},50^{th},75^{th} and 95^{th} percentiles of the combined distribution.

Appendix A.5. Highest median return for each study by technology

Table A4 shows the Highest median return for each study by technology.

Appendix A.6. List of experts for each study by technology

Tables A5–A17 show the experts and their respective affiliations.

Table A4. The rankings of the returns to R&D technologies, by median, for each analysis. We consider the highest median return for each technology.

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

Table A5. Bioenergy Experts for Harvard.

Harvard	Bioenergy (bioelectricity and biofuels)
Name	Affitiation
David Austgen	Shell
Joe Binder	UC Berkeley
Harvey Blanch	UC Berkeley
Andr 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

Table A6. Nuclear Experts for Harvard.

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, 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.

Table A7. CCS Experts for Harvard.

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

Table A8. PV Experts for Harvard.

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

Table A9. Biofuels Experts for U MASS.

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

Table A10. Nuclear Experts for U MASS.

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

Table A11. CCS Experts for U MASS.

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

Table A12. PV Experts for U MASS.

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

Table A13. Bio-eletricity Experts for U MASS.

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

Table A14. PV Experts for FEEM.

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 Jger-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 Wstenhagen	University of St. Gallen
Paul Wyers	Energy Research Centre

Table A15. Bio-electricity Experts for FEEM.

FEEM Bio-electricity	
Name	Affiliation
Alessandro Agostini	JRC - Joint Research Centre
Gran Berndes	Chalmers University of Technology
Rolf Bjrheden	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 Universitt Berlin
Andr 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

Table A16. Biofuels Experts for FEEM.

FEEM - Biofuels	
Name	Affiliation
David Chiaramonti	Universit 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 l'nergie atomique et aux nergies 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

Table A17. Nuclear Experts for FEEM.

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
Bruno Merk	Institute of Safety Research Forschungszentrum Dresden-Rossendorf
Julio Martins Montalvo 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

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