



NOTA DI LAVORO

47.2016

**The Future Prospects of Energy
Technologies: Insights from
Expert Elicitations**

Elena Verdolini, CMCC and FEEM

Laura Diaz Anadón, John F. Kennedy
School of Government, Harvard

University and University College London

Erin Baker, University of Massachusetts
Amherst

Valentina Bosetti, CMCC, FEEM and
Bocconi University

Lara Aleluia Reis, CMCC and FEEM

Mitigation, Innovation and Transformation Pathways Series Editor: Massimo Tavoni

The Future Prospects of Energy Technologies: Insights from Expert Elicitations

By Elena Verdolini, CMCC and FEEM

Laura Diaz Anadón, John F. Kennedy School of Government, Harvard
University and University College London

Erin Baker, University of Massachusetts Amherst

Valentina Bosetti, CMCC, FEEM and Bocconi University

Lara Aleluia Reis, CMCC and FEEM

Summary

Expert elicitation is a process for eliciting subjective probability distributions from experts about items of interest to decision makers. These methods have been increasingly applied in the energy domain to collect information on the future cost and performance of specific energy technologies and the associated uncertainty. This article reviews the existing expert elicitations on energy technologies with three main objectives: (1) to provide insights on expert elicitation methods and how they compare/complement other approaches to inform public energy decision making; (2) to review all recent elicitation exercises about future technology costs; and (3) to discuss the main results from these expert elicitations, in terms of implied rates of cost reduction and the role of R&D investments in shaping these reductions, and compare it with insights from backward looking approaches. We argue that the emergence of data on future energy costs through expert elicitations provides the opportunity for more transparent and robust analyses incorporating technical uncertainty to assess energy and climate change mitigation policies.

Keywords: Energy Technologies, R&D Investments, Expert Elicitations, Uncertainty

JEL Classification: Q5, Q55

This paper was commissioned by the United Nations Environment Program and produced through the Green Growth Knowledge Platform (GGKP) Research Committee on Technology and Innovation. The original paper can be accessed at: <http://www.greengrowthknowledge.org/resource/future-energy-technologies-overview-expert-elicitations>. The authors alone are responsible for the views expressed in this paper and they do not necessarily represent the decisions or policies of the United Nations Environment Programme.

Address for correspondence:

Elena Verdolini

Fondazione Eni Enrico Mattei

Corso Magenta, 63

20123 Milan

Italy

E-mail: elena.verdolini@feem.it

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

The Future Prospects of Energy Technologies: Insights from Expert Elicitations

Elena Verdolini^{1*}, Laura Diaz Anadón^{2,3}, Erin Baker⁴, Valentina Bosetti^{1,5}, Lara Aleluia Reis¹

¹ Euro-Mediterranean Center on Climate Change (CMCC) and Fondazione Eni Enrico Mattei (FEEM), Milano, Italy

² John F. Kennedy School of Government, Harvard University, Cambridge, MA, United States

³ Department of Science, Technology, Engineering & Public Policy, University College London, London, United Kingdom

⁴ Department of Mechanical and Industrial Engineering, University of Massachusetts Amherst, Amherst, MA, United States

⁵ Department of Economics, Bocconi University, Milano, Italy

* Corresponding author: elena.verdolini@feem.it. Corso Magenta 62, 20123 Milano, Italy. tel. +39 02 250 36814.

Abstract

Expert elicitation is a process for eliciting subjective probability distributions from experts about items of interest to decision makers. These methods have been increasingly applied in the energy domain to collect information on the future cost and performance of specific energy technologies and the associated uncertainty. This article reviews the existing expert elicitations on energy technologies with three main objectives: (1) to provide insights on expert elicitation methods and how they compare/complement other approaches to inform public energy decision making; (2) to review all recent elicitation exercises about future technology costs; and (3) to discuss the main results from these expert elicitations, in terms of implied rates of cost reduction and the role of R&D investments in shaping these reductions, and compare it with insights from backward looking approaches. We argue that the emergence of data on future energy costs through expert elicitations provides the opportunity for more transparent and robust analyses incorporating technical uncertainty to assess energy and climate change mitigation policies.

Key Words: energy technologies; R&D investments; expert elicitations; uncertainty

Disclaimer: This paper was commissioned by the United Nations Environment Program and produced through the Green Growth Knowledge Platform (GGKP) Research Committee on Technology and Innovation. The original paper can be accessed at: <http://www.greengrowthknowledge.org/resource/future-energy-technologies-overview-expert-elicitations>. The authors alone are responsible for the views expressed in this paper and they do not necessarily represent the decisions or policies of the United Nations Environment Programme.

1. Introduction

When making decisions about energy systems, policy makers need to consider several aspects. First, fossil-fuel technologies give rise to a negative environmental externality due to the pollution they produce.¹ Since pollution is not always priced, private incentives for RD&D in low-carbon technologies have been low with respect to the societal need for such investments (Popp 2010). Second, in research, development and demonstration (RD&D) there is significant uncertainty associated with the returns and much of the value is associated with low probability but high value outcomes (Scherer and Harhoff 2000). Such uncertainty may be particularly large in the case of energy: energy systems and investments are long-lived and are embedded in costly infrastructures that make it hard for new technologies to compete (Unruh 2000). Third, parts of the energy sector, such as electricity provision, are characterized by high government regulation, which often prevents utilities from directly investing in RD&D (Walker 2000). Hence, the general under-provision of (RD&D) effort from the private sector due to the presence of market failures is even more acute in the case of energy technologies, since environmental market failures compound the problem and the negative role of uncertainty may prove particularly problematic in the energy domain (Popp 2010, Popp et al. 2010). Finally, there are concerns regarding energy security, access and safety.

These reasons provide strong grounds to justify government investments in clean energy RD&D to meet environmental, security and competitiveness goals. One of the pressing needs of public decision makers is to design cost-effective and robust portfolios of public energy technology RD&D investments. Such portfolios should allocate funding across the sometimes complementary, sometimes competing energy technologies in a way that accounts for their societal benefits and for the uncertainties inherent to technology innovation. Environmental policies encompass technology-neutral policies in terms of innovation and deployment (for instance, this is the case for carbon taxes) or more technology-specific policies, such as wind feed-in-tariffs, and provide incentives to private firms to focus on those technologies that are closer to the market. RD&D policies should on the other hand be designed to address RD&D needs to meet the long-run climate and energy objectives and concerns. Governments may in fact want to be strategic in selecting which broad category of energy technologies to fund through RD&D allocations to ensure the development of technologies which are cost-effective in the long run or have a large option value, even though they may raise costs in the short run (Popp 2010).

But how can governments design energy technology RD&D portfolios that are robust to both the uncertainty surrounding the development of energy technology and the uncertainty surrounding climate or (more broadly) energy policies? What methods can be used to quantify such uncertainty in order to inform the decision-making process?

One way to inform policy decisions is learning from experience, studying the development of a particular technology (or similar technologies) in the past, and whether and how government RD&D spending shaped its evolution. The history of government involvement in energy RD&D provides several examples (Keller and Block 2008). Recent research suggests that governments have played major roles as investors in RD&D in high risk areas, including climate-friendly research (Mazzucato 2013). Econometric analysis of past trends in energy technologies has also been used to predict future trajectories, for instance in the learning or experience curve literature (Wiesenthal et al. 2012a; Nagy et al. 2013; Bettencourt et al. 2013), or in the extensive literature looking at the determinants of energy innovation (Popp et al 2010). However, estimating the uncertainty around future technology cost and performance from past data and experiences does not reflect the fact that RD&D is, by its

¹ The U.S. National Research Council estimated that the “external costs” of energy conversion in the United States totaled over \$120 billion in 2005, noting that many additional external costs were not quantifiable (NRC, 2010).

nature, uncertain and that different technologies may evolve differently at different points in time. Past trends may not correctly predict the future evolution of costs and performance and are unlikely to differentiate between different technologies and funding amounts (NRC 2007, Baker et al 2009a; Chan et al. 2011, Anadón et al. 2014b).

A second, complementary, process to inform public decisions on energy technology RD&D funding is that of expert elicitations, which entail collecting experts' views on the future evolution of a technology and how government funding might facilitate it. Expert elicitations are structured processes for eliciting subjective probability distributions from scientists, engineers, and other analysts who are knowledgeable about the metrics of interest (Morgan and Henrion 1990), in this case the costs and performance of energy technologies. Expert elicitations overcome the limitations associated with learning or experience curves by drawing on the best available information (which may not yet be codified in the literature) and relaxing the assumption that the previous technological trajectory will continue (Chan et al. 2011). Furthermore, expert elicitations can be used to identify the most important technological and non-technological bottlenecks. Over the past 8 years, various research groups carried out structured expert elicitations on several energy technologies. Some of these groups had an explicit objective to inform RD&D investment decisions and thus included specific questions about the outcomes of different levels of RD&D investments.

This article reviews the existing expert elicitations on energy technologies with three main objectives: (1) provide insights on expert elicitation methods and how they compare/complement other approaches to inform public energy decision making; (2) to review all recent elicitation exercises about future technology costs; and (3) to discuss main results from these expert elicitations, in terms of future technology costs and implied cost reduction rates.

In Section 2 we introduce the reader to the basics of expert elicitations, providing some background on their applications and potential limitations. Section 3 discusses and compares results for a subset of studies and technologies, while Section 4 concludes.

2. Expert elicitation methods applied to energy technology

2.1 What is an expert elicitation

Expert elicitation, as we will use the term, is a process for eliciting subjective probability distributions from experts about items of interest to decision makers (Hora and Von Winterfeldt 1997). These methods were pioneered in the 1960s and 1970s, mainly in applications concerning decisions in the face of extreme events (Howard et al 1972; North et al 1975). While most applications of expert elicitation have taken place in the private sector (Morgan 2014), they are increasingly used to inform policy making, particularly in areas related to the environment and health (Peerenboom et al 1989; Hora and Von Winterfeldt 1997; Kraymer von Krauss et al 2004; Cooke et al. 2007; Roman et al. 2008; InterAcademy Council 2010; Zickfeld et al 2010; Morgan 2014; EC 2015; US EPA 2015). A detailed review of existing studies in environmental policy applications is provided in the companion paper in this symposium [Cooke, 2016, this journal]. While elicitations were first envisioned as a way to collect existing knowledge stored in the heads of experts, it was later realized that the process helps experts develop probability distributions that represent their knowledge (Morgan and Henrion 1990; Hora 2007).

In this paper we focus on expert elicitations in the energy domain, which focus on the future cost and performance of specific energy technologies and, crucially, the associated uncertainty.

2.2 Challenges in expert elicitation design and use

The main challenge of expert elicitation is that it relies on individuals who are experts in the field under investigation but not necessarily proficient at expressing themselves in terms of probability (Winkler 1967). Experts, like most people, are subject to common biases (Tversky and Kahneman 1974), including anchoring, status quo trap, framing, overconfidence, base-rate trap, and motivational bias (Hammond et al 1999). Protocols and methodologies for structured expert elicitations were developed to reduce these biases (Morgan and Henrion 1990). The vast literature on this topic point to two sets of critical issues in designing and using an expert elicitation: how to properly design the elicitation protocol to reduce expert biases as much as possible (Hora 2007; O'Hagan et al. 2006a) and how to present and analyze the data collected, with a focus on different aggregation methods (Clemen and Winkler 1999, Hora et al. 2013, Lichtendahl et al 2013, Baker and Olaleye 2013).

The assessment of the quality of the information resulting from specific expert elicitations is very difficult. The main reason is that subjective probabilities reflect an individual's degree of belief: unless a probability is 1 or 0, it is impossible to say that it is "right" or "wrong". It is possible, however, (at least in theory) to evaluate the calibration or precision of experts on particular questions for which the answer is known, in a process of external validation. An expert is well calibrated on a particular set of questions if about $p\%$ of the events to which he assigns $p\%$ probability, are known to actually occur. This reasoning can be extended to intervals as well. It is most typical for people to be poorly calibrated by being overconfident.

Experts are overconfident if their stated probability intervals are too narrow, leading the realized values to fall outside of the intervals more frequently than they should. For example, Capen (1976) found, in a large scale experiment using almanac questions, that approximately 68% of the true values fell outside intervals provided by experts, regardless of what probability range participants were asked for.

Furthermore, an expert may be well calibrated but imprecise. For example, an expert who gives the long term average probability of rain to predict the probability of rain on a particular day would be perfectly calibrated, but poorly resolved, and therefore not very useful. The combination of calibration and precision can be evaluated (ex-post) using Proper Scoring Rules (Bickel 2007) in experimental settings, an approach which has led to improvements in protocol design. In addition, the use of scoring rules provides an important feedback to experts, a feedback which is crucial for improvement.

Regarding the analysis and presentation of the data from expert elicitations, a controversial question is whether and how to aggregate the information provided by different experts. Morgan (2014) argues that expert distributions should not be aggregated at all, but simply presented to decision makers to more accurately represent the wide diversity of views. This has the advantage of allowing decision makers to see, and possibly understand, the range of disagreement about key parameters. The downside is that the decision makers are left to aggregate the set of views themselves, which is challenging and vulnerable to bias (Cooke 2015; Bolger and Rowe 2015). One approach to support decision making in cases like this is to apply what are called "bottom up exploratory" methods, such as Robust Decision Making (Lempert and Collins 2007), Decision Scaling (Brown et al 2012), and Info Gap (Ben-Haim 2004). Each of these methods analyze alternative actions or policy decisions and visually represent how they perform under the full set of alternative beliefs, with a focus on generating new, more robust alternatives. Kalra et al (2014) discuss how these types of models can help lead to agreement over decisions in the policy realm. Related to this, Baker et al (2016) introduce a new technique that identifies sets of alternatives that are non-dominated across all expert beliefs. These sets of alternatives can then be used in conjunction with the bottom up methods.

An emerging literature argues in favor of aggregating expert judgments in the context of a specific decision problem through the use of non-traditional decision rules. For example, there are a number of papers applying Ambiguity Aversion frameworks to the climate change problem (Athanasoglou and Bosetti 2015; Millner et al. 2013; Heal and Millner 2014, Berger et al 2015). A similar approach is Robust Optimization (Gabrel et al 2014, Bertsimas et al 2011; Mortazavi-Naeini 2015). All of these approaches use a version of worst-case analysis, identifying an alternative that does not perform too badly in the worst case.

The traditional approach is to mathematically or behaviorally aggregate expert views. While there is little agreement on which method is best, Clemen and Winkler (1999) conclude that “simple combination rules (e.g., a simple average) tend to perform quite well” and that “more complex rules sometimes outperform the simple rules, but they can be somewhat sensitive, leading to poor performance in some instances.” Recent work indicates that other mathematical aggregation methods, such as by median or quantiles, may have some attractive properties (Hora et al. 2013; Lichtendahl et al 2013).

As discussed in [Cooke 2016, this journal] evaluating elicitation responses from experts through a set of seed questions can play an important role in the aggregation phase by providing weightings to apply to expert answers. Regarding energy technologies, seed questions might cover topics such as the level and composition of current costs trends and drivers of performance improvements in the past. These questions could be designed to have a known correct answer, allowing researchers to evaluate experts’ calibrations to those questions. However, it is not clear whether the ability to accurately answer short term questions is a good proxy for the ability to accurately estimate the distributions of costs and performance 20 years in the future. Given this challenge, a fruitful direction for future research would be to perform experiments similar to those described in [Cooke 2016, this journal], but using elicitations with answers that will be realized some decades into the future.

2.3 Energy technology expert elicitations: process and characteristics

Expert elicitations are typically codified in a protocol, which includes a set of steps (see, e.g., Kotra et al. 1996; Budnitz et al. 1997; Cooke and Goossens 2000; O’Hagan et al. 2006; Meyer and Booker 1991; Jenni and van Luik 2010 for an overview). Below we discuss each of these steps and how they differ across a set of existing energy technology elicitations, which were performed between 2007 and 2014.

Table 1 lists the studies, organized by technology, along with some key characteristics. We also summarize the results of three meta-analyses which study how design and expert characteristics affect elicited estimates (Anadón et al 2013; Verdolini et al. 2015; Nemet et al. 2016 – AVN hereafter. A more detailed summary is included in Appendix B).

Table 1: Overview of Expert Elicitations on energy technologies.

Research Group, Source/Publication	Experts (#, characteristics)	Year Of Elicitation	Target year	Type of question	RD&D scenarios (see Table 3)	Elicitation Mode
Bioelectricity						
UMass* Baker et al. (2008a)	4 (academia, government, private sector)	2007	2050	Probabilities	yes	F2F, mail, phone
Harvard*	7 (academia,	2010	2030	Percentile	yes	Mail & phone

Anadón et al. (2011); Anadón, et al. (2014a)	private sector)			(medians for some metrics)		
FEEM* Fiorese et al. (2014)	16 (academia, government, private sector)	2011	2030	Percentiles and Probabilities	yes	F2F
Biofuel						
UMass* Baker and Keisler (2011)	6 (academia, government)	2008	2050	Probabilities	yes	F2F, mail, phone
Harvard* Anadón et al. (2011); Anadón, et al. (2014a)	8 (academia, private sector)	2010	2030	Percentile (medians for some metrics)	yes	Mail & phone
FEEM* Fiorese et al. (2013)	15 (academia, government, private sector)	2011	2030	Percentiles and Probabilities	yes	F2F
CCS						
UMass Baker et al. (2009b)	4 (academia, government)	2007	2050	Probabilities	yes	F2F & survey
Harvard* Chan et al. (2011) *	13 (academia, government, private sector)	2010	2030	Percentiles and Probabilities	yes	F2F & survey
Duke Chung et al (2011)	13 (private sector, government)	2011	2030	Percentiles	no	Survey & F2F or phone
UMass Jenni et al (2013)	15 (academia, government, private sector)	2011	2025	Percentiles	yes	F2F
FEEM Ricci et al. (2014)	12 (academia, government, private sector)	2012	2030	Percentiles	yes	online
CMU Rao et al. (2006)	12 (academia, private sector)	2006	2030, 2050	Percentiles	yes	F2F
NRC (NRC 2007)	12 (academia, private sector)	2006	2022	Probabilities	yes	F2F Panel
Nuclear						
UMass* Baker et al (2008b)	4 (academia, government)	2007	2050	Probabilities	yes	F2F & mail

Harvard* and FEEM* Anadón et al. (2012)	60 (academia, government, private sector)	2010	2030	Percentile (medians for some metrics)	yes	Online & group workshop
CMU (<u>GEN III only</u>)* Abdulla et al (2013)	12 (government, private sector)	2011	estimate for an NOAK plant	Probabilities & percentiles	no, but consistent with BAU	F2F
Solar						
UMass Baker et al 2009a*	3 (Academic)	2007	2050	Probabilities	yes	F2F followed by survey
Harvard* Anadón et al. (2011); Anadón, et al. (2014a)	11 (academia, government, private sector)	2010	2030	Percentile (medians for some metrics)	yes	Online
FEEM* Bosetti et al. (2012) *	16 (academia, government, private sector, academic)	2011	2030	Probabilities & percentiles	yes	F2F
NearZero Inman (2012)	21 (academia, government, private sector)	2011	Year for deployment target defined by expert	Percentiles	not specified	Online
CMU* Curtright et al. (2008)	18 (academia, government, private sector)	2008	2030; 2050	Probabilities	yes	Mail survey
Vehicles						
UMass Baker et al. (2010)	7 (academia, government, private sector)	2008	2050	Probabilities	yes	F2F & mail
FEEM Catenacci et al. (2013)	14 (academia, government, private sector)	2012	2030	Percentiles & proba-bilities	yes	F2F
Harvard Anadón et al. (2011); Anadón, et al. (2014a)	9 (academia, government, private sector)	2011	2030	Percentile (medians for some metrics)	yes	Mail and F2F for some
Other						
Harvard - Utility scale energy storage Anadón et al. (2011); Anadón, et al. (2014a)	25 (academia, government, private sector)	2011	2030	Percentile (medians for some metrics)	yes	Mail and F2F for some
NRC – IGCC	8	2006	2025	probabilities	yes	F2F Panel

NRC (2007)	(academia,private sector)					
Stanford-Natural Gas Bistline (2013)	4 (government, private sector)	2013??	2025	Cumulative probabilities	yes	F2F
GHG MI – Wind Gillenwater (2013)	7 (private sector)	2010	2011	Percentiles	no	Phone
UCL -- Low Carbon Energy Usher and Strachan (2013)	25 (academia, government, private sector)	2010	2030	Percentiles	no	F2F

*Note: The studies shaded in grey are those for which the original data could not be retrieved. * identifies the studies for which costs have been standardized(see the online Appendix for process, Section 4 for results).*

Define the Objective. The objective of most of the elicitations listed in Table 1 is to inform public energy technology RD&D policy. The specific quantities that were elicited are metrics defining cost and other technological performance parameters. In 80% of the studies the focus on RD&D was explicit, asking experts to judge cost evolution conditional on RD&D budgets; in the remaining studies no mention of the RD&D funding is made. Even within the former group of studies, objectives varied. For instance, the FEEM, Harvard and UMass solar studies were developed specifically to support further modeling and portfolio analysis, whereas the CMU solar PV study was designed to stand alone. This likely shaped the specific set of questions asked.

Select an Elicitation Mode. Elicitation mode refers to the way in which the expert judgments were collected: mail or online surveys, or telephone or face-to-face (F2F) interviews. Until recently, most elicitations were carried out as F2F interviews, generally assumed to be the gold standard (Meyer and Booker 1991; O’Hagan et al. 2006), since it allows for targeted “debiasing” and follow-up questions. Recently, however, many groups have been moving toward other modes including interactive mail and online surveys complemented with follow-up interactions with researchers (Nordhaus 1994; Curtright et al. 2008; Chan et al. 2011; Anadón et al. 2012). There has been work in developing interactive online tools for supporting expert elicitation (James et al 2010; Spaccasassi and Deleris 2011; Speirs-Bridge et al. 2010; Shearer et al. 2014; Dalal et al. 2011; Anadón et al. 2012), motivated primarily by concerns of expense and scope. There has been little research aimed at quantitatively evaluating the impact of elicitation mode and expert selection. Recent non-controlled studies (Baker et al. 2014; AVN) found that In-person surveys are associated with broader uncertainty ranges. This suggests that current online methods are not as good as an interviewer in getting experts to think more broadly. Within the studies reviewed here, 42% involved F2F elicitations with all experts; 72% included some F2F interactions; the remainder used remote modes, including phone, internet, or mail.

Identify Experts. Selecting a highly qualified and diverse pool of experts can help avoid anchoring on the current state of technology (see for instance Raiffa 1968; Keeney and Winterfeld 1991; Meyer and Booker 1991; Phillips 1999; Clemen and Reilly 2001;). There are often questions about the appropriate number of experts, however ideas of statistical significance are not entirely appropriate. First, informed experts are necessarily correlated since there is a limited set of literature and results on any technology. Second, the idea of expert elicitation is to derive a representation of the views of the community of experts; it is not a draw from some kind of underlying existing probability distribution. Some studies have found that there are diminishing marginal returns to additional experts after as few as 3 or 4 (Clemen and Winkler 1985; Ferrell 1985; Clemen and Winkler 1999;

Clemen and Winkler 2007), but the optimal number is not set and may depend on the technology area and type of questions. One study (US EPA, 2015) reviewed 38 expert elicitation studies: 90% used fewer than 12 experts, and 60% had six to eight experts. The studies reviewed in this article vary on the number of experts assessed, from 3 to 60. On average, they are a bit larger than typical studies, with an average of 11.5, and only 44% having fewer than 12. Just over half the studies had at least one participant each from Academia, Government, and the Private Sector. Diversity is important: experts in different technology areas, sectors or regions may have different experiences, impacting their estimates (Tversky and Kahneman 1974). Confirming this, AVN find that expert background and geographic location are often associated with lower or higher cost estimates, but this effect is technology specific and cannot be generalized. This likely reflects the experience of experts with a given technology.

Structure the elicitation. This is typically done in conjunction with a subset of the experts and includes the definition of the uncertain quantity to be assessed (metrics in a given target year for specific technologies) and the conditioning variables, the way in which uncertainty will be encoded, consistency checks, and possibly assessment and self-assessment of experts.

Metrics. The metrics refer to the specific quantity that experts are asked to assess. The definition of the uncertain quantity must pass “the clarity test” (Howard 1988): there must be a clear quantity that can be universally agreed upon once the event of interest has taken place. The studies covered here vary in the degree of aggregation in the metrics they assess, ranging from very specific technical metrics such as “sorber concentration” for Carbon Capture and Storage (CCS), through aggregated characteristics of technologies such as capital cost and efficiency, to highly aggregated cost metrics such as LCOE of a specific technology. There are tradeoffs inherent in the choice of metric. Disaggregated metrics require a great deal of time to assess, and may be less intuitive for experts. Aggregated cost metrics have one foot in technological understanding and one foot in economics, making them useful. However, experts who deeply understand the technology and experts who understand economic interactions may not be the same.

Target Year. This refers to the year for which the parameters are being estimated, and ranges between 2022 and 2050, with some studies (Harvard, CMU-Curtright) including two different time points (2010 and 2030).

Technologies covered. Some studies assess a single specific technology category (say, small modular reactors). Other studies asked separate questions about different technologies within a technology area (say, large scale Gen III/III+, large-scale Gen IV, and small modular reactors). Other studies aggregate the technologies in some way, either by having experts assess only those specific technologies they believe will be most commercially viable (e.g., enzymatic hydrolysis for biofuels), or by having the experts assess the future of an entire technology class (i.e. CCS).

Conditioning variables. Analysts must define which conditions will be considered explicitly, and which will be considered implicitly, leaving the experts to make judgments about them. Conditions of interest include assumptions about future input prices, the characterization of government or private RD&D efforts to support the specific technology, or any other key energy or environmental policy (e.g. a carbon tax) as well as assumptions about the future state of the economy (for instance, business-as-usual conditions for economic growth).

The most important conditioning variable in these studies is the RD&D budget. Twenty-one studies specify budgets explicitly, using a range of approaches. These include asking the experts to consider BAU budget scenarios, to provide their own suggested RD&D investment level, or to condition on budget amounts pre-determined by the research team. The ranges of budgets vary widely, with the UMass studies generally having the smallest budgets and Harvard generally having the largest (see online Appendix for more details).

Five of the 26 studies do not specify a public RD&D budget: it is an implicit part of the expert assessment to think about what future budgets may be and to average over all the possible futures. There is a tradeoff between fully specifying external conditions (such as economic growth, trade policies, etc.) and ensuring that the burden on experts' time to participate is not too onerous.

Encoding Uncertainty. Assessing subjective probabilities can be done in two ways: assessing specific percentiles, such as 5-50-95, or asking for probabilities of achieving a certain specified endpoint. Among these studies, 46% used percentiles, 36% used probabilities, and 18% used both. Percentiles are easy to translate to probability distributions and avoid anchoring the experts; but are prone to over-confidence, with experts often reporting ranges that are too small compared to other experts and compared to experimental findings. Probabilities are less prone to over-confidence (Juslin et al 1999), but may anchor experts, and may lead to a situation where only a small portion of the probability distribution is assessed. The gold standard would be to use both methods. However, the tradeoff is that with more methods for assessing values, fewer values can be assessed. For example, the FEEM solar study used both, but the elicited metric was aggregated (LCOE), while the Harvard solar survey elicited only percentiles, but focused on a finer level of detail (for instance, inverter costs/module costs, etc.).

Assessment and Self-assessment of Experts. Some studies ask experts to assess their level of expertise in general or specific technology areas. This has appeal, since it allows researchers to determine whether experts are systematically favoring technologies they are most expert in (see for instance Anadón et al. 2014a and all elicitations by FEEM). However, no relationship has been found between an expert's self-assessment and the assessments by that expert (Bolger and Rowe 2014). There is some evidence that there is value in asking seed questions (questions whose exact answer will be known by the researcher) and then weighting experts by how well they answer the seed questions (Cooke 1991; Lin and Cheng 2009). Only one of the studies considered here used a test question, but it was on an unrelated subject, aimed at generally assessing experts' overconfidence.

Train Experts. Providing experts with background information, training, and pretesting the survey before the full implementation of the elicitation are key steps to reduce biases and errors.. Background information generally includes previous cost estimates for different sub-technologies, a discussion about overconfidence and other biases and how to reduce them, and data on previous RD&D budgets (see for instance the supplementary information of Anadón et al. 2012). Pre-testing is done for most protocols, but often is not described in the resulting published papers.

Perform Assessment. The expert elicitation is conducted with the full set of experts.

Analyze and Present Results. Elicitation data can be analyzed and reported in a number of ways as discussed above. There is much current research on how to communicate uncertain data to final users (Spiegelhalter et al 2011), which has relevance to the presentation of expert elicitation results. The results of the studies reviewed here are presented at various levels of aggregation.

In order to compare results of expert elicitations, it is necessary to standardize the data from the different studies to some degree. In the remaining of this paper, we focus on the standardized cost estimates from four expert elicitation groups (UMass, Harvard, FEEM and CMU) for five key technologies (bioelectricity, biofuel, CCS, nuclear and solar). For details on the standardization, see the online Appendix as well as AVN and Baker et al. (2015a).

3. Cost-estimates and the impact of RD&D from energy technology expert elicitation

First, we turn to what can be learned from backward looking studies on the impacts of RD&D. A number of specific case studies conclude that public energy RD&D investments played a major role in cost and performance improvements. This is the case, for instance, for the development of the GE High Efficiency Gas Turbine, Nanosolar, Energy Efficient Appliances, LED lighting, 3D imaging and other shale gas recovery technologies (Keller and Block 2008). DOE (2000) quantifies the benefits of 20 of its most successful energy efficiency and renewable energy programs and finds they saved about 5.8EJ, equivalent to around 6 percent of US energy consumption in 2005. As pointed out in Anadón and Holdren (2010) “These energy savings were three times greater than the total amount of funding for energy efficiency and renewable energy (EERE) appropriated by DOE”. Similarly, NRC (2001) found that six specific efficiency programs co-funded by the DOE and the private sector between 1978-2000 resulted in benefits of about \$30 billion 2000\$;² whereas the amount spent by DOE on *all* energy efficiency programs in that period was \$7.3 billion. However, Anadón and Holdren (2010) point out that the fossil energy returns “were modest in comparison, and they did not allow the ... claim that those ...programs had produced enough ... to cover the (investment) by DOE ...”. Overall, understanding of the historic RD&D investments of both the public and private sector is poor (see online Appendix for more details). This notwithstanding, there is growing quantitative evidence supporting the notion that public support for RD&D increases innovation in energy technologies as measured by patenting and results in lower technology costs in developed countries such as the US, Japan, Denmark, Germany, and the UK (for instance, Howell 2015; Klaassen et al., 2005; Wiesenthal et al. 2012a). However, insights about the relative merits of different grant funding mechanisms, type of private sector partnership, and extent of crowding in vs. out are still few. Furthermore, to the best of our knowledge, no quantitative evidence is yet available for countries outside the OECD.. Overall, the available backward looking studies suggest that public RD&D investments in energy technologies give rise to significant returns.

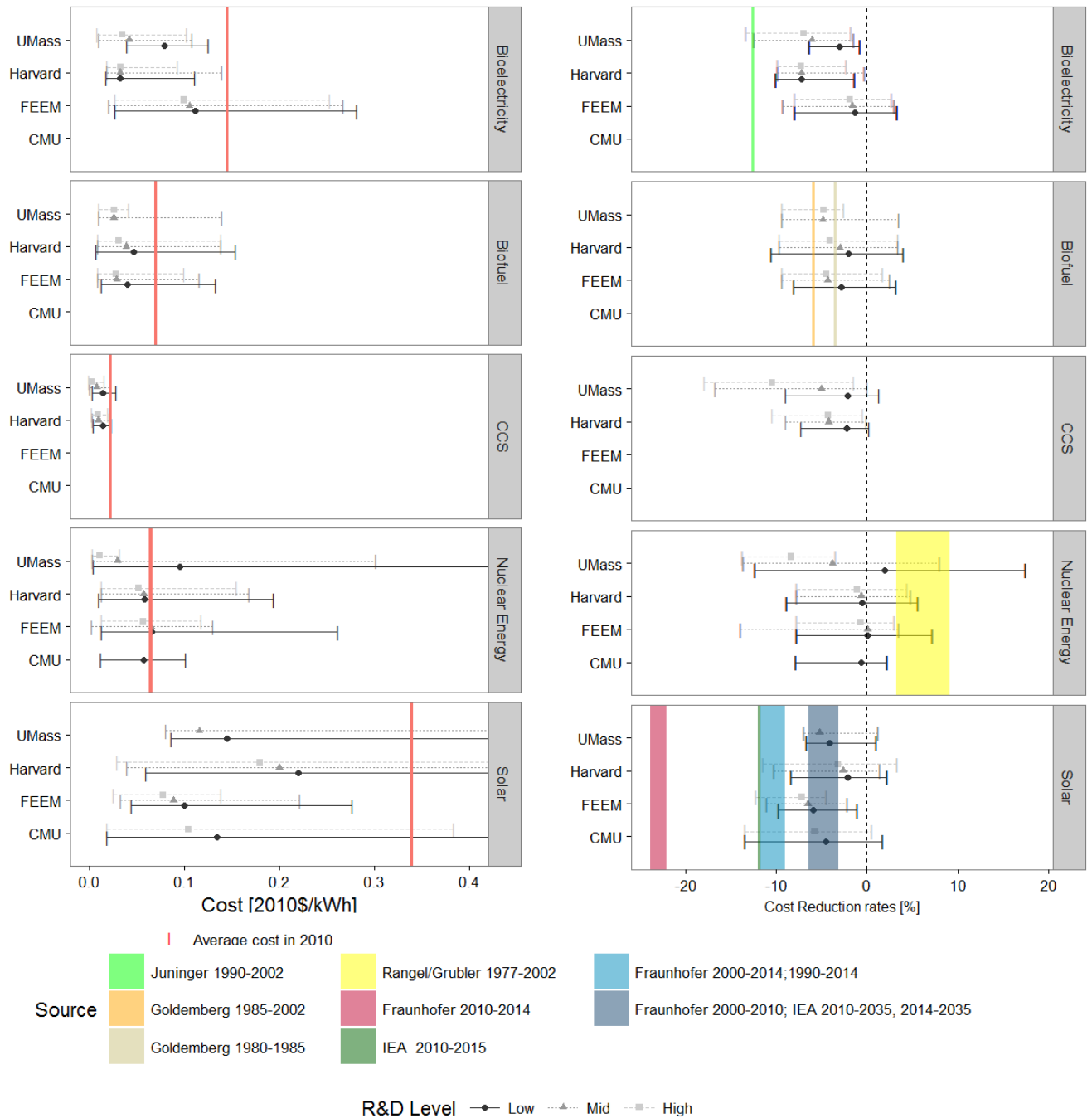
Similarly, both a descriptive analysis of elicitation data and AVN provide strong indication that higher public RD&D investment give rise to lower elicited costs, both at the median and at the extremes of the distribution. Returns to RD&D investment differ significantly by technology reflecting different technological maturity and perceived cost-reduction options. Conversely, the level of public RD&D investment considered in expert elicitations does not generally affect the uncertainty range of elicited costs.

We now turn to a comparison of the standardized cost with historical data from similar or related technologies and present insights on the *implied average annual rate* from these data. Figure 1 summarizes the future technology cost distributions (left panel) and the respective cost change rate (right panel).

On the left panel, (with the exception of the CCS data) the ends of the lines show the lowest 10th percentile and the highest 90th percentile among all of the experts in each study, and the marker the median of the medians. For CCS, each line shows the 10th, 50th and 90th percentile of the aggregated distributions from Baker et al 2015a; thus these values are less extreme than the others.

² The specific programs analyzed were: advanced refrigerator/freezer compressors, electronic ballast for fluorescent lamps, low-emission glass, advanced lost foam casting, oxygen-fueled gas furnace, and advanced turbine systems.

Figure 1: Summary of the elicitation data showing the cost-estimates from energy technology expert elicitations (left panel) and the implied average annual rate of cost change (right panel).



Notes: For all technologies, with the exception of CCS, the horizontal lines range from the minimum of the 10th percentile to the maximum of the 90th percentile across all experts in that particular study. The middle marker represents the median of the medians. In the case of CCS we show the 10th, the 50th and the 90th percentiles of the joint distribution across experts. The vertical red lines in the left-hand-side panels show the average price of the technologies in 2010 (See SI for further details). The right-hand panels present the distribution of the annual rate of cost changes between 2010 and 2030 of elicited cost distributions assuming the 2010 costs shown on the left panel. These are then plotted against the historical rates calculated from data in the literature, represented by the shaded vertical colored areas. Both panels show results by R&D level scenario.

While each study was translated into common units of \$/kWh, the metrics for each technology vary somewhat. The solar metric is the full LCOE, accounting for all costs (other than grid integration). This cost, was calculated assuming a capacity factor of 12% (to be consistent with the implicit assumptions of the FEEM study); the costs would be about 35% lower if the the capacity factor were 18.5% instead. Both bioenergy metrics are levelized non-energy cost (thus exclude fuel costs), which may vary between \$1-2/GGE or \$.03-.06/kWh. The nuclear metric is levelized capital cost (thus exclude O&M, fuel cost, or waste storage), which currently are around \$.024/kWh (NEI 2016). The CCS metric is levelized additional capital cost. It does not account for the energy penalty from CCS, and would need to be added to the levelized cost of fossil generation to get the full cost of electricity.

For comparison, the vertical red lines in the left-hand-side panel show the average of the 2010 costs (see Appendix D for detail on sources). It may appear surprising that some of the 2030 costs provided by experts are higher than the 2010 values. However, the line shows only the average of 2010 costs, rather than an entire cost distribution; the elicited Harvard distributions for 2010, for example, were wide, consistent with data from IRENA.

Overall, insights from the left-hand panel indicate that most of the technologies are expected to improve, in the sense that the medians, along with a large part of the future cost distribution, are lower than the 2010 cost. However, the median of the nuclear cost is estimated to remain close to the 2010 average cost, and there are many 90th percentiles that are above current costs. The average impact of additional R&D expenditures tends to be small relative to the entire range of uncertainty. The value of these elicitation results, however, does not rest simply in the medians, but in the full range of uncertainty.

The right-hand-side panel of Figure 1 compares *historical average annual rates* of change from several sources in the literature with the *implied average annual rate from the relevant expert elicitations*. For both the historical data and the elicitations, the average annual rate of cost change was calculated as follows:

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

Where $t0$ is the starting year and $t1$ the final year of the interval considered, and Cost_{t0} and Cost_{t1} are the relevant cost at those two years. The rates are highly dependent on the choice of $t0$ and $t1$ (Nemet 2009); thus we show multiple ranges when they exist. We report the linear average rate of change for the historical data and the elicitations instead of a non-linear function that would be more consistent with historical experience for two reasons. First, most elicitation studies only asked experts about future costs for one date (mainly in 2030). The lack of intermediate points makes it impossible to estimate the two parameters needed for a non-linear fit consistent with Moore's law (Nagy et al. 2013). Second, linear averages are easier to interpret than the two parameters resulting from a non-linear fit. For example, the right panel from Figure 2 can be interpreted by seeing that historical costs and future-looking elicitations lead to the ranges shown in terms of X% decrease in costs per year on average. In Appendix E we show that the ranking across technologies regarding the historical rate of change over time does not change if we estimate the parameters for Moore's law..

Note that the analogies that were used for the historical comparisons were more similar for some technologies than for others. The historical rates of bioelectricity represent the change in capital cost of biomass fluidized-bed combined heat and power in Sweden between 1990 and 2002. The historical range shown for biofuels represents the cost evolution of sugarcane ethanol in Brazil from the periods of 1980-1985 (slower rate of decrease) and for 1985 and 2002 (faster rate of decrease) (Goldemberg et al 2004). The expert elicitation exercise covered other processes, such as second generation cellulosic technologies. We did not identify a good historical analogue for the additional capital cost of CCS. We show two estimates of the evolution of the capital cost of nuclear power in

France between 1977-2002 and 1977-2002 from Gruebler (2010) and Escobar Rangel and Lévêque (2012); they overlap considerably and so are shown as a single range. Finally, we compare solar PV the elicitation data with seven studies, covering different periods and lengths of time and showing very different cost reduction rates. The IEA studies span 2010 to 2035; they include global module prices and include both historical and prospective components (IEA 2014). Fraunhofer (2015) covers historical data of solar PV prices in Germany.

Overall, there appears to be a relationship between past experience and experts' beliefs. Technologies with the biggest past decreases have medians farthest to the left, whereas nuclear, with past increases, has medians farthest to the right. However, the technologies differ in the degree to which the experts see the future as being similar to the past. The elicitations for biofuels indicate median rates of change very similar to that seen historically. While the experts are not terribly optimistic about nuclear, putting the median rate of change near zero, they are nevertheless more optimistic than past data would imply, as nuclear has shown primarily cost increases in the past. This may reflect optimism, or it may be a sign that experts believe that current research, modelling, and licensing practices make it less likely for costs to continue to increase in the future. Note that most of the nuclear elicitations overlap with the historical data, and thus, continued increases would not be a surprise. The experts appear to expect a significant slowdown in the rate of change of bioelectricity costs, at least when compared to the experience from Sweden. The figure indicates that only the UMass experts foresaw a reasonable chance of continuing to achieve such rapid cost decreases. This indicates either (1) the experts in the studies believe that much of the cost reduction has been achieved; or (2) the experts in the study were over-confident and did not account for the kind of rapid cost reduction that was recently seen in Sweden. Solar is of particular interest. The band of color on the far left indicates a recent significant annual cost decreases over a short period of time. The experts appear to believe, however, that in the long term, the annual decrease rate will be, on average, similar to what it has been over longer historical periods and estimated by Fraunhofer and IEA. This is consistent with statistical expectations in general: it is not unusual to have an outlier over a short period of time (such as between 2010 and 2014 in the Fraunhofer estimate), but experts seem to expect future changes to have some reversion to the mean. Again, there are two interpretations. First, it is possible that experts in the elicitations missed a fundamental change to the trajectory of costs that started in 2010 and will continue; this is a real possibility since most of the elicitations took place before 2010 when prices started falling rapidly. Second, an alternative interpretation is that the experts correctly estimated the long term trajectory of solar, with the short term rapid reductions in cost not indicating a change in the trajectory, but rather simply a random deviation. The three IEA forecasts overlap with most of the medians of the expert elicitations, but do not provide information about the range of outcomes around the median.

This comparison informs on the value of elicitations in combination with past data. Elicitations are able to provide insights about the range of possibilities, meaning that there will be far fewer surprises than when decisions are based on historical estimates. Elicitations, such as these, can include the impact of prospective policies, and can consider deviations in rates of technological change that may be enabled by new scientific developments; it is difficult or impossible to get this information from past data. Past data and elicitations together can be particularly revealing. When compared, they can tell us when experts think the future will be different from past; this information can be further explored and considered in policy decisions.

4 Future research needs and conclusions

This paper provides a comprehensive overview of existing expert elicitation studies on the future of energy technologies with a focus on the impact of RD&D investments. Understanding the future performance of energy

technologies, and how those may be affected by RD&D, is key to the design of energy RD&D portfolios and to the development of better projections of the costs of future emissions scenarios. Although looking at past performances of R&D programs and at the evolution of technological costs is a key input to the process of designing careful strategies for the future, this data may, by itself, not make the best use of all information available to anticipate unexpected and unprecedented patterns due to characteristics that may be technology specific or related to unprecedented phases in the boundary conditions. For these reasons, expert elicitations are an important, and complementary, source of information.

Taken all together, the expert elicitation data summarized here show some regularities. Most simply, experts largely believe that increased public R&D investments will result in reductions in future technology costs by 2030, although possibly with diminishing marginal returns. Implicit median annual rates in cost reduction collected through expert elicitations partly reflect historical trends in those technologies. However, the information collected is much richer and allows us to look into the extremes of the tails (breakthroughs and failures) thus allowing the design of more robust policies. For all technologies, experts see the possibility of breakthroughs that would make the technology cost competitive, envisioning sustained annual rates of cost reduction on the order of 10% per year. These tails seem to be more extreme under higher R&D; it is more difficult to say what would happen under decreased funding. The range of uncertainty and disagreement among the technologies and teams seems to imply that there are benefits in a portfolio approach to technology R&D, rather than picking a small number of winners (Anadón et al. 2015). However, it is important to note that any improvements in technology must be evaluated in the context of the economy before decisions about R&D investment are made.

In general, many results differ substantially across studies. This finding, corroborated by three meta-analysis studies, indicates that differences in elicitation design (including choice of experts, mode of elicitation, and format of the questions) may lead to differences in estimates. In order to extract the full value of these elicitations, it is important to explore the role of key features in elicitation design, perhaps experimentally, and to bring these lessons to practice in the design of shared protocols that allow a more systematic collection of data. As the cost of elicitation can be very high, a possible way forward would be to design web-based protocols that maximize the effectiveness of the elicitation while allowing repeated communication with experts as well as the participation of a broader set of experts.

A few important gaps in the literature emerge from this overview. First, although many studies conditioned on current or increased RD&D investments, very few (considered drastic reductions in current RD&D spending Jenni et al. 2013; Fiorese et al. 2014; Ricci et al. 2014; NRC 2007 are exceptions). In times of tight governmental budgets, it is important to assess what would happen if entire RD&D programs were scaled down. Second, as the geography of experts appears to be a key driver of elicited costs, and given that energy RD&D investments data show an increasing role for emerging economies, it will be important to extend expert elicitations to include experts from emerging economies to obtain a more exhaustive picture of how technologies might progress. Third, some technology areas, such as utility scale energy storage, wind, vehicles, gas turbines, geothermal and energy efficiency technologies, have been the subject of few, or no, publicly available expert elicitations. As a result, our ability to analyze these technologies and how they fit into energy RD&D portfolios is limited, particularly given insights presented on some of the drivers of the estimates.

Overall, the recent emergence of data on future energy costs through expert elicitations is providing the opportunity and (we would argue) the obligation of more rigorously and transparently introducing considerations of uncertainty around technical change on discussions about energy policies and climate change mitigation. We believe this is essential given the magnitude of the uncertainties involved and their impact on costs. The elicited probabilistic information summarized in this paper sheds light on where technological progress is most likely, and

how it is influenced by public RD&D efforts. Expert elicitation data can serve as input to the calibration of integrated assessment and energy system models that are commonly used to design and evaluate energy and climate policies. Finally, it can be used in more complex analyses aiming at the definition of energy RD&D portfolios that account for multiple societal objectives and that are robust to key uncertainties affecting the innovation process.

In the spirit of the suggestions by Convery and Wagner (2015), this review provides an up to date summary of what we know, and what we do not know, about the future of technological progress in energy and how it is influenced by public RD&D efforts. While scientists and economists are often more comfortable with point estimates derived from past data, this work shows that the uncertainty about the future is much wider than can be derived from past data, and that surprises, both happy and unhappy, are real possibilities that need to be accounted for. The presence of multiple studies covering similar technologies underlines that representing uncertainty is a complex task, one in which insights can most certainly be drawn, but where humility is a necessary trait.

References

- Abdulla, A., I. Azevedo, M. Morgan. 2013. "Expert Assessments of the Cost of Light Water Small Modular Reactors." *Proceedings of the National Academy of Sciences* 110 (24): 9686–91.
- Anadón, L. D., E. Baker, V. Bosetti, L. Aleluia Reis. 2015. "Too Early to Pick Winners: Disagreement across Experts Implies the Need to Diversify R&D Investment." *Submitted*.
- Anadón, L. D., J. P. Holdren (2010). Policy for Energy Technology Innovation. in K. Gallagher, ed., *Acting in Time on Energy Policy*, Brookings Institution Press.
- Anadón, L. D., M. Bunn, M. Chan, C. Jones, R. Kempener, G. Chan, A. Lee, N. J. Logar, V. Narayanamurti. 2011. "Transforming US Energy Innovation." Retrieved from <http://dash.harvard.edu/handle/1/10594301>.
- Anadón, L. D., V. Bosetti, M. Bunn, M. Catenacci, A. Lee. 2012. "Expert Judgments about RD&D and the Future of Nuclear Energy." *Environmental Science & Technology* 46 (21): 11497–504.
- Anadón, L. D., G. Nemet, E. Verdolini. 2013. "The Future Costs of Nuclear Power Using Multiple Expert Elicitations: Effects of RD&D and Elicitation Design." *Environmental Research Letters* 8 (3): 034020.
- Anadón, L. D., M. Bunn, V. Narayanamurti. 2014a. *Transforming US Energy Innovation*. UK: Cambridge University Press. <http://www.cambridge.org/US/academic/subjects/earth-and-environmental-science/environmental-policy-economics-and-law/transforming-us-energy-innovation>.
- Anadón, L. D., G. Chan, A. Lee. (2014b) 'Expanding, and improving targeting of, U.S. investment in energy innovation: an analytical approach.' In 'Transforming U.S. Energy Innovation'. Anadón, LD, Bunn, M, Narayanamurti, V. (Editors). Cambridge University Press, Cambridge, UK.
- Athanassoglou, S., V. Bosetti (2015). Setting environmental policy when experts disagree, *Environmental and Resource Economics* 61/4, 495-516.
- Baker, E., O. Olaleye (2013). "Combining Experts: Decomposition and Aggregation Order." *Risk Analysis* 33.(6): 1116-1127.
- Baker, E, V. Bosetti, A. Salo. (2016). Finding common ground when experts disagree: Belief dominance over portfolios of alternatives; *Management Science*, under review
- Baker, E., J. Keisler. 2011. "Cellulosic Biofuels: Expert Views on Prospects for Advancement." *Energy* 36 (1): 595–605.
- Baker, E., H. Chon, J. Keisler. 2008a. "Electricity from Biomass: Combining Economic Analysis with Expert Elicitation Data to Inform Climate Policy." Working Paper. University of Massachusetts, Amherst.
- Baker, E., H. Chon, J. Keisler. 2008b. "Advanced Nuclear Power: Combining Economic Analysis with Expert Elicitations to Inform Climate Policy."
- Baker, E., H. Chon, J. Keisler. 2009a. "Advanced Solar R&D: Combining Economic Analysis with Expert Elicitations to Inform Climate Policy." *Energy Economics* 31: S37–49.
- Baker, E., H. Chon, J. Keisler. 2009b. "CCS: Combining Economic Analysis with Expert Elicitations to Inform Climate Policy." *Climatic Change* 96 (3): 379–408.
- Baker, E., H. Chon, J. Keisler. 2010. "Battery Technology for Electric and Hybrid Vehicles: Expert Views about Prospects for Advancement." *Technological Forecasting and Social Change* 77 (7): 1139–46.
- Baker, E., V. Bosetti, K. Jenni, E. Ricci. 2014. "Facing the Experts: Survey Mode and Expert Elicitation." *FEEM Nota di Lavoro* 1.2014.
- Baker, E., V. Bosetti, L. Anadón, M. Henrion, L. Aleluia Reis. 2015a. "Future Costs of Key Low-Carbon Energy Technologies: Harmonization and Aggregation of Energy Technology Expert Elicitation Data." *Energy Policy* 80: 219-232.
- Baker, E., O. Olaleye, L. Aleluia Reis. 2015b. "Decision Frameworks and the Investment in R&D." *Energy Policy* 80: 275–285
- Ben-Haim, Y. (2004). Uncertainty, Probability and Information-Gaps. *Reliability Engineering & System* 819 Safety, 85(1-3):249-266
- Berger, L., J. Emmerling, M. Tavoni (2015). Managing catastrophic climate risks under model uncertainty aversion. Accepted, *Management Science*.
- Bertsimas, D, D. Brown, C. Caramanis. "Theory and applications of robust optimization." *SIAM review* 53.3 (2011): 464-501.

- Bettencourt, L. , J. Trancik, J. Kaur (2013). "Determinants of the Pace of Global Innovation in Energy Technologies." *PloS One* 8 (10): e67864.
- Bickel, J., 2007. Some Comparisons between Quadratic, Spherical, and Logarithmic Scoring Rules, *Decision Analysis* 4(2) 49-65. 2007
- Bistline, J 2013. "Energy Technology Expert Elicitations: An Application to Natural Gas Turbine Efficiencies." *Technological Forecasting and Social Change* 86: 177-187.
- Bolger, F., G. Rowe. 2015. "The Aggregation of Expert Judgment: Do Good Things Come to Those Who Weight?" *Risk Analysis* 35(1): 5–11.
- Bosetti, V., M. Catenacci, G. Fiorese, E. Verdolini. 2012. "The Future Prospect of PV and CSP Solar Technologies: An Expert Elicitation Survey." *Energy Policy* 49: 308–17.
- Brown, C., Y. Ghile, M. Laverty, K. Li (2012). Decision Scaling: Linking Bottom-up Vulnerability Analysis with Climate Projections in the Water Sector. *Water Resources Research*, 48, W09537.
- Budnitz, R. J. et al. 1997. *Recommendations for Probabilistic Seismic Hazard Analysis: Guidance on Uncertainty and Use of Experts*. Vol. 1. US Nuclear Regulatory Commission Washington, DC.
- Capen, E. 1976. "The Difficulty of Assessing Uncertainty." *Journal of Petroleum Technology* 28 (8): 843–50.
- Catenacci, M., E. Verdolini, V. Bosetti, G. Fiorese. 2013. "Going Electric: Expert Survey on the Future of Battery Technologies for Electric Vehicles." *Energy Policy* 61: 403–13.
- Chan, G., L. D. Anadón, M. Chan, A. Lee (2011a) Expert elicitation of cost, performance, and RD&D budgets for coal power with CCS. *Energy Procedia*, 4:2685–2692.
- Chung, T. S., D. Patiño-Echeverri, T. L. Johnson. 2011. "Expert Assessments of Retrofitting Coal-Fired Power Plants with Carbon Dioxide Capture Technologies." *Energy Policy* 39 (9): 5609–20.
- Clemen, R., R. Winkler (1999) Combining probability distributions for experts in risk analysis, *Risk Analysis*, 19(2):187-203
- Clemen, R., R. Winkler. 1985. "Limits for the Precision and Value of Information from Dependent Sources." *Operations Research* 33 (2): 427–42.
- Clemen, R. , T. Reilly. 2001. *Making Hard Decisions with Decision Tools*. CA, Duxbury: Pacific Grove.
- Clemen, R. , R. Winkler. 2007. "Aggregating Probability Distributions." in: W. Edwards, R. Miles, & D. von Winterfeldt (Eds.) *Advances in Decision Analysis*, Cambridge, UK : Cambridge University Press.
- Cooke (2016) THIS SYMPOSIUM**
- Cooke, R. , A. Wilson, J. Tuomisto, O. Morales, M. Tainio, J. Evans 2007. "A Probabilistic Characterization of the Relationship between Fine Particulate Matter and Mortality: Elicitation of European Experts." *Environmental Science and Technology* 41 (18): 6598–6605.
- Cooke, R., L. Goossens. 2000. "Procedures Guide for Structural Expert Judgement in Accident Consequence Modelling." *Radiation Protection Dosimetry* 90 (3): 303–9.
- Cooke, R. (2015) The Aggregation of Expert Judgment: Do Good Things Come to Those Who Weight? *Risk Analysis*, 35(1):12-15
- Convery, F., G. Wagner. "Reflections—Managing Uncertain Climates: Some Guidance for Policy Makers and Researchers." *Rev Environ Econ Policy* (Summer 2015) 9 (2): 304-320.
- Curtright, A. , M. Morgan, D. Keith. 2008. "Expert Assessments of Future Photovoltaic Technologies." *Environmental Science & Technology* 42 (24): 9031–38.
- Dalal, S., D. Khodyakov, R. Srinivasan, S. Straus, J. Adams. 2011. "Expert Lens: A System for Eliciting Opinions from a Large Pool of Non-Collocated Experts with Diverse Knowledge." *Technological Forecasting and Social Change* 78 (8): 1426–44.
- Dewispelare, A. , L. Herren, R. Clemen. 1995. "The Use of Probability Elicitation in the High-Level Nuclear Waste Regulation Program." *International Journal of Forecasting* 11 (1): 5–24.
- DOE. 2000. *A Decade of Success, Office of Energy Efficiency and Renewable Energy*. United States Department of Energy. Vol. DOE/EE-0213. Washington D.C.
- EC, European Commission. 2015. "Energy Technologies and Innovation [COM(2013) 253]."
- Escobar Rangel. L. , F. Lévêque. (2012). Revisiting the cost escalation curse of nuclear power: New lessons from the French experience, I3 Working paper.

- Ferrell, W. 1985. "Combining Individual Judgments." In G. Wright, ed. *Behavioral Decision Making*, 111–45. Springer.
- Fiorese, G., M. Catenacci, E. Verdolini, V. Bosetti. 2013. "Advanced Biofuels: Future Perspectives from an Expert Elicitation Survey." *Energy Policy* 56: 293–311.
- Fraunhofer Institute (2015), ISE with support of PSE AG Freiburg, 17 November 2015.
- Fiorese, G., M. Catenacci, V. Bosetti, E. Verdolini. 2014. "The Power of Biomass: Experts Disclose the Potential for Success of Bioenergy Technologies." *Energy Policy* 65: 94–114.
- Gabrel, V., C. Murat, A. Thiele. "Recent advances in robust optimization: An overview." *European Journal of Operational Research* 235.3 (2014): 471-483.
- Gillenwater, M. 2013. "Probabilistic Decision Model of Wind Power Investment and Influence of Green Power Market." *Energy Policy* 63: 1111–25.
- Goldemberg, J., S. Coelho, P. Nastari, O. Lucon (2004). Ethanol learning curve—the Brazilian experience, *Biomass and Bioenergy* 26:301 – 304.
- Grubler, A. (2010), 'The cost of the French nuclear scale-up: A case of negative learning by doing', *Energy Policy* 38, 5174–5188.
- Hammond, J. , R. Keeney, and H. Raiffa. 1999. *Smart Choices: A Practical Guide to Making Better Decisions*. Vol. 226. Harvard Business Press.
- Heal, G., A. Millner (2014). Reflections: Uncertainty and decision making in climate change economics, *Review of Environmental Economics and Policy* 8/1, 120-137.
- Hora, S. 2007. "Eliciting Probabilities from Experts" in: W. Edwards, R. Miles, & D. von Winterfeldt (Eds.) *Advances in Decision Analysis*. pp. 154-176. Cambridge , UK : Cambridge University Press.
- Hora, S. , D. Von Winterfeldt. 1997. "Nuclear Waste and Future Societies: A Look into the Deep Future." *Technological Forecasting and Social Change* 56 (2): 155–70.
- Hora, S. , B. Franssen, N. Hawkins, I. Susel. 2013. "Median Aggregation of Distribution Functions." *Decision Analysis* 10 (4): 279–91.
- Howard, R. A. 1988. "Decision Analysis: Practice and Promise." *Management Science* 34 (6): 679–95.
- Howard, R. , J. Matheson, and D. North. 1972. "The Decision to Seed Hurricanes." *Science* 176 (4040): 1191–1202.
- Howell, S., 2015. Financing constraints as barriers to innovation: Evidence from R&D grants to energy startups. Available at: <http://scholar.harvard.edu/showell/home>.
- IEA. Technology Roadmap Solar Photovoltaic Energy. 2014 Edition. IEA.
- IEA, 2014b. World Energy Outlook 2014. OECD/IEA. Paris: IEA Publishing. ISBN 978-92-64-20805-6
- Inman, M. 2012. "How Low Will Photovoltaic Prices Go? An Expert Discussion." Nearzero.
- InterAcademy Council. 2010. "Climate Change Assessments, Review of the Processes & Procedures of the IPCC." Retrieved from https://www.ipcc.ch/pdf/IAC_report/IAC%20Report.pdf
- James, A., S. Low Choy, K. Mengersen. 2010. "Elicitor: An Expert Elicitation Tool for Regression in Ecology." *Environmental Modelling & Software* 25 (1): 129–45.
- Jenni, van Luik, "Assessment of Expert Judgements for safety analysis and performance assessment of geological repository systems, in Ahn, J., M. Apted, eds. 2010. *Geological Repository Systems for Safe Disposal of Spent Nuclear Fuels and Radioactive Waste*. Woodhead Publishing Limited.
- Jenni, K. , E. Baker, and G. Nemet. 2013. "Expert Elicitations of Energy Penalties for Carbon Capture Technologies." *International Journal of Greenhouse Gas Control* 12: 136–45.
- Juninger, M. et al., 2006. Technological learning in bioenergy systems. *Energy Policy*, 34(18), pp.4024–4041.
- Juslin, P., P. Wennerholm, H. Olsson. 1999. "Format Dependence in Subjective Probability Calibration." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 25 (4): 1038.
- Kalra, N., S. Hallegatte, R. Lempert, C. Brown, A. Fozzard, S. Gill, A. Shah. 2014. Agreeing on robust decisions : new processes for decision making under deep uncertainty. Policy Research working paper no. WPS 6906. Washington, DC: World Bank Group.
- Keeney, R., D. Winterfeldt. 1991. "Eliciting Probabilities from Experts in Complex Technical Problems." *Transactions on Engineering Management* 38: 191–201.

- Keller, M., Bloch, F. (2008) "Hidden Success Stories: Highlights of Federally Supported Innovations" Report Released at Policy Briefing, *How Will a New Administration and Congress Support Innovation in an Economic Crisis?* 1 December
- Klaassen, G., Miketa, A., Larsen, K., Sundqvist, T., 2005. The impact of R&D on innovation for wind energy in Denmark, Germany and the UK. *Ecological Economics* 54 (2–3), 227-240.
- Kotra, J. , M. Lee, N. Eisenberg, A. DeWispelare. 1996. "Branch Technical Position on the Use of Expert Elicitation in the High-Level Radioactive Waste Program." Nuclear Regulatory Commission, Washington, DC (United States). Retrieved from http://www.iaea.org/inis/collection/NCLCollectionStore/_Public/28/038/28038065.pdf.
- Krayer von Krauss, M. , E. Casman, M. Small. 2004. "Elicitation of Expert Judgments of Uncertainty in the Risk Assessment of Herbicide-Tolerant Oilseed Crops." *Risk Analysis* 24 (6): 1515–27.
- Lempert, R., M. Collins (2007). Managing the risk of uncertain threshold responses: Comparison of robust, optimum, and precautionary approaches, *Risk Analysis* 27/4, 1009-1026.
- Lichtendahl, K., Y. Grushka-Cockayne, and R. Winkler. 2013. "Is It Better to Average Probabilities or Quantiles?" *Management Science* 59 (7): 1594–1611.
- Lin, S., C. Cheng. 2009. "The Reliability of Aggregated Probability Judgments Obtained through Cooke's Classical Model." *Journal of Modelling in Management* 4 (2): 149–61.
- Mazzucato M. (2013) *The Entrepreneurial State: debunking public vs. private sector myths*, Anthem
- Meyer, M. , J. Booker. 1991. *Eliciting and Analyzing Expert Judgment: A Practical Guide*. Vol. 7. ASA-SIAM Series on Statistics and Applied Mathematics.
- Millner, A., S. Dietz, G. Heal. 2013. "Scientific ambiguity and climate policy." *Environmental and Resource Economics* 55.1: 21-46.
- Morgan, M. 2014. "Use (and Abuse) of Expert Elicitation in Support of Decision Making for Public Policy." *Proceedings of the National Academy of Sciences* 111 (20): 7176–84.
- Morgan, M. , M. Henrion. 1990. "Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis Cambridge University Press." *New York, New York, USA*.
- Mortazavi-Naeini, M., Kuczera, G., Kiem, A. S., Cui, L., Henley, B., Berghout, B., Turner, E. (2015). Robust optimization to secure urban bulk water supply against extreme drought and uncertain climate change. *Environmental Modelling & Software*.
- Nagy, B., J. Farmer, Q. Bui, and J. Trancik. 2013. "Statistical Basis for Predicting Technological Progress." *PloS One* 8 (2): e52669. DOI: 10.1371/journal.pone.0052669
- NEI, Nuclear Energy Institute (2016). <http://www.nei.org/>
- Nemet, G.(2009) "Interim monitoring of cost dynamics for publicly-supported energy technologies" *Energy Policy*, 37(3): 825-835.
- Nemet, G. , L. D. Anadón, and E. Verdolini. 2016. "Expert Selection and Elicitation Design Affect Confidence in Probabilistic Judgments about Future Technologies." *Submitted*.
- Nordhaus, W. 1994. "Expert Opinion on Climatic Change." *American Scientist*, 45–51. Retrieved from http://stephenschneider.stanford.edu/Publications/PDF_Papers/NordhausSM.pdf
- North, D. , F. Offsend, C. Smart. 1975. "Planning Wildfire Protection for the Santa Monica Mountains." *Fire J* 69.
- NRC, National Research Council, 2001. *Energy Research at DOE: Was it Worth it? Energy Efficiency and Fossil Energy Research 1978 to 2000*. National Research Council. Washington D.C.: National Academy Press.
- NRC, National Research Council, 2007. "Prospective Evaluation of Applied Energy Research and Development at DOE (phase Two)." National Academies Press, Washington D.C., United States: National Research Council.
- O'Hagan, A., C.Buck, A. Daneshkhah, J. Eiser, P. Garthwaite, D. Jenkinson, J. Oakley, T. Rakow. 2006. *Uncertain Judgements: Eliciting Experts' Probabilities*. John Wiley & Sons.
- Peerenboom, J., W. Buehring, and T. Joseph. 1989. "OR Practice—Selecting a Portfolio of Environmental Programs for a Synthetic Fuels Facility." *Operations Research* 37 (5): 689–99.
- Phillips, L. 1999. *Group Elicitation of Probability Distributions: Are Many Heads Better than One?* Kluwer Academic Publishers.
- Popp, D. (2010). "Innovation and Climate Policy", *Annual Review of Resource Economics*, 2: 1, pp. 275-298

- Popp, D., R. Newell, and A. Jaffe, (2010). "Energy, the Environment, and Technological Change", In Bronwyn H. Hall and Nathan Rosenberg: Handbook of the Economics of Innovation- Volume-II, Burlington: Academic Press, 2010, pp. 873-938.
- Raiffa, H. 1968. *Decision Analysis: Introductory Lectures on Choices under Uncertainty*. Addison-Wesley. Oxford.
- Rao, A. , E. Rubin, D. Keith, and M. Morgan. 2006. "Evaluation of Potential Cost Reductions from Improved Amine-Based CO₂ Capture Systems." *Energy Policy* 34 (18): 3765–72.
- REN (2012). Renewables 2012, Global Status Report,
- Ricci, E. , V. Bosetti, E. Baker, K. Jenni. 2014. "From Expert Elicitations to Integrated Assessment: Future Prospects of Carbon Capture Technologies." FEEM Nota di Lavoro 2014.044
- Roman H., K. Walker, T. Walsh, L. Conner, H. Richmond, B. Hubbell, P. Kinney (2008) Expert judgment assessment of the mortality impact of changes in ambient fine particulate matter in the U.S. *Environ Sci Technol* 42(7):2268–2274.
- Romer, P. (1990). "Endogenous Technical Change", *Journal of Political Economy* 98: 5, pp.
- Scherer, F., D. Harhoff. (2000) "Technology policy for a world of skew-distributed outcomes." *Research Policy* 29, no. 4 (2000): 559-566.
- Shearer, C., J. Bistline, M. Inman, S. Davis. 2014. "The Effect of Natural Gas Supply on US Renewable Energy and CO₂ Emissions." *Environmental Research Letters* 9 (9): 094008.
- Spaccasassi, C., L. Deleris. 2011. "A Web-Based Tool for Expert Elicitation in Distributed Teams." In *Proceedings of the 8th Bayesian Modelling Applications Workshop of UAI*. Vol. 2011. Citeseer. Retrieved from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.232.3602&rep=rep1&type=pdf#page=128>.
- Speirs-Bridge, A., F. Fidler, M. McBride, L. Flander, G. Cumming, M. Burgman. 2010. "Reducing Overconfidence in the Interval Judgments of Experts." *Risk Analysis* 30 (3): 512–23.
- Spiegelhalter, D., M. Pearson, I. Short. 2011. "Visualizing Uncertainty About the Future." *Science* 333 (6048): 1393–1400.
- Tversky, A., D. Kahneman. 1974. "Judgment under Uncertainty: Heuristics and Biases." *Science* 185 (4157): 1124–31.
- Unruh, G. (2010). "Understanding Carbon Lock In", *Energy Policy*, 28:12, pp. 817–830
- US EPA, US Environmental Protection Agency. 2015. "Expert Elicitation Task Force White Paper.
- Usher, W., and N. Strachan. 2013. "An Expert Elicitation of Climate, Energy and Economic Uncertainties." *Energy Policy* 61: 811–21.
- Verdolini, E., L. D. Anadón, J. Lu, G. Nemet, 2015. The effects of expert selection, elicitation design, and R&D assumptions on experts' estimates of the future costs of photovoltaics, *Energy Policy*, 80: 233-243, ISSN 0301-4215, <http://dx.doi.org/10.1016/j.enpol.2015.01.006>
- Walker, W. (2000). "Entrapment in large technology systems: Institutional commitment and power relations", *Research Policy* 29: 7–8, pp. 833-846.
- Wiesenthal, T., P. Dowling, et al. 2012a. "Technology Learning Curves for Energy Policy Support." *JRC Scientific and Policy Reports*. <ftp://ftp.jrc.es/users/publications/public/JRC73231.pdf>.
- Winkler, R. L. 1967. "The Assessment of Prior Distributions in Bayesian Analysis." *Journal of the American Statistical Association* 62 (319): 776–800.
- Zickfeld K, Morgan M, Frame D, Keith D (2010) Expert judgments about transient climate response to alternative future trajectories of radiative forcing. *Proc Natl Acad Sci USA* 107(28): 12451–12456.

Appendix A: Individual Survey Data

In all following graphs, when one expert elicited more than one specific sub-technology category, the values for that expert were aggregated. The aggregation was carried out taking the minimum of the 10th percentile, the median of the 50th percentile and the maximum of the 90th percentile.

Harmonized surveys

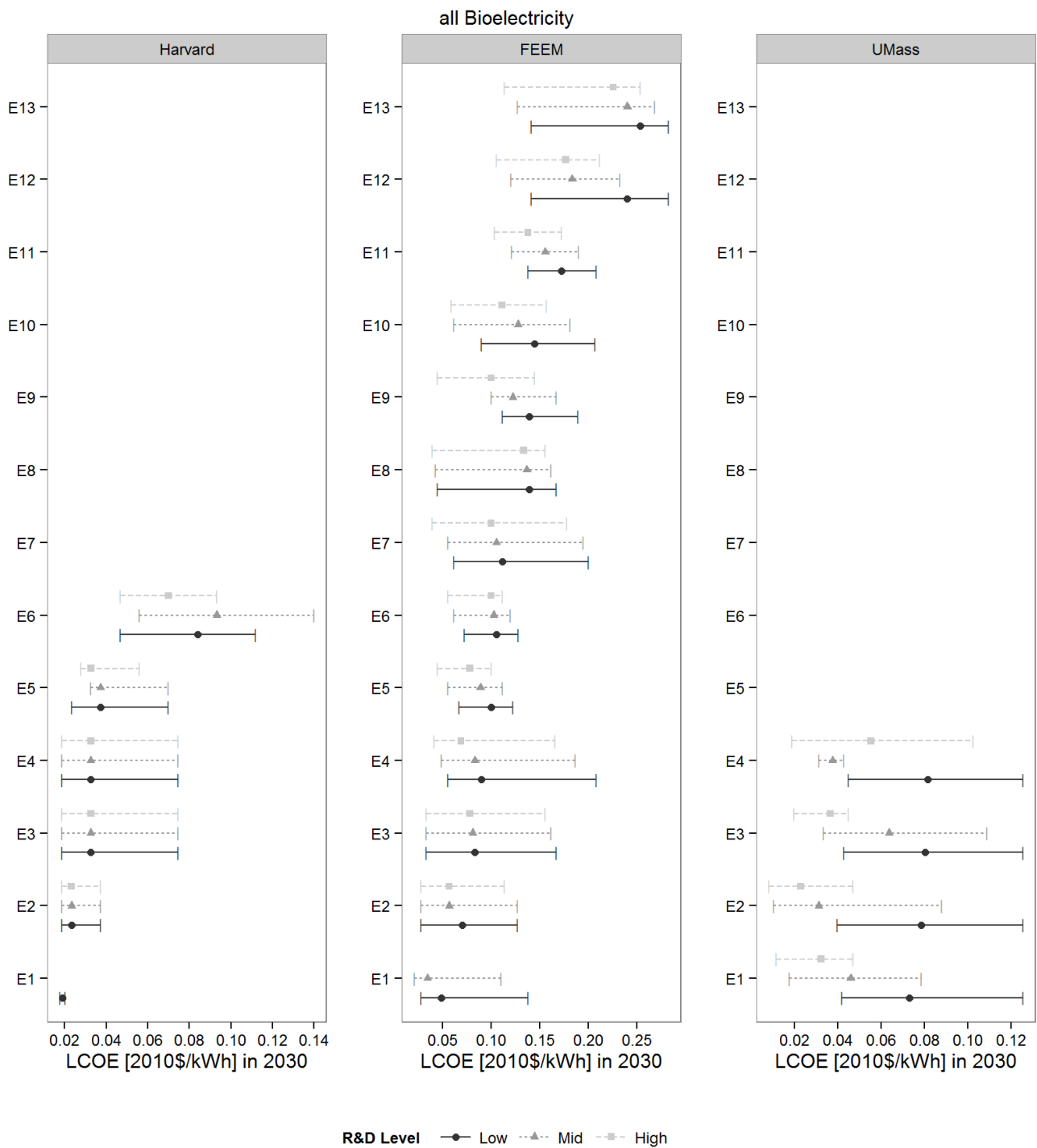


Figure 1: Experts' results of the bioelectricity surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

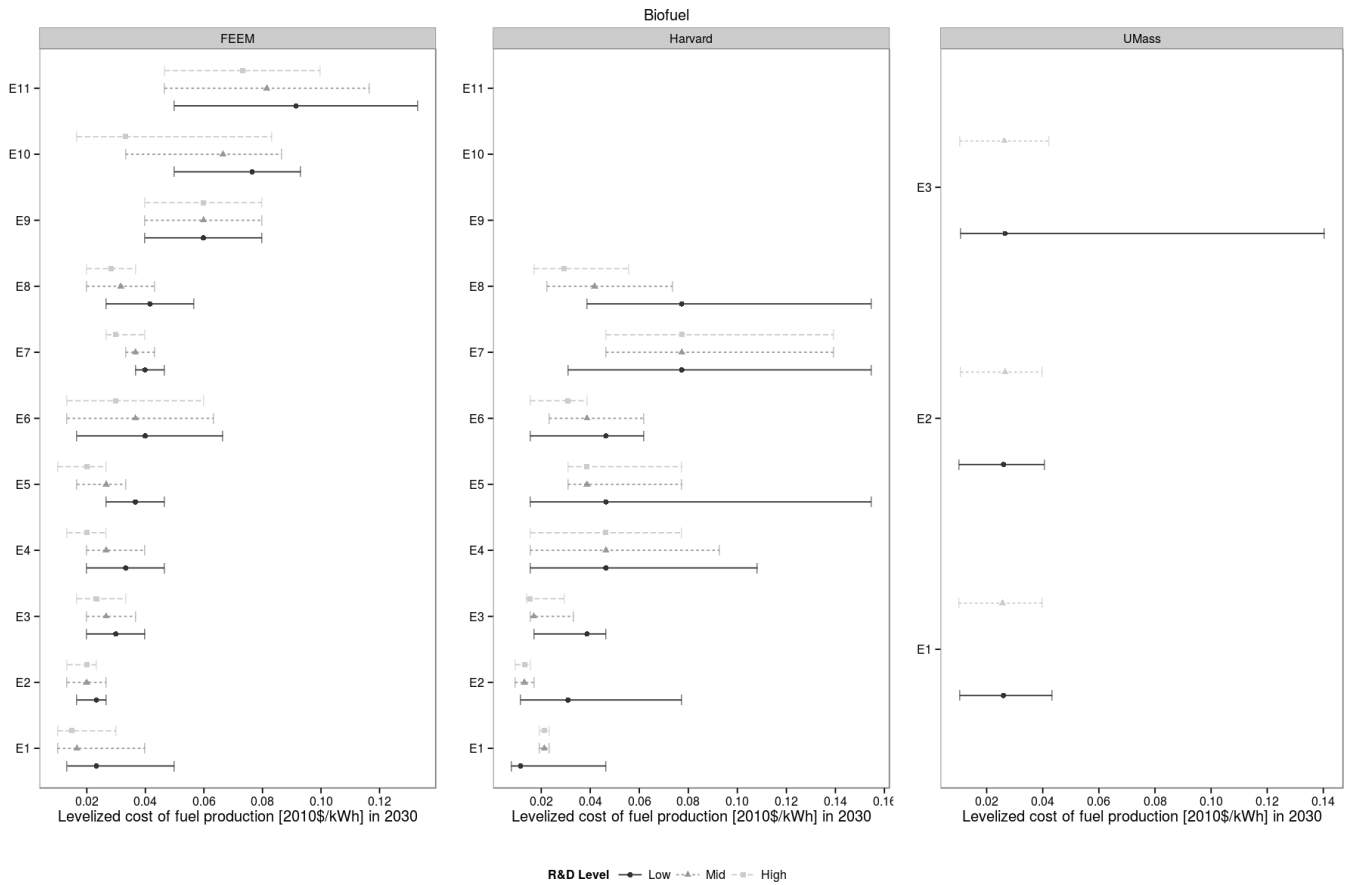


Figure 2: Experts' results of the biofuel surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

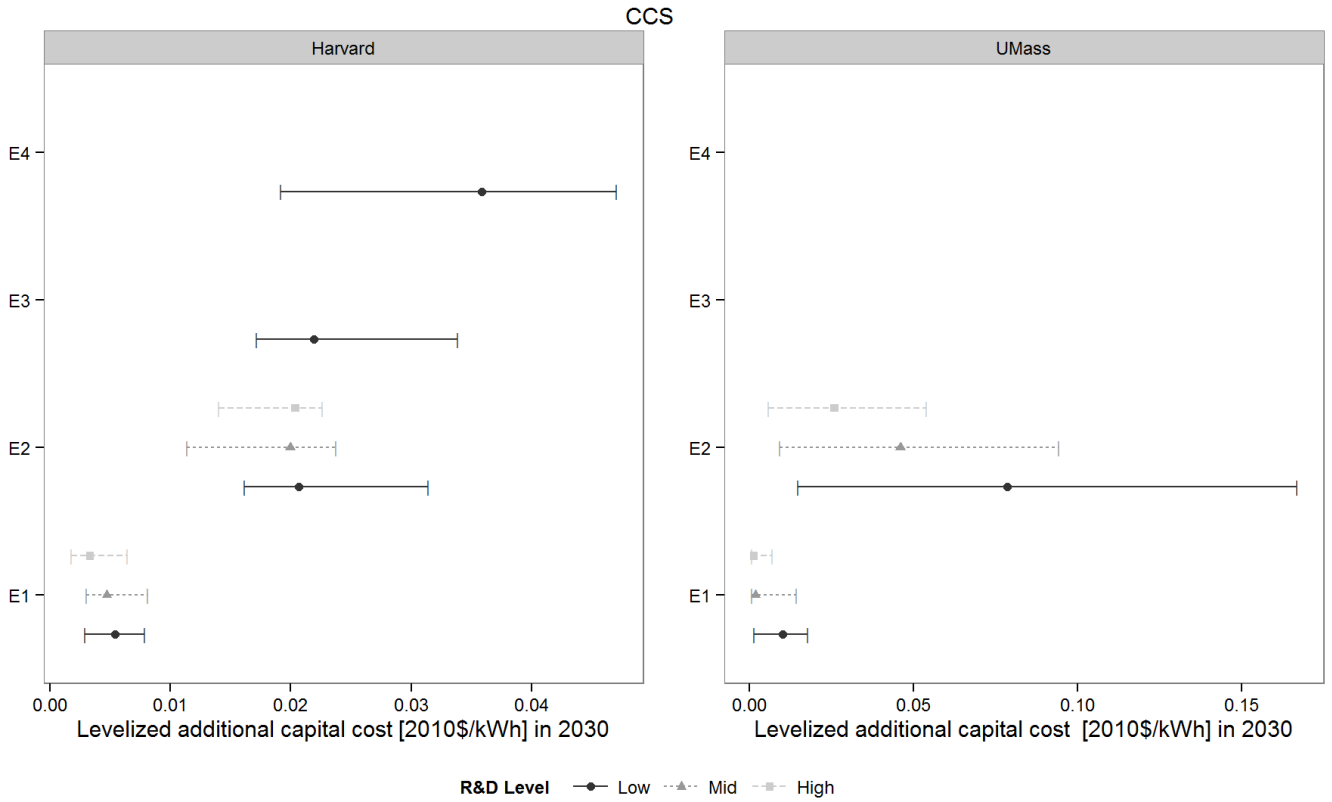


Figure 3: Experts' results of the CCS surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

GenIII/III+

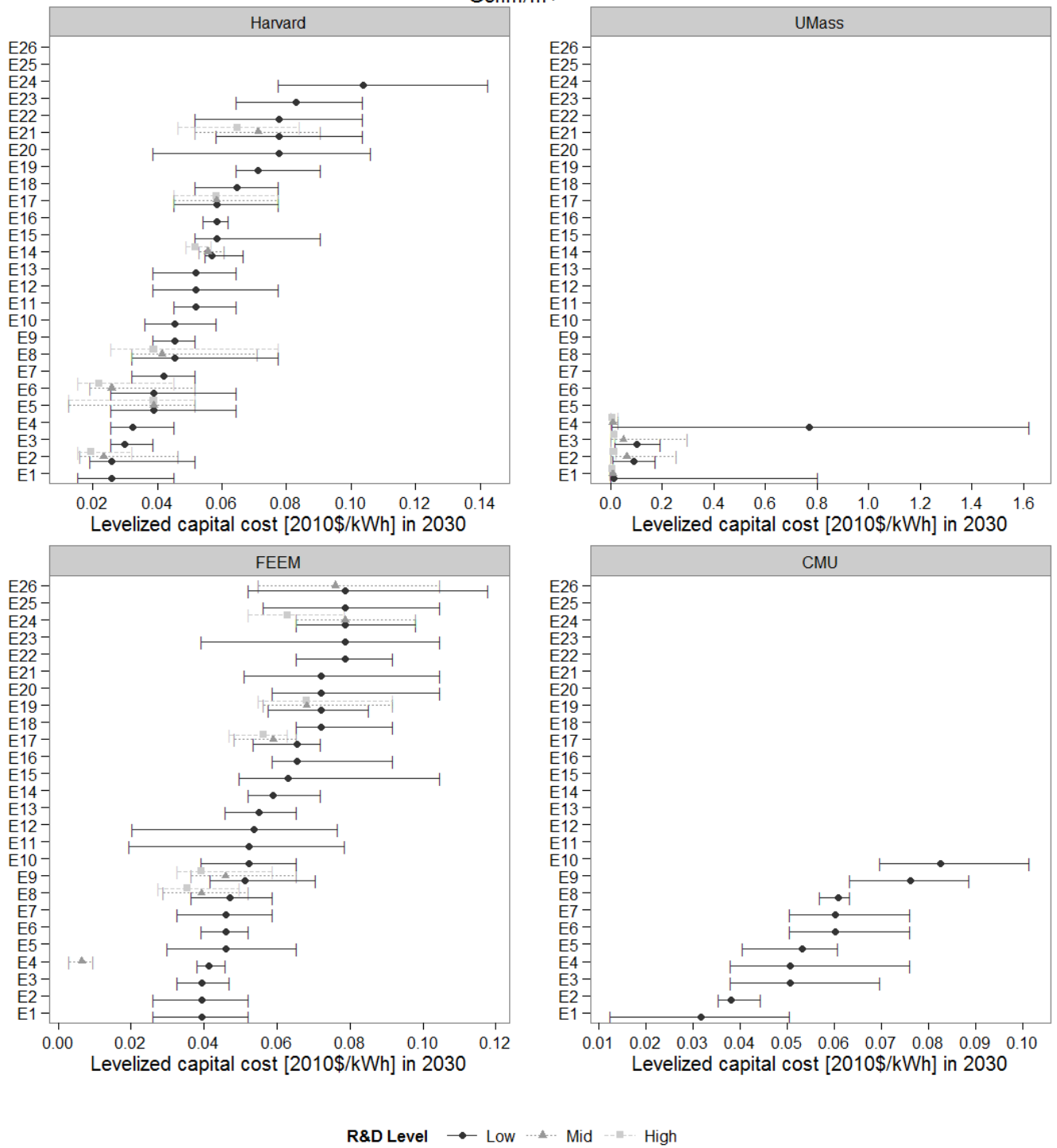


Figure 4: Experts' results of the nuclear GenIII/III+ surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

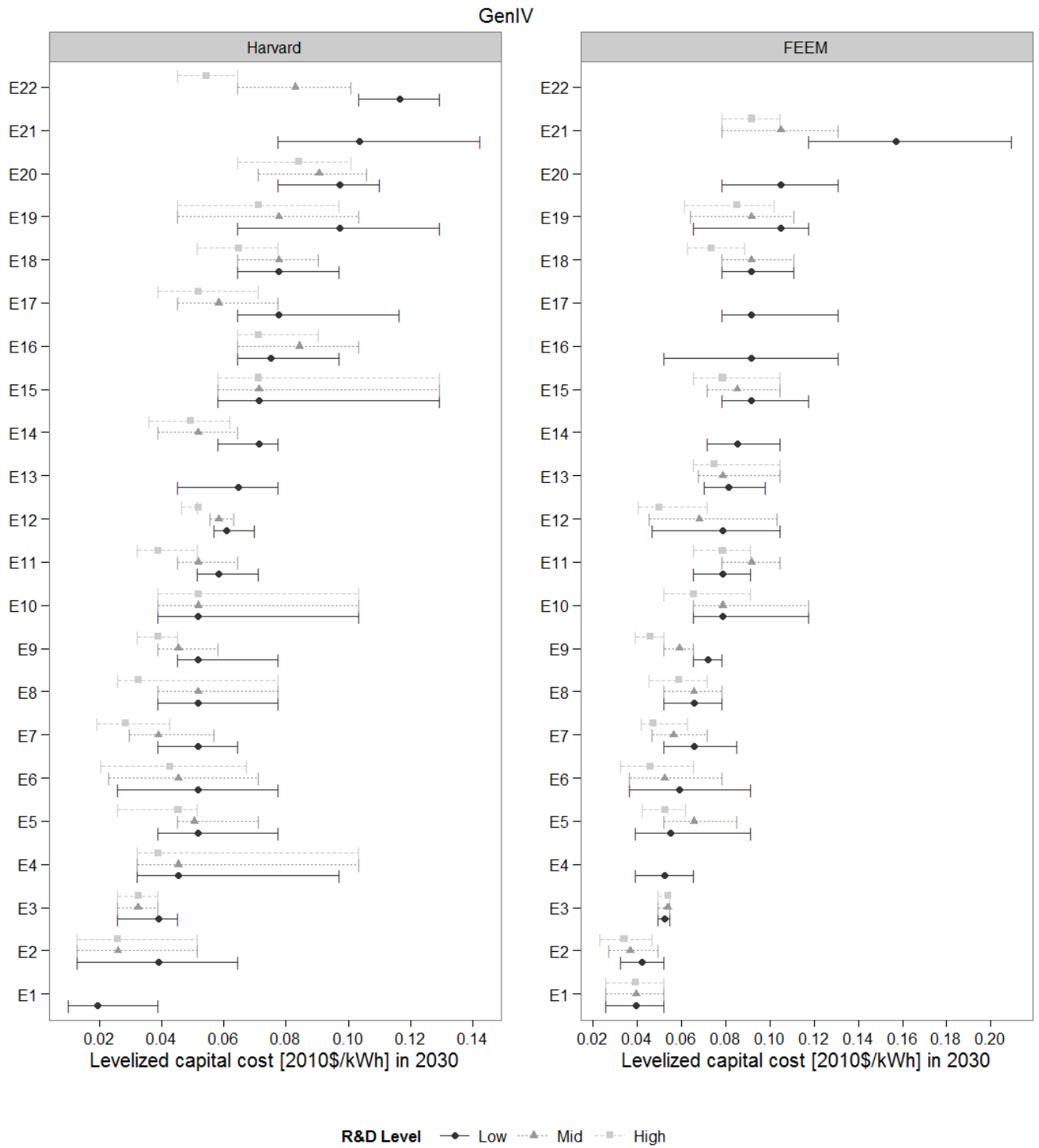


Figure 5: Experts' results of the nuclear GenIV surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

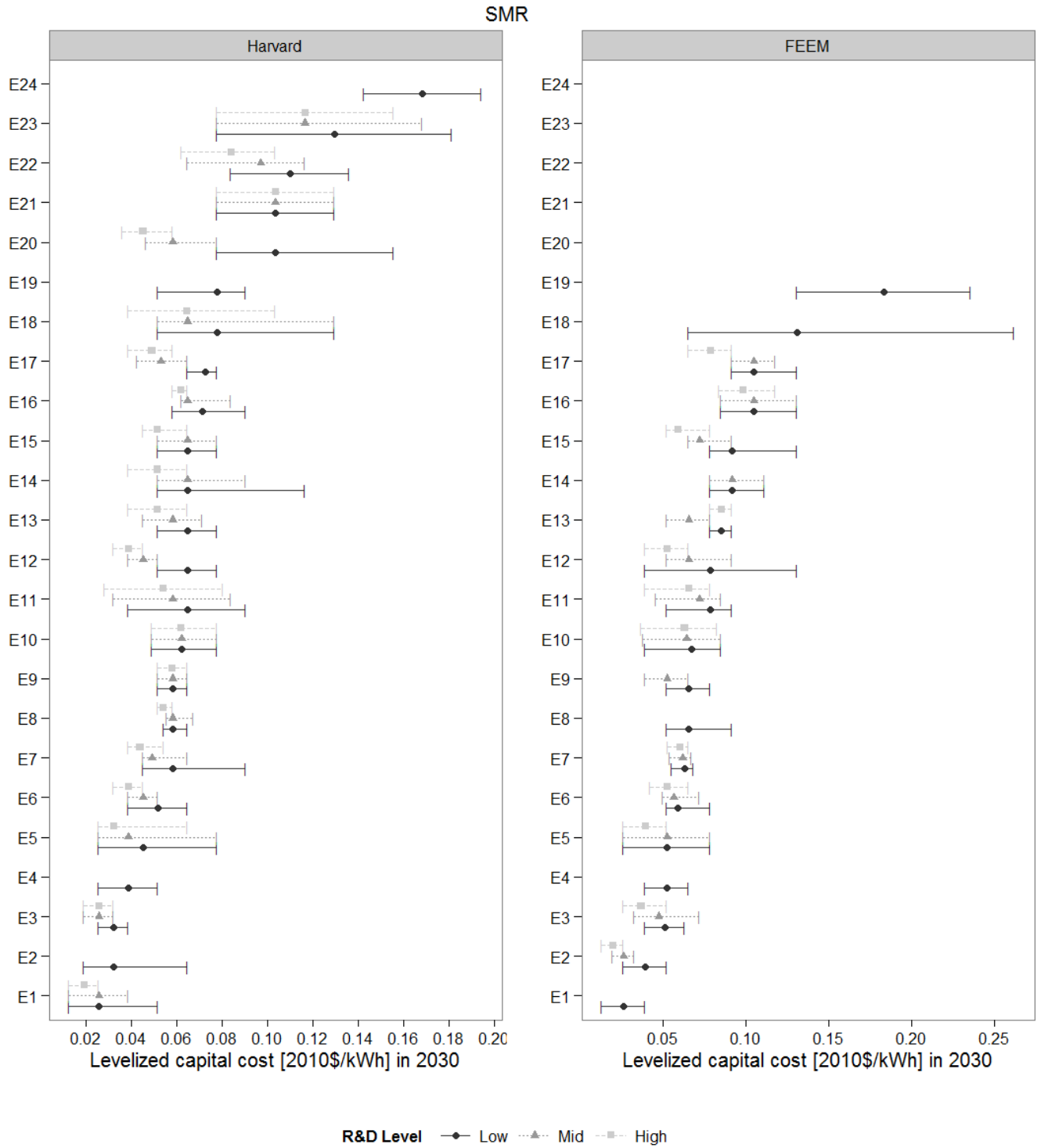


Figure 6: Experts' results of the nuclear SMR surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

SOLAR PV

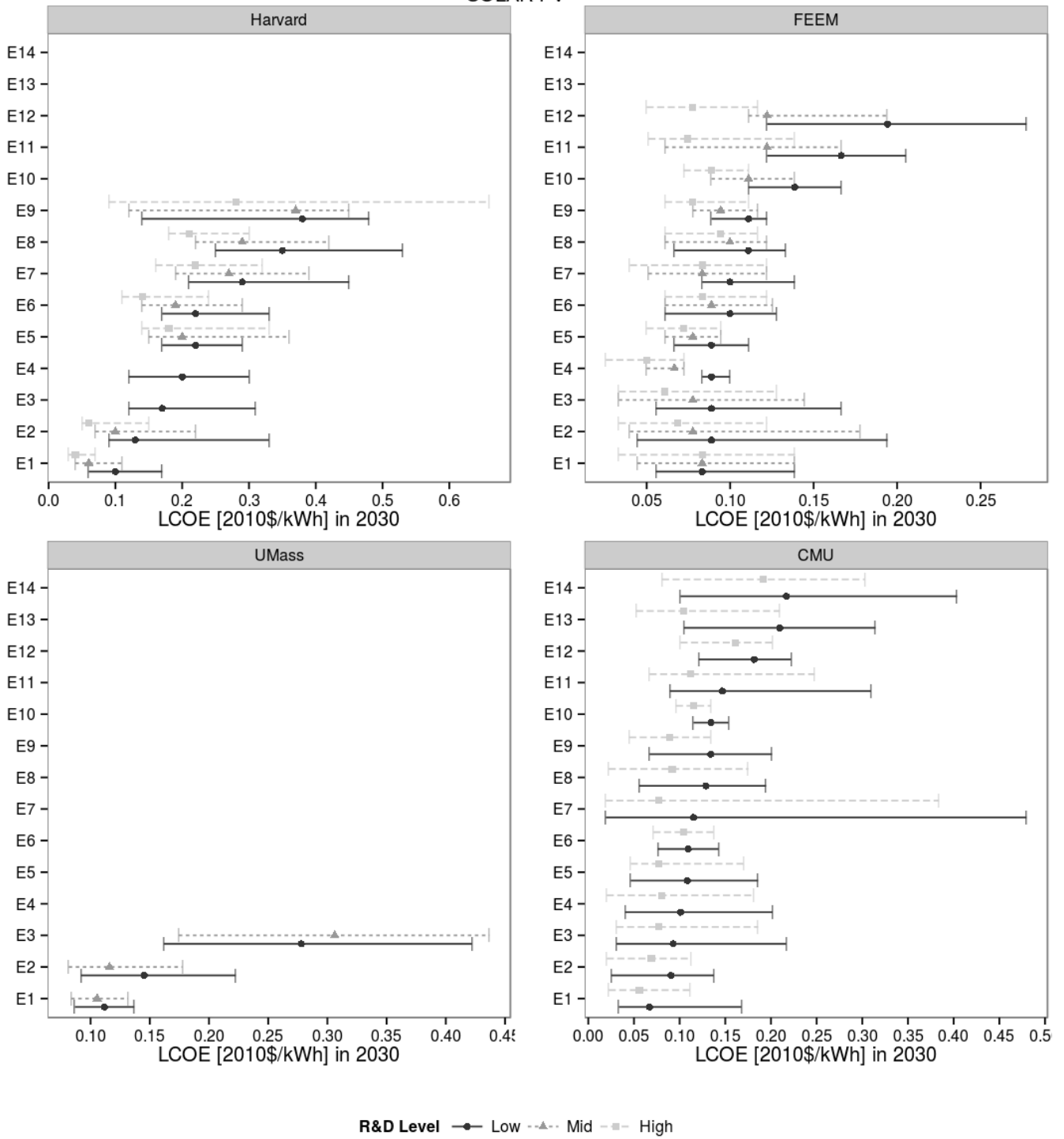


Figure 7: Experts' results of the PV surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

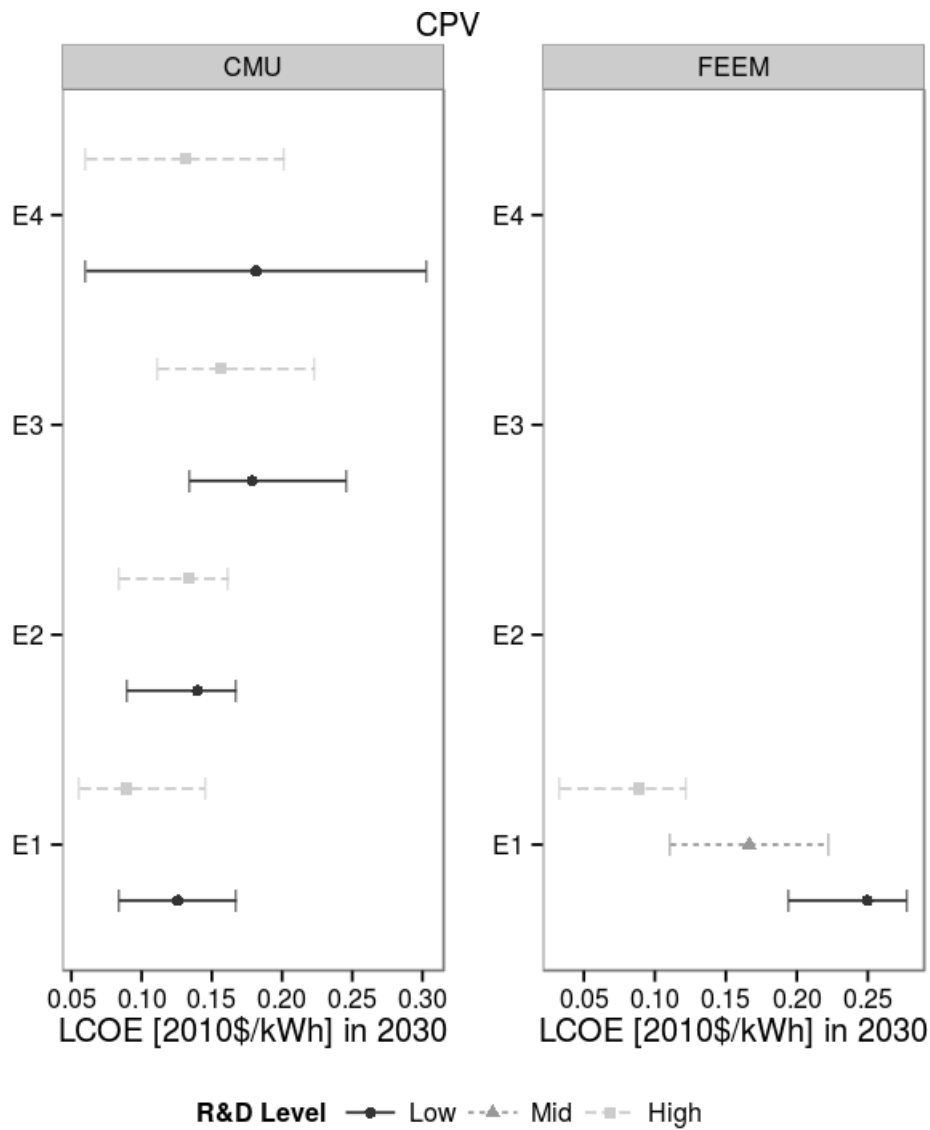


Figure 8: Experts' results of the CPV surveys per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

Individual experts non harmonized surveys

CCS

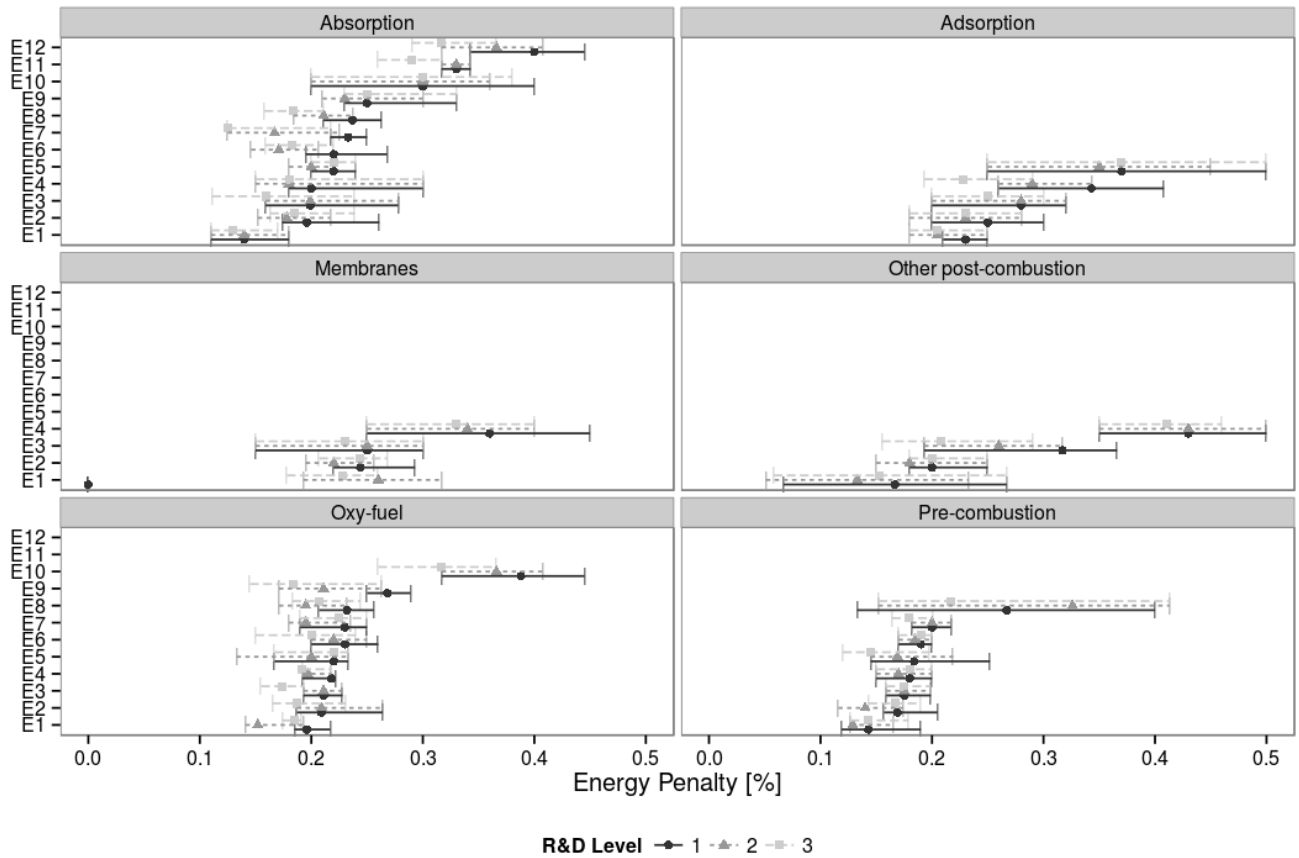


Figure 9: Experts' results of the UMass (Jenni et al 2013a) CCS survey per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

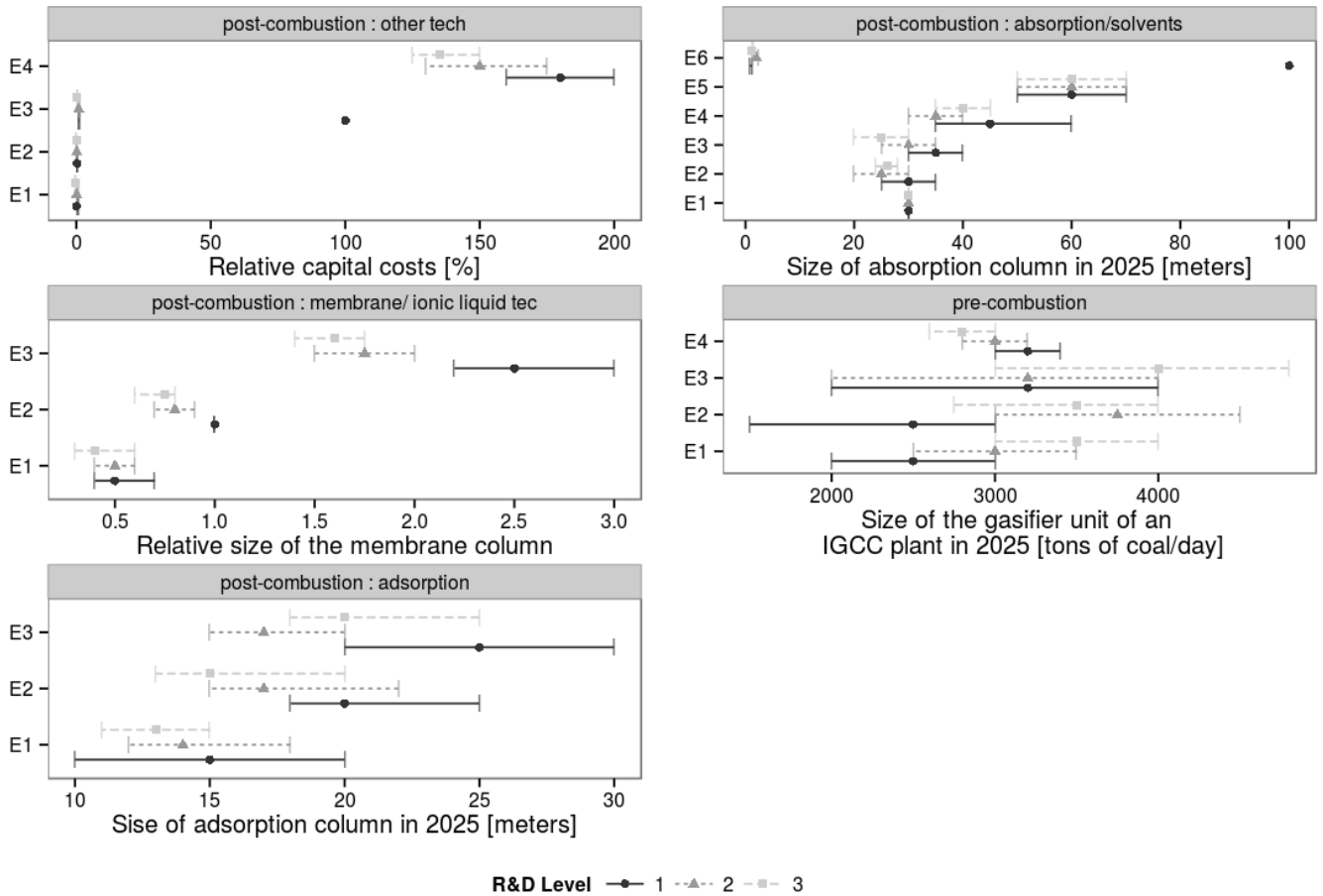


Figure 10: Experts' results of FEEM CCS survey per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile. R&D level 1 corresponds to no further R&D for the specific capture technology is funded by the EU; R&D level 2 is as level 1 but some type of carbon price is enacted worldwide, beginning in 2015 (assumes that whatever form the policy takes, it has the effect of about a \$100/tonCO₂ Carbon Tax worldwide); R&D level 3 assumes that the EU increases investments in a specific capture technology R&D substantially, to about \$250 million per year, starting in 2015 and continuing at that level through to 2025. (Consider that since 2002 annual R&D investments for capture technologies in the EU have ranged between 0.6-111.0 Million 2010US\$, with an average of 41.6 Million 2010US\$).

Vehicles

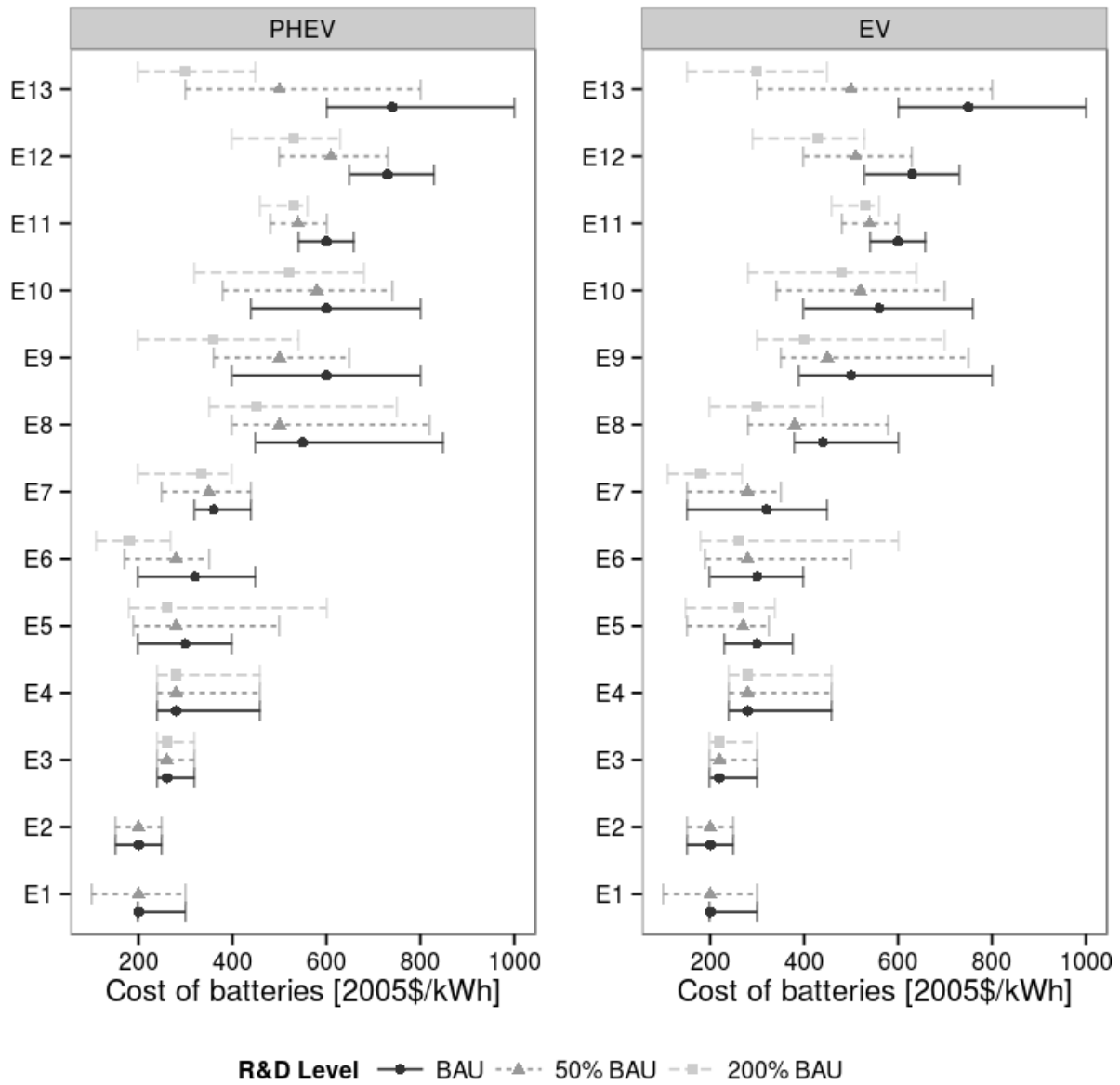


Figure 11: Experts' results of the FEEM vehicle batteries survey per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

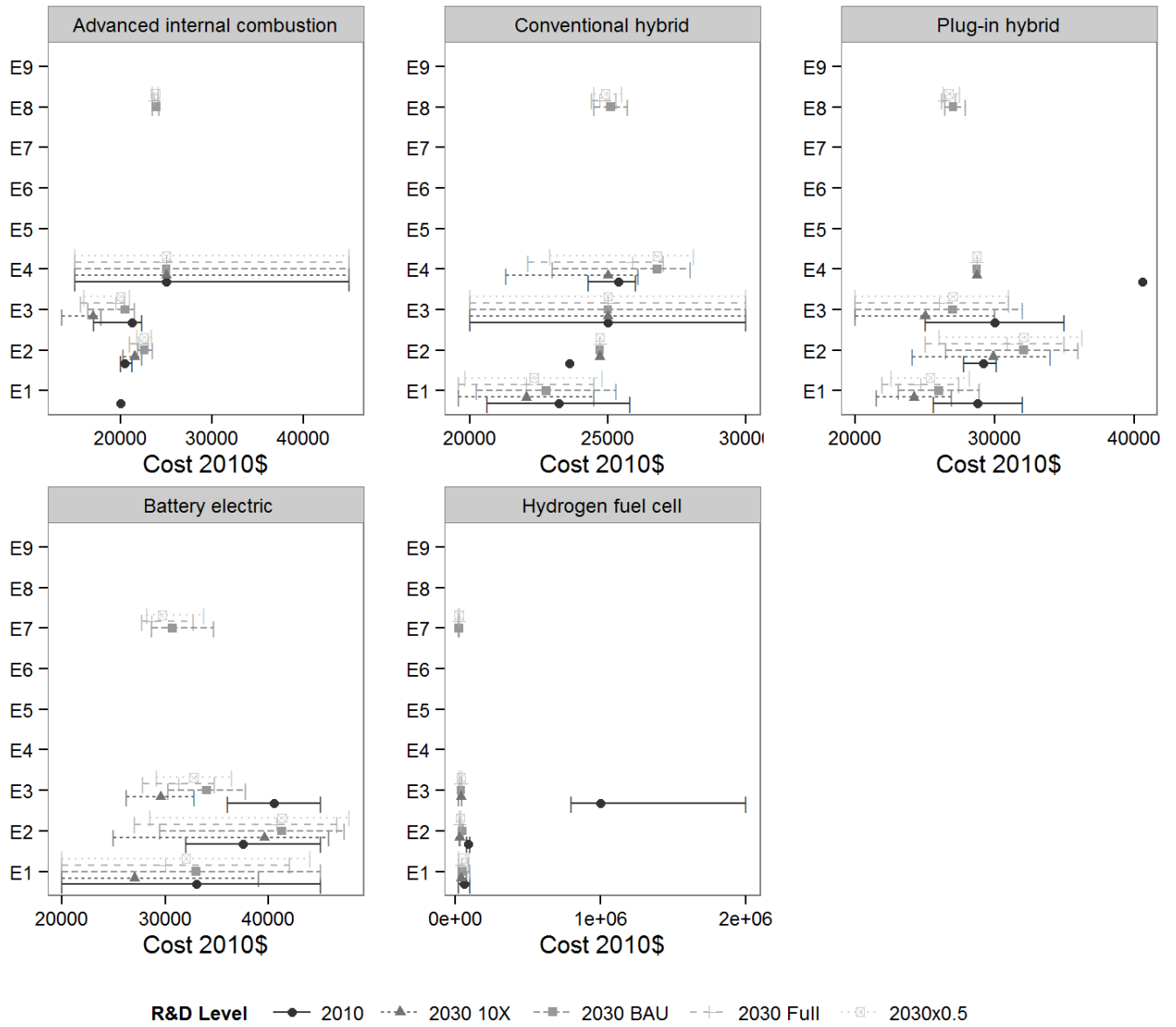


Figure 12: Experts' results of the Harvard vehicles survey per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

Utility Energy Storage

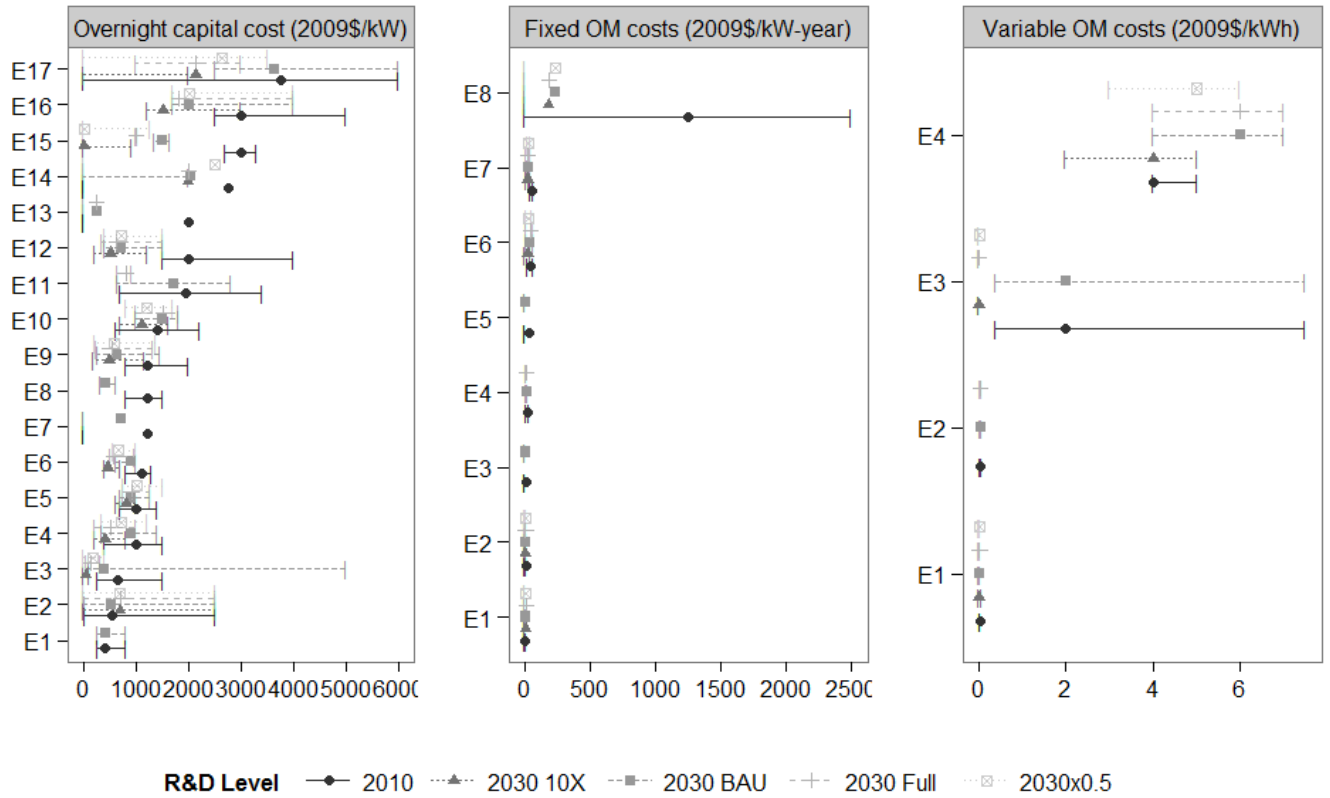


Figure 13: Experts' results of the Harvard storage survey per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

Natural Gas

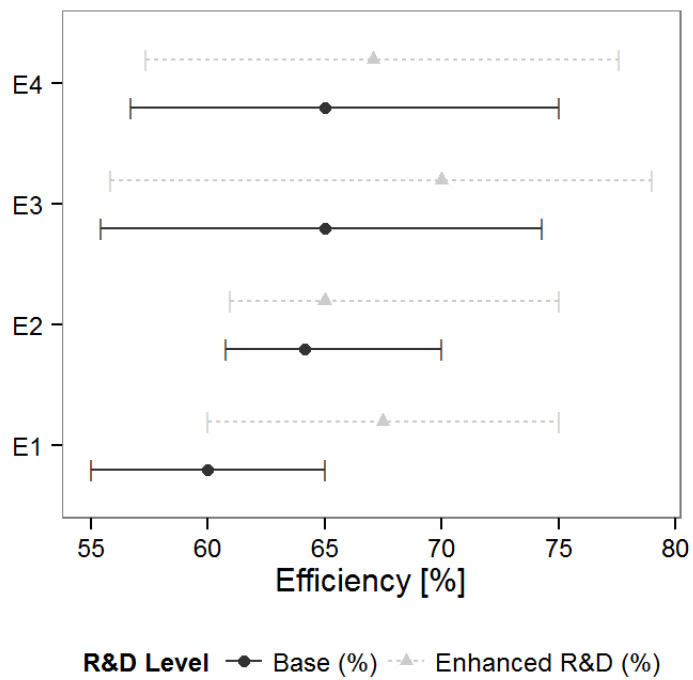


Figure 14: Experts' results of the Stanford (Bistline 2013) natural gas survey per expert and per R&D scenario. The lines range from the 10th to the 90th percentiles and the marker in between represents the 50th percentile.

Appendix B. Data Standardization Process

As noted in the appendix of Anadón et al. (2015): *“In order to compare and aggregate the values that were elicited in the individual surveys, a set of harmonizing assumptions had to be made to allow a meaningful comparison. For each of the assumptions that differ across studies (i.e., as currencies and currency years, endpoint years, and other underlying technical factors) we had to make a decision on what value to converge to. The harmonization process per se required months of research and discussions between the authors of the different elicitation studies”*. This Appendix briefly summarizes the data cleaning and harmonization procedures. We refer the interested reader to the original articles (Anadón et al 2013; Anadón et al.2015; Baker et al. 2015; Verdolini et al. 2015; Nemet, et al 2016) for further details. This Appendix borrows heavily from the Appendices and explanations included in these articles. First, whenever elicitation groups collected different metrics, the harmonization process entailed constructing a model to make the data comparable using common assumptions (e.g., insolation and discount rates). Details in this respect are explained below in subsection B.1 and organized by technology (Nemet et al. 2016). Second, all surveys included in the harmonization procedure elicited costs in 2030, with the exception of the UMass studies, which asked experts about 2050. The explanation of how UMass elicited values were adjusted is presented in subsection B.2. Third, harmonization of the R&D levels is discussed in subsection B.3.

Section B.1: Harmonization of cost estimates

As argued in Section 2 of the paper, differences among studies make it challenging to compare the results of the expert elicitations. For instance, it is impossible to gather insights on the impacts of RD&D investment levels across the different studies if the elicited metrics are different. To address the issue of data comparability across different energy technology expert elicitations, a set of papers performed a standardization process on a subset of the studies listed in **Errore. L'origine riferimento non è stata trovata.** (Anadón et al 2013, Baker et al. 2015a; Verdolini et al. 2015; Nemet et al. 2016). We summarize here the main aspects of the standardization process. Details on the standardization of the budget amounts with which experts were confronted are discussed in Appendix C.

First, all elicited values were transformed in the common metric of 2010\$/kWh using common assumptions (e.g., insolation and discount rates). This common metric represented an LCOE for solar photovoltaics, a non-energy LCOE for bioelectricity, a non-energy levelized cost of fuel for biofuels, a partial levelized cost of electricity for nuclear (including only capital cost), and a levelized additional cost of CCS. Harmonization assumptions are detailed below for each technology and study. Table B.1 below was compiled using information from Anadón et al (2013); Anadón et al. (2015); Baker et al. (2015); Verdolini et al. (2015); Nemet et al (2016) and summarizes the elicited values and key assumptions for the UMass, Harvard, CMU and FEEM harmonized studies.

Another aspect is that different elicitation studies use different levels of granularity in the assessed technologies (e.g. general CCS versus absorption) and metrics. This was addressed by identifying the level of technology granularity that allowed for the largest number of elicitations, generally the most-aggregated level. For example, some nuclear surveys focused on collecting information on the most commercially-viable large-scale Gen. IV nuclear system and its future cost, while others focused on specific reactor configurations such as fast reactors and high temperature reactors. When experts provided cost estimates for different sub-technologies, only the

lowest cost sub-technology estimate is used, assuming that this would be the technology that would be most successful in the economy.

Table B1. Summary of key assumptions in harmonization process (Nemet et al. 2016)

Group	Biofuels	Bioelectricity	CCS	Nuclear	Solar
UMass metrics elicited	Capital cost per gge (gallon of gasoline equivalent), capacity,	Various technical endpoints	Various technical endpoints	Various technical endpoints	Manufacturing cost per m2 efficiency lifetime
FEEM metrics elicited	Cost per gge O&M cost	Cost per kwh O&M cost	N/A	Overnight capital cost	LCOE
Harvard metrics elicited	Cost per gge Plant life yield (gge/dry ton feedstock) feedstock costs	Cost per kwh Plant life yield (gge/dry ton feedstock)	Overnight capital cost (\$/ Generating efficiency HHV Capacity factor Book life	Overnight capital cost (\$/ Fixed O\M cost Variable O\M cost Fuel cost Thermal burnup	Module capital cost per Wp Module efficiency Inverter cost Inverter efficiency Inverter lifetime
CMU metrics elicited	N/A	N/A	N/A	Overnight capital cost	Module prices in \$/W for different solar systems
Common Metrics Harmonized	Non-energy levelized cost of fuel	Non-energy LCOE	Levelized capital cost	Levelized capital cost	LCOE
Key Assumptions	0.031 kwh=1gge See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates	See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates	Interest Rate=0.1 Lifetime=40 See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates	Interest Rate=0.1 Lifetime=40 Capacity Factor=0.9 See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates	Capacity Factor: 12% Factor Discount rate: 10% Hours per year: 8760 Lifetime: 20 BOS m2: 75 UMass, 250 Harvard Cost of Power Cond (\$/Wp): 0.1 Moduel Area Costs (\$/m2): 350 Peak Power Insolation (Wp/m2): 1,000 See description below about assumptions needed to turn UMass 2050 estimates to 2030 estimates For CMU solar, Module prices \$/W were converted into LCOE \$/kWh using the average values from the Harvard study for the other cost components and BOS as well as other assumptions above

Section B.2 Temporal harmonization of UMass data

As explained in Anadón et al. (2015): “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 using Moore's Law and parameters from Nagy et al. (2013). Nagy et al. (2013) analyzed a large dataset for several technologies, and concluded that the estimated costs that used only the parameter time performed approximately as well as the traditional experience curve. Thus, we use the following relation based on Moore's Law:

$$c_t = t_t e^{-m(t-\tau)}$$

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

$$m = Bg$$

This method is used to estimate the values for 2030:

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

The parameter m is calculated using the learning parameters B , taken from the literature, and the growth parameter g provided in Nagy et al. (2013). A summary for all technologies is reported in Table B.2.

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 B.2. reprinted with permission from Baker et al 2014(a)

Section B.3: RD&D investment assumptions in expert elicitation and harmonization of R&D levels

Twenty-four of the studies reviewed here specifically conditioned on RD&D funding scenarios. As noted in appendix of Anadón et al. (2015), the UMass, Harvard and FEEM experts were confronted with different R&D scenarios as explained below: “Experts were asked to assess future costs and performance of energy technologies, for three given levels of R&D funding by governments in order to study the effect of government R&D on reducing the costs of clean energy technologies. Each team defined R&D funding levels differently. [...] 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, and 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). And, while both Harvard and FEEM included demonstration expenditures, UMass asked questions about smaller R&D scenarios that did not include demonstration expenditures.

The CMU nuclear cost elicitation made R&D assumptions consistent with a BAU scenario (Low R&D). Conversely, the solar CMU study made assumptions about both R&D investment and specific deployment levels. Specifically, experts were asked for their estimates under four scenarios:

- a) Status quo, defined as 2008 government RD&D funding levels for the PV technology being considered and current government incentive levels for deployment of PV technologies in general;
- b) 10x RD, defined as 10 times the 2008 RD&D level
- c) 10X deploy, defined as a 2008 RD&D investment level, accompanied by a 10-fold increase in deployment in the United States
- d) 10X deploy and 10X RD&D, defined as a combination of scenarios (b) and (c).

Scenario (a) was categories as “low” RD&D and elicitation, while scenarios (b) as “high” RD&D. Data for scenarios c and d were not used.

Table 3 summarizes the details of the assumptions about RD&D funding scenarios for the studies which underwent the standardization process described in Section 2.

Table B.1: RD&D levels in expert elicitations

Group	RD&D Level (million 2010\$)				Comments
	Low	Medium	High	Excluded from present study	
Bioelectricity					
UMass	15	50	150		
Harvard	BAU: 214	Ave. REC RD&D (585)	10 REC RD&D	0.5 REC RD&D	<i>Includes biofuels budget</i>
FEEM	169	254	338		
Biofuel					
UMass	13	201	838		
Harvard	BAU: 214	Ave. REC RD&D (585)	10 REC RD&D	0.5 REC RD&D	<i>(includes bioelectricity budget)</i>
FEEM	168	252	336		
Carbon Capture and Storage					
UMass	13	48	108		
Harvard	BAU: 701	Ave. REC RD&D (2,250)	10 REC	0.5 REC	<i>includes coal and gas CCS budget</i>
CMU	BAU	10 BAU		Deployment scenarios	
Nuclear power					
UMass	40	480	1980		
Harvard	BAU: 466	Ave. REC RD&D (1,883)	10 REC	0.5 REC	<i>(includes Gen III+ and IV, both large-scale and SMRs)</i>
FEEM	BAU: 800	Ave. REC RD&D (1,514)	10 REC	0.5 REC	<i>(includes Gen III+ and IV, both large-scale and SMRs)</i>
CMU	BAU: 466				<i>No explicit assumptions on RD&D, but consistent with BAU RD&D budget.</i>
Solar power					
Umass	25	140			
Harvard	BAU: 143	Ave. REC RD&D (409)	10X REC	0.5X REC	
FEEM	171	257	342		
CMU	BAU	10 BAU		Deployment scenarios	

Section B.4. Quantitative analysis of results from multiple elicitations

We now summarize the results of three studies which investigated the impact of study design on the outcomes of expert elicitations, using the standardized data from a subset of the expert elicitations presented above. As discussed in Section 2, differences in the protocol design (i.e., metrics, target year, mode, RD&D scenarios) and the background and geographic area of the experts make it difficult to draw insights through a simple juxtaposition of elicited cost estimates.

Anadón et al (2013); Verdolini et al. (2015); Nemet et al. (2016) use a meta-analytic approach to test whether expert or survey characteristics, including assumptions about technology granularity and R&D levels, impact elicited values in a statistically significant way. The three papers use similar methods, but cover different sets of studies: Anadón et al. (2013) focus on nuclear power, Verdolini et al. (2015) on solar PV, and Nemet et al. (2016) pulls together 16 surveys on five energy technologies (solar, nuclear, biofuels, bioelectricity and coal with CCS). The studies investigate two sets of independent variables: percentiles (10th, 50th, and 90th representing “best-case/breakthrough scenario,” median expected future costs and “worst case scenario”) and a normalized measure of the range of uncertainty. The four key categories of variables included: (1) technology characteristics,

(2) R&D levels, (3) expert characteristics (sectoral background and geographic area), and (4) study characteristics (elicitation mode, year of elicitation, whether elicitation was published in a peer-reviewed journal).

Overall, the three studies provide strong indication that: public RD&D investment has an impact on elicited costs, both at the median and at the extremes of the distribution. Such impact is, however, technology specific in that the returns to RD&D investment differ by technology in a significant way. This reflects different technological maturity and perceived cost-reduction options. Conversely, the level of public RD&D investment considered does not generally affect the uncertainty range of elicited costs. In a number of cases, expert background and geographic location are associated with lower or higher cost estimates, but this effect is technology specific and cannot be generalized. This probably reflects the experience of experts with a given technology. It also raises the issue of selecting experts from different backgrounds to capture a wider variation in elicited costs. In-person surveys are associated with broader uncertainty ranges. This suggests that current online methods are not as good as an interviewer in getting experts to think more broadly. While it would be ideal to explore these findings further within an experimental design in which only one variable is changing at a time, they provide initial evidence that elicitation design impacts the elicited metrics.

Appendix C. Energy RD&D Investments

In this section, we present an overview of historical energy RD&D budget levels and allocations globally by public and private actors, and of experts' future looking recommendations about public U.S. energy RD&D levels and allocation.

Section C.1. Sources of Public and Private RD&D data

There are two main sources of information on public energy technology RD&D budgets for developed countries. The International Energy Agency collects RD&D Budget/Expenditure Statistics for 29 IEA Member countries for several large technology categories: energy efficiency; fossil fuels; renewable energy sources; nuclear fission and fusion; Hydrogen and fuel cells; other power and storage techs; Total other cross-cutting technologies or research.¹ Data includes both budgeted and expenditure amounts, and is generally available starting in the 1980s. More granular information on the allocation of RD&D within each technologies (for instance, for the categories of “solar heating and cooling,” “PV,” “solar thermal power and high-temperature applications,” and “unallocated solar energy” within solar energy more in general) has become available only recently and not for all countries.

Statistics on energy-related public RD&D budgets (but not expenditures) are also collected as part of the GBAORD database by EUROSTAT and the OECD (OECD 2016). Statistics include government-funded RD&D performed in government establishments but also government-financed RD&D in the other sectors (business enterprise, private non-profit, higher education) as well as abroad (including international organizations) and are collected under different socio-economic objective (SEO).² One of the 13 SEOs of public RD&D funding is “Production, Distribution and Rational Utilization of Energy”, which also includes research on processes designed to increase the efficiency of energy production and distribution, and the study of energy conservation.

In addition to these public efforts in funding energy R&D, private investments also have a crucial role, although information on private energy R&D investments is rather poor. The few available data sources in this respect offer a partial picture of private investments in the broad category of energy technologies. The comprehensiveness of data on private RD&D in electricity generation technologies, especially renewables, is relatively good. Conversely, information on other technologies, such as vehicles and batteries, is very limited.

The data sources reporting the level of private energy RD&D investments in developed countries include:

- The US National Science Foundation Industrial Surveys (the BRDIS – Business Research and Development and Innovation Survey, NSF 2015), described in Anadón et al. 2014. Before 2008, BRDIS had 3 broad

¹ Countries covered include: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Republic of Korea, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States. Iceland, Chile, and Mexico are OECD members, but are not IEA members. For further details see (IEA 2015).

² The SEOs are based on the Nomenclature for the Analysis and comparison of Scientific programs and Budget (NABS) 2007 classification. These include Exploration and exploitation of the earth, Infrastructure and general planning of land-use, Control and care of the environment, Protection and improvement of human health, Production, distribution and rational utilization of energy, Agricultural production and technology, Industrial production and technology, Social structures and relationships, Exploration and exploitation of space, Research financed from GUF, Non-oriented research, Other civil research, Defense.

technology classes (nuclear energy, fossil energy and all other) and only covered about 100 large firms. After 2008 it covered over 11,000 firms, and provided a clear definition of “energy”, but it did not provide results disaggregated by technology area. Data is available since 2000, and the most recent available estimate (2010) from this sources indicates private energy R&D investments in the United States for over \$16 billion in 2010\$ for a total of 11,557 firms.

- The EU Joint Research Center (Wiesenthal et al. 2012), which estimates private investments in technologies that are part of the Strategic Energy Technology Plan for the year 2007. The SET Plan technologies include wind energy, photovoltaics (PV) and concentrating solar power (CSP), CCS, biofuels, hydrogen and fuel cells, smart grids, nuclear fission, and nuclear fusion. Wiesenthal et al. (2012) use a bottom up approach refining basic data on individual companies taken from the EU Industrial RD&D Investment Scoreboard and companies’ annual reports with other publicly available data and direct contacts with individual enterprises and. Information details totals by technology and country, but not firm counts. Using this methodology, they estimate that corporate R&D in 2007 for non-nuclear technology areas was around €1.66 billion €2007, with a margin of error of 24%. Given the broader definition of energy R&D used in the NSF BRDIS survey, the EU and US numbers presented are not comparable.
- The JRC-IPTS Scoreboard which contains information on corporate R&D financed by the top 1400 EU and non EU firms. R&D expenditures are allocated to the parent company, thus effectively assigning all the R&D investment to the country where the parent company is located, independently of where the actual R&D expenditure took place. A focus on the power sector is available for the time period 2007- 2010, where the sectors Electricity, Gas, water & multi-utilities, and Alternative energy are defined. However, some firms reported in the Scoreboard and that perform R&D relevant to the power sector are classified elsewhere, as their main product segment is not power generation. For example, the Japanese Company Hitachi Kokusai Electric is classified under the Electronic equipment sector, but it sells most of its products (69% of total sales) to the power sector. General Electric, which according to the ICB classification standards falls under General Industries, perform research in many areas closely connected to power generation such as wind turbines and sells 9% of its products to the power sector.
- The OECD ANBERD Database (BERD) database, which is a source of information on sectoral RD&D expenditure performed. Within the database, expenditures for the sector “Electricity, water and gas distribution industry” sector are detailed. There are two main challenges in using the ANBERD data. First, the statistics are presented by sector of performance expenditures regardless of whether funding was sourced from private or public spending, and expenditures by large energy authorities are frequently classified in the service sector and this can distort the international comparison at the industrial level. Second, the sector “Electricity, water and gas distribution industry” is clearly not capturing in a satisfactory way the R&D expenditure related to power production and distribution, as much of it is carried out in other sectors such as mining and machinery which provide capital and material inputs to energy production.

Both public and private energy RD&D data in middle- and low-income countries is also hard to find, since it is not compiled systematically. A recent Harvard study showed that middle- and low-income countries’ investments in energy technology R&D are however becoming sizeable and must be taken into account in an effort to think about the future evolution of technologies. Kempener et al. (2010) and Kempener et al. (2014) present data for the each of the BRIMCS countries (Brazil, Russia, India, Mexico and South Africa) for one year into categories compatible with the IEA technology categorization. Kempener et al (2010) show estimates for 2008 of *at least* \$13.8 billion 2008\$ PPP (an estimate that includes funding from state owned enterprises

where the government has a majority stake). The data are only available namely: fossil (including CCS), nuclear, electricity, transmission, distribution and storage, renewable energy sources, energy efficiency, and other. The “at least” caveat mentioned above is important because there were many categories for which data was not available for a particular country, which does not mean that there was no expenditure in the area. In the same year, governments in IEA member countries reported investing \$12.7 billion 2008\$ PPP.

Recently, the Bloomberg New Energy Finance (BNEF 2014) started collecting data on renewable energy investments globally. These include not only public and private RD&D expenditures, but also information on venture capital, private equity, asset finance focusing on energy technologies. The Frankfurt School, UNEP, and Bloomberg New Energy Finance used this information to publish a yearly report on energy investment with global coverage since 2010. While including information on key developing countries, the data only covers renewable power and fuels (thus, it does not include, for example, vehicles, efficiency, nuclear, or CCS). Other major limitations of this data source are that the number and size of the firms included in the estimates are not specified, that it is unclear how the renewables R&D budget for big corporations active in both energy and non-energy technology areas is determined, and what the criteria are for including firms. Nonetheless, this source indicates a budget of \$5 billion 2014\$ in corporate RD&D in renewables in 2013, which, according to their estimates, is roughly the same size as the amount of government R&D for clean energy.

Section C.2. Past RD&D investments

A clear understanding of the magnitude and impact of past energy RD&D would help towards designing robust RD&D investments portfolios. Unfortunately, there is a pervasive lack of data compounded by difficulties in attributing technological change to individual causes; this has made it difficult to assess the effectiveness of public RD&D investments. As evident from Table 2, it is extremely hard to grasp the magnitude of energy-related RD&D investments from these different data sources. Estimates are not comparable across different sources given differences in the technologies considered, the methodologies used to collect data (budget versus expenses, whether the data is allocated to parent company in the home country or in the country where it is spent, etc.). Furthermore, insights on the trends in energy-related RD&D expenditures are hard to draw given the lack of time-series data, with the exception of public investments in OECD countries reported by the IEA. The USA and Europe lead in terms of investments. However, fast-developing countries are increasing their investments, with China doing so at an impressive rate (Anadón 2012).

Table C.2 provides information on public and private RD&D investments from several of the sources described in Section C.1 above. As evident from the table, it is extremely hard to grasp the magnitude of energy-related RD&D investments from these different data sources. Estimates are not comparable across different sources given differences in the technologies considered, the methodologies used to collect data (budget versus expenses, whether the data is allocated to parent company in the home country or in the country where it is spent, etc.). Furthermore, insights on the trends in energy-related RD&D expenditures are hard to draw given the lack of time-series data, with the exception of public investments in OECD countries reported by the IEA. The USA and Europe lead in terms of investments. However, fast-developing countries are increasing their investments, with China doing so at an impressive rate (Anadón 2012).

Table C.2: Energy RD&D investments by country (or region), public and private, various sources, 2010USD.

Country	Source	Source	Technology	2004	2005	2006	2007	2008	2009	2010	2011
Brazil	BNEF (2012)	Corporate R&D	Renewable energy ¹	9	9	19	47	38	47	38	38
	Kempener et al. (2010)	Government R&D	Fossil energy (incl.CCS)	65	69	90	102	80			
	Kempener et al. (2010)	Other	Fossil energy (incl.CCS)	603	755	1,208	1,256	1,182			
	Kempener et al. (2010)	Government R&D	Renewable energy	47	45	67	47	15			
China	BNEF (2012)	Corporate R&D	Renewable energy	19	19	28	85	19	304	437	304
	Kempener et al. (2010)	Government R&D	Fossil energy (incl.CCS)	3,545	3,810	4,646	5,614	6,844			
	Kempener et al. (2010)	Other	Fossil energy (incl.CCS)	41	56	47	106	293			
	Kempener et al. (2010)	Government R&D	Renewable energy								
	Binz et al. (2015)	Special Programs relevant for Energy	energy expenditure of 973 project	11	12	12	20	22	31	38	41
	Binz et al. (2015)	Special Programs relevant for Energy	energy expenditure of Gongguan project	8	15	24	23	31	20	20	23
Europe*	IEA (2016)	Government R&D	Renewable energy	364	487	559	676	733	1,082	1,282	
	IEA (2016)	Government R&D	Fossil Fuels	244	264	291	323	309	377	425	
	OECD (2016)	Government R&D (Federal budget)	Energy	2,191	2,656	2,687	3,101	3,875	3,770	3,960	3,827
	BNEF (2012)	Corporate R&D	Renewable energy	1,083	712	883	703	1,102	1,216	1,339	921
	Wiesenthal et al. (2012b)	Corporate R&D	non nuclear SET Plan Technologies ²				2,312				
India	BNEF (2012)	Corporate R&D	Renewable energy	0	0	9	9	28	57	57	38
	Kempener et al. (2010)	Government R&D	Fossil energy (incl.CCS)	148	97	311	188	107			
	Kempener et al. (2010)	Other	Fossil energy (incl.CCS)	2,420	1,585	566	1,396	703			
	Kempener et al. (2010)	Government R&D	Renewable energy	39	18	31	46	58			
United States	IEA (2016)	Government R&D	Renewable energy	272	272	214	571	451	2,202		
	IEA (2016)	Government R&D	Fossil Fuels	483	436	435	464	569	3,351	454	
	OECD (2016)	Government R&D (Federal)	Energy	1,578	1,478	1,347	2,027	2,148	3,895	2,607	2,251
	BNEF (2012)	Corporate R&D	Renewable energy	2,184	712	826	722	959	883	1,007	978
	Jones et al (2014) - NSF SIRD	Private RD&D	Energy applications ³	2,429	2,934	4,206	5,671				
	Jones et al (2014) - BRDIS	Private RD&D	Energy applications ³					16,107	16,482	16,477	

* EUROPE refers to the EU27. Note that IEA and OECD do not collect data for some of the EU27 (see sources for details)

¹ Biofuels, Biomass & Waste, Geothermal, Marine, Small Hydro, Solar, Wind

² Includes fuels cells and smart grids

³ Energy applications, including energy production, distribution, storage, and efficiency (excluding exploration and prospecting). Energy R&D in industry from the NSF SIRD survey (from 2000 to 2007) and the BRDIS survey (for 2008-2010).

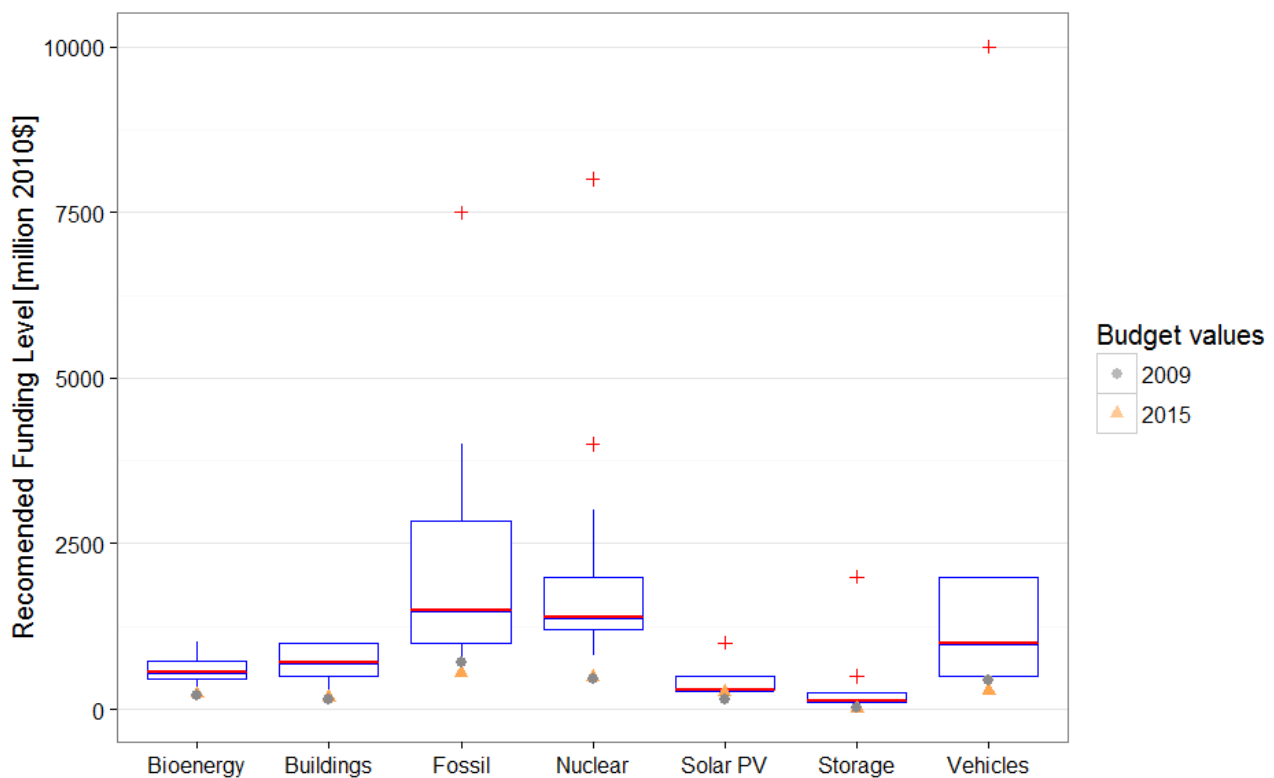
As argued in Section 3 of the paper, there are number of reports and assessments that analyze specific case studies, of, concluding that public energy RD&D investments have played a major role in cost and performance improvements.

Section C.3. RD&D Budgets in Energy Elicitations

Most of the elicitation studies listed in Table 1 considered multiple levels of RD&D funding to prompt experts to think about both business-as-usual and extreme funding scenarios. Four studies – Jenni et al 2013, Ricci et al 2014 and two NRC studies -- explicitly considered a “No RD&D” scenario. Many studies defined budgets based on multiples of current governmental RD&D budgets, including the FEEM studies (EU budgets); Curtright et al. (2008) and Chung et al (2011) (US budgets); the NRC studies, Jenni et al. (2013) (USDOE budgets). Rao et al. (2006) only specified “modest but steady growth” of the current DOE budget.

The UMass studies developed budget amounts in a bottom-up manner in conjunction with a subset of the experts for each sub-technology (e.g. purely organic solar cells, post-combustion CCS). These budgets did not include demonstration plants, and were primarily aimed at inducing scientific breakthroughs that would enable better technologies. The Harvard studies asked experts to develop a recommendation in a bottom-up fashion by allocating funding amounts to specific research areas within a technology, and to cover the spectrum from basic RD&D, applied RD&D, and demonstration plants. They then made assessments conditional four RD&D scenarios: BAU, and ½X, 1X, and 10X their recommended budget. Figure 15, sourced from Anadón et al (2014a), displays the median, minimum and maximum amount of recommended RD&D budgets by technology area, and compares it to the 2009 and 2015 U.S. Department of Energy funding allocations (see also Table ES-1 in Anadón et al 2011). Overall, Harvard experts recommended increasing public RD&D funding for specific technology on average by a factor of 2.5 (for fossil, solar, and bioenergy) to about 11 (for energy storage).

Figure 15: Recommended budgets from the Harvard studies per expert and technology.



Source: Anadón et al (2014a), *Transforming US Energy Innovation*, page 118, Figure 2.5. The figure presents range of budget recommendations from experts, by technology area. The red line represents the median recommendation; the blue box encompasses the 25th and 75th percentiles; the black lines represent the highest and

lowest recommendations within 1.5 times the interquartile range of budget recommendations. The recommendations outside this range are show with cross marks.

Section C.4. Expert recommendations on funding allocation by technology and types of RD&D

Some elicitations asked experts to provide a recommended allocation of the RD&D funds for a particular technology area across different technological paths or focus areas explored in the elicitation (e.g. how much to allocate to enzymatic hydrolysis or thermochemical conversion processes, among other areas, in the biofuels survey). In general, experts indicate that more than one sub-technological path should be explored and pursued within each technology (see for instance the discussion in Bosetti et al. 2012 and Anadón et al. 2014a). The highest allocations for more specific technology areas within each energy technology for the Harvard elicitations were for thermochemical conversion processes (pyrolysis and liquefaction) in bioenergy; oxy-fueling and IGCC in fossil and CCS; SFR (Sodium Cooled Fast Reactors) and fuel cycle for nuclear; thin films and concentrators for solar; Li-ion batteries for vehicles; and batteries and flow batteries for utility-scale storage. For the FEEM studies, thermochemical conversion process received roughly 27 percent of the biomass technology budget, Li-ion batteries 28 percent of the storage for electric vehicles budget, Algae about 14 percent of the budget for biofuel-related RD&D, and Crystalline-Si and Thin-film PV roughly 20 percent each of the solar RD&D public budget

In a related question, the Harvard and FEEM surveys asked experts to allocate funding for specific pathways across different “types” of research, namely: basic research, applied research, pilots and experiments as well as demonstration. Figure 16 shows the breakdown of the budget in the four different types of RD&D by technology for both the Harvard and FEEM studies. To provide a benchmark, the fraction of federal RD&D in the United States for all technology areas (energy and non-energy) devoted to the basic research, applied research and development in 2011 was 32%, 24% and 44%.³ As seen in Figure 2, the emphasis varied by technology area.

Figure 16. Expert’s recommended budget allocation to different phases of RD&D process (percent of total budget by technology)

FEEM					R&D Phase	Harvard				
Bioenergy	Batteries	Biofuels	Solar	Nuclear		Vehicles	Fossil R&D (including CCS)	Energy Storage	Bioenergy	Nuclear
15%	33%	20%	31%	21%	Basic Research	38%	12%	19%	20%	21%
48%	38%	38%	44%	29%	Applied Research	37%	21%	24%	22%	31%
-	-	-	-	30%	Experiments and Pilots	19%	25%	26%	29%	29%
37%	29%	42%	25%	20%	Commercial Demonstration	6%	43%	31%	29%	20%
100%	100%	100%	100%	100%	Total	100%	100%	100%	100%	100%

³ Corresponding values for the EU cannot be calculated from the available government energy statistics.

Appendix D. Current Cost of Technologies

This Appendix details the current costs used in to calculate the annual cost change rates presented in Section 5 (table D.1) and compares the annual cost decrease rates presented in section 5, Figure 3, with the parameters estimated using Moore's law as in Nagy et al. (2013) (Table D.2)

Table D.1: Technology LCOE in 2010 per technology and source.

Technology Group	Technology	Price in 2010	Unit	Source
Solar	PV	224.64	US\$2005/MWh	POLES ADVANCE
Solar	PV	177.463	US\$2005/MWh	REMIND 1.5
Solar	PV	523.912	US\$2005/MWh	WITCH
Nuclear Energy	Nuclear	4675.35	\$/kW	POLES ADVANCE
Nuclear Energy	Nuclear	3540	\$/kW	REMIND 1.5
Nuclear Energy	Nuclear	4012	\$/kW	REMIND 1.6
Nuclear Energy	Nuclear	3807.1	\$/kW	WITCH
Bioelectricity	electricity biomass	107.503	US\$2005/MWh	AIM/CGE
Bioelectricity	electricity biomass	205.396	US\$2005/MWh	GCAM 3.0
Bioelectricity	electricity biomass	130.465	US\$2005/MWh	POLES ADVANCE
Bioelectricity	electricity biomass	53.1	US\$2005/MWh	REMIND 1.6
Bioelectricity	electricity biomass	55.353	US\$2005/MWh	WITCH
Bioelectricity	Biomass gasifier	10	cUS\$/kWh	REN21 Global Status Report
Bioelectricity	Biomass power	12.75	cUS\$/kWh	Global Status Report
Bioelectricity	PV	33	cUS\$/kWh	Global Status Report
Nuclear Energy	Nuclear	4216.666667	\$/kW	IEA 2014b
CCS	CCS	0.022	2009\$/kWh	Harvard CCS survey
Biofuel	Gasoline substitute	0.063781802	2009\$/kWh	Harvard CCS survey
Biofuel	Diesel substitute	0.07681302	2009\$/kWh	Harvard CCS survey

Table D.2: Linear annual cost decreases and Moore's law estimate

Technology	Data Source	Reference Years	Coefficient from model estimating Moore's law (= -m)	Ranking based on m
Solar	Fraunhofer	2000-2014	-0.118	1
Solar	IEA	1976-2015	-0.093	2
Biofuel (Ethanol)	Goldemberg	1980-2002	-0.059	3
Solar	IEA	2015-2035	-0.042	4
Nuclear	Rangel	1978-2002	0.017	5

Nuclear	Gruebler	1977-1999	0.055	6
---------	----------	-----------	--------------	---

Technology	Source	Linear Annual Cost Decrease Rate	Ranking based on Linear Annual Cost Decrease Rate
Solar	Fraunhofer 2010-2014	-0.237/-0.222	1
Bioelectricity	Juninger 1990-2002	-0.126	2
Solar	IEA 2010-2015	-0.119	3
Solar	Fraunhofer 2000-2014;1990-2014	-0.116/-0.091	4
Solar	Fraunhofer 2000-2010; IEA 2010-2035, 2014-2035	-0.062/-0.0326	5
Biofuel	Goldemberg 1985-2002	-0.0582	6
Biofuel	Goldemberg 1980-1985	-0.0349	7
Nuclear Energy	Rangel/Gruebler 1977-2002	0.035/0.090	8

References for Supplementary Information

- Anadón, L. D. 2012. 'Missions-oriented RD&D institutions in energy: a comparative analysis of China, the United Kingdom, and the United States.' *Research Policy* 41(10): 1742-1756.
- BNEF. 2012. "Bloomberg New Energy Finance Database."
- BNEF, and Frankfurt School/UNEP Center. 2014. "Global Trends in Renewable Energy Investments 2014." Frankfurt School of Finance & Management gGmbH 2014. Retrieved from <http://fs-unep-centre.org/system/files/globaltrendsreport2014.pdf>
- IEA 2016. Energy Technology RD&D Statistics. Accessed January 2016
- Kempener, R., L. D. Anadón, and J. Condor. 2010. *Governmental Energy Innovation Investments, Policies, and Institutions in the Major Emerging Economies: Brazil, Russia, India, Mexico, China, and South Africa*. Harvard Kennedy School, Cambridge, MA. Retrieved from http://belfercenter.hks.harvard.edu/publication/20517/governmental_energy_innovation_investments_policies_and_institutions_in_the_major_emerging_economies.html.
- Kempener, R., M. Bunn and L. D. Anadón. 2014 " Maximizing the benefit from international energy innovation cooperation ", in *Transformign US Energy Innovation*. Edited by Anadón, L.D., Bunn, M., Narayanamurti, V. Cambridge University Press 2014.
- OECD 2016. GBAORD – Government Budget Appropriation and Outlines for R&D. accessed January 2016
- Wiesenthal, T., A. Mercier, B. Schade, H. Petric, P. Dowling. 2012. "A model-based assessment of the impact of revitalised R&D investments on the European Power Sector", *Renewable and Sustainable Energy Reviews* 16: 105– 112
- Wiesenthal, T., G. Leeduc, K. Hegenman, H. Schwartz. 2012b. Bottom-up estimation of industrial and public R&D investment by technology in support of policy-making: The case of selected low-carbon energy technologies. *Research Policy* 41(1):116– 131.

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/>
<http://labs.jstor.org/sustainability/>

NOTE DI LAVORO PUBLISHED IN 2016

ET	1.2016	Maria Berrittella, Carmelo Provenzano: An Empirical Analysis of the Public Spending Decomposition on Organized Crime
MITP	2.2016	Santiago J. Rubio: Sharing R&D Investments in Breakthrough Technologies to Control Climate Change
MITP	3.2016	W. Brock, A. Xepapadeas: Spatial Heat Transport, Polar Amplification and Climate Change Policy
ET	4.2016	Filippo Belloc: Employee Representation Legislations and Innovation
EIA	5.2016	Leonid V. Sorokin, Gérard Mondello: Sea Level Rise, Radical Uncertainties and Decision-Maker's Liability: the European Coastal Airports Case
ESP	6.2016	Beatriz Martínez, Hipòlit Torró: Anatomy of Risk Premium in UK Natural Gas Futures
ET	7.2016	Mary Zaki: Access to Short-term Credit and Consumption Smoothing within the Paycycle
MITP	8.2016	Simone Borghesi, Andrea Flori: EU ETS Facets in the Net: How Account Types Influence the Structure of the System
MITP	9.2016	Alice Favero, Robert Mendelsohn, Brent Sohngen: Carbon Storage and Bioenergy: Using Forests for Climate Mitigation
EIA	10.2016	David García-León: Adapting to Climate Change: an Analysis under Uncertainty
ESP	11.2016	Simone Tagliapietra: Exploring the Potential for Energy Efficiency in Turkey
MITP	12.2016	Gabriel Chan, Carlo Carraro, Ottmar Edenhofer, Charles Kolstad, Robert Stavins: Reforming the IPCC's Assessment of Climate Change Economics
MITP	13.2016	Kenneth Gillingham, William Nordhaus, David Anthoff, Valentina Bosetti, Haewon McJeon, Geoffrey Blanford, Peter Christenn, John Reilly, Paul Sztorc: Modeling Uncertainty in Climate Change: A Multi-Model Comparison
ET	14.2016	Paolo M. Panteghini, Sergio Vergalli: Accelerated Depreciation, Default Risk and Investment Decisions
ET	15.2016	Jean J. Gabszewicz, Marco A. Marini, Ornella Tarola: Vertical Differentiation and Collusion: Cannibalization or Proliferation?
EIA	16.2016	Enrica De Cian, Ian Sue Wing: Global Energy Demand in a Warming Climate
ESP	17.2016	Niaz Bashiri Behmiri, Matteo Manera, Marcella Nicolini: Understanding Dynamic Conditional Correlations between Commodities Futures Markets
MITP	18.2016	Marinella Davide, Paola Vesco: Alternative Approaches for Rating INDCs: a Comparative Analysis
MITP	19.2016	W. Brock, A. Xepapadeas: Climate Change Policy under Polar Amplification
ET	20.2019	Alberto PENCH: A Note on Pollution Regulation With Asymmetric Information
EIA	21.2019	Anil Markandya, Enrica De Cian, Laurent Drouet, Josué M. Polanco-Martínez, Francesco Bosello: Building Uncertainty into the Adaptation Cost Estimation in Integrated Assessment Models
MITP	22.2016	Laura Diaz Anadon, Erin Baker, Valentina Bosetti, Lara Aleluia Reis: Too Early to Pick Winners: Disagreement across Experts Implies the Need to Diversify R&D Investment
ESP	23.2016	Claudio Morana: Macroeconomic and Financial Effects of Oil Price Shocks: Evidence for the Euro Area
EIA	24.2016	Wei Jin, ZhongXiang Zhang: China's Pursuit of Environmentally Sustainable Development: Harnessing the New Engine of Technological Innovation
EIA	25.2016	Doruk İriş, Alessandro Tavoni: Tipping Points and Loss Aversion in International Environmental Agreements
ET	26.2016	Doruk İriş, Jungmin Lee, Alessandro Tavoni: Delegation and Public Pressure in a Threshold Public Goods Game: Theory and Experimental Evidence
EIA	27.2016	Stefan P. Schleicher, Angela Köppl, Alexander Zeitlberger: Extending the EU Commission's Proposal for a Reform of the EU Emissions Trading System
EIA	28.2016	Tomas Ekvall, Martin Hirschnitz-Garbers, Fabio Eboli, Aleksander Sniegocki: A Systemic Approach to the Development of a Policy Mix for Material Resource Efficiency
EIA	29.2016	Silvia Santato, Jaroslav Mysiak, Carlos Dionisio Pérez-Blanco: The Water Abstraction License Regime in Italy: A Case for Reform?
MITP	30.2016	Carolyn Fischer: Strategic Subsidies for Green Goods
MITP	31.2016	Carolyn Fischer: Environmental Protection for Sale: Strategic Green Industrial Policy and Climate Finance
ET	32.2016	Fabio Sabatini, Francesco Sarracino: Keeping up with the e-Joneses: Do Online Social Networks Raise Social Comparisons?
MITP	33.2016	Aurora D'Aprile: Advances and Slowdowns in Carbon Capture and Storage Technology Development
EIA	34.2016	Francesco Bosello, Marinella Davide, Isabella Alloisio: Economic Implications of EU Mitigation Policies: Domestic and International Effects
MITP	35.2016	Shouro Dasgupta, Enrica De Cian, and Elena Verdolini: The Political Economy of Energy Innovation

MITP	36.2016	Roberta Distante, Elena Verdolini, Massimo Tavoni: <u>Distributional and Welfare Impacts of Renewable Subsidies in Italy</u>
MITP	37.2016	Loic Berger, Valentina Bosetti: <u>Ellsberg Re-revisited: An Experiment Disentangling Model Uncertainty and Risk Aversion</u>
EIA	38.2016	Valentina Giannini, Alessio Bellucci, Silvia Torresan: <u>Sharing Skills and Needs between Providers and Users of Climate Information to Create Climate Services: Lessons from the Northern Adriatic Case Study</u>
EIA	39.2016	Andrea Bigano, Aleksander Śniegocki, Jacopo Zotti: <u>Policies for a more Dematerialized EU Economy. Theoretical Underpinnings, Political Context and Expected Feasibility</u>
ET	40.2016	Henry Tulkens: <u>COP 21 and Economic Theory: Taking Stock</u>
MITP	41.2016	Shouro Dasgupta, Enrica De Cian: <u>Institutions and the Environment: Existing Evidence and Future Directions</u>
MITP	42.2016	Johannes Emmerling, Laurent Drouet, Lara Aleluia Reis, Michela Bevione, Loic Berger, Valentina Bosetti, Samuel Carrara, Enrica De Cian, Gauthier De Maere D'Aertrycke, Tom Longden, Maurizio Malpede, Giacomo Marangoni, Fabio Sferra, Massimo Tavoni, Jan Witajewski-Baltvilks, Petr Havlik: <u>The WITCH 2016 Model - Documentation and Implementation of the Shared Socioeconomic Pathways</u>
MITP	43.2016	Stefano Carattini, Alessandro Tavoni: <u>How Green are Economists?</u>
ET	44.2016	Marco Di Cintio, Sucharita Ghosh, Emanuele Grassi: <u>Firm Employment Growth, R&D Expenditures and Exports</u>
ESP	45.2016	Nicola Cantore, Patrick Nussbaumer, Max Wei, Daniel Kammen: <u>Energy Efficiency in Africa: A Framework to Evaluate Employment Generation and Cost-effectiveness</u>
MITP	46.2016	Erin Baker, Valentina Bosetti, Ahti Salo: <u>Finding Common Ground when Experts Disagree: Belief Dominance over Portfolios of Alternatives</u>
MITP	47.2016	Elena Verdolini, Laura Diaz Anadón, Erin Baker, Valentina Bosetti, Lara Aleluia Reis: <u>The Future Prospects of Energy Technologies: Insights from Expert Elicitations</u>