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The future costs of nuclear power using multiple expert elicitations: effects of RD&D and elicitation design

Laura Díaz Anadón[1,5], Gregory Nemet[2,3,5] and Elena Verdolini[4,5]

[1] Belfer Center for Science and International Affairs, John F Kennedy School of Government, Harvard University, Cambridge, MA, USA
[2] Nelson Institute Center for Sustainability and the Global Environment (SAGE), University of Wisconsin—Madison, Madison, WI, USA
[3] La Follette School of Public Affairs, University of Wisconsin—Madison, Madison, WI, USA
[4] Fondazione Eni Enrico Mattei and CMCC, Corso Magenta 63, I-20123 Milano, Italy

E-mail: laura_diaz_anadon@harvard.edu, nemet@wisc.edu and elena.verdolini@feem.it

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Abstract
Characterization of the anticipated performance of energy technologies to inform policy decisions increasingly relies on expert elicitation. Knowledge about how elicitation design factors impact the probabilistic estimates emerging from these studies is, however, scarce. We focus on nuclear power, a large-scale low-carbon power option, for which future cost estimates are important for the design of energy policies and climate change mitigation efforts. We use data from three elicitations in the USA and in Europe and assess the role of government research, development, and demonstration (RD&D) investments on expected nuclear costs in 2030. We show that controlling for expert, technology, and design characteristics increases experts' implied public RD&D elasticity of expected costs by 25%. Public sector and industry experts' cost expectations are 14% and 32% higher, respectively than academics. US experts are more optimistic than their EU counterparts, with median expected costs 22% lower. On average, a doubling of public RD&D is expected to result in an 8% cost reduction, but the uncertainty is large. The difference between the 90th and 10th percentile estimates is on average 58% of the experts' median estimates. Public RD&D investments do not affect uncertainty ranges, but US experts are less confident about costs than Europeans.

Keywords: nuclear power, uncertainty, returns to RD&D, expert elicitations, meta-analysis

S Online supplementary data available from stacks.iop.org/ERL/8/034020/mmedia

1. Introduction

Developing energy policies that are robust to a broad set of possible future conditions typically requires explicit (Nakicenovic and Riahi 2001) or implicit (Nordhaus 2008) characterization of the anticipated performance of individual energy technologies. Representing future technological change introduces considerable uncertainty into decision making because, as we know from past data, energy technologies have been dynamic (Grubler *et al* 1999). And even though future change is uncertain, we are not completely ignorant. Dispersed researchers have produced data and developed tools that, in combination, provide the basis for probabilistic estimates of future improvements in technology. A well-established methodology used to this end is expert elicitation.

[5] All authors contributed equally.

Expert elicitations gather the informed opinions of experts on technical questions that fall within their area of knowledge and expertise. Data collection is carried out using elicitation protocols carefully designed to reduce heuristics and biases (Hogarth 1987, Morgan and Henrion 1990, Cooke 1991). These data-gathering efforts are particularly useful in decisions that require an assessment of the future evolution of energy technologies because historic data may not inform on future performance and costs or the relevant data might not be available.

Energy policy making relies on experts' estimates of the future performance, costs, and safety of energy technologies (Apostolakis 1990). A prominent one is the study undertaken by the European Commission and the United States Nuclear Regulatory Commission during the 1990s on the uncertainty surrounding accident consequence codes for nuclear power plants (Cooke and Goossens 2004). Six years ago, the National Research Council released a report with a strong recommendation that the US Department of Energy begin to use expert elicitation for their RD&D allocation decisions, to explicitly characterize probabilistic estimates of the outcomes of RD&D investments (NRC 2007). Over the past few years, research groups on both sides of the Atlantic have gathered data from expert elicitations on the future of several energy technologies to inform energy RD&D policy (Anadon *et al* 2011a, 2011b, 2012, Baker and Keisler 2011, Baker *et al* 2009a, 2009b, Chan *et al* 2011, Curtright *et al* 2008, Bosetti *et al* 2012). The ability to use probabilistic data from various elicitations to characterize future energy technology uncertainty and improve the reliability of estimates is valuable for impact assessment evaluations such as the Energy Modeling Forum (EMF) and the International Panel on Climate Change (IPCC), especially in light of the magnitude of investments being considered to support energy technologies and the costs and time involved in collecting elicitation data.

This letter takes a first step in this direction and focuses on three recent expert elicitations on the future costs of nuclear fission technologies carried out by groups at Carnegie Mellon, Fondazione Eni Enrico Mattei (FEEM), and Harvard. This collection of experts' estimates provides a rich resource with which to inform RD&D, energy, and nuclear policy decisions on future nuclear costs and on the uncertainty surrounding them. However, substantial differences in expert composition, elicitation design and technology considered make it difficult to draw more than very general conclusions when looking at the multiple elicitations. Such differences are very likely to affect experts' estimates. Previous studies, for example, pointed at the importance of protocol design and expert selection as key for elicitation results (Raiffa 1968, Keeney and Winterfeldt 1991, Meyer and Booker 2001, Phillips 1999, Clemen and Reilly 2001, Walls and Quigley 2001). However, no empirical assessments of the impact and size of differences in expert selection and elicitation design have been carried out to date. Similarly, no empirical analysis exists on the size and shape of the relationship between public RD&D investments and the future cost of nuclear power (or any other technology) emerging from elicitations data.

Our contribution fills this gap in the literature. First, we provide important insights on the bias introduced by specific elicitation design decisions by assessing how experts' characteristics affect estimates of cost and uncertainty. The FEEM and Harvard studies are similar in elicitation design and method (both were conducted online), but include a heterogeneous group of experts in terms of affiliation and nationalities, allowing investigation of how characteristics of the expert influence their beliefs about the returns to public RD&D. Conversely, the CMU elicitation was administered in person, but only includes data for Gen. III/III+ consistent with a business as usual US public RD&D funding scenario. Hence we provide some preliminary results on whether or not in-person elicitations are associated with statistically significant differences on costs under a BAU public RD&D scenario. Second, we derive an average estimate of the elasticity of (future) nuclear costs to (future) nuclear public RD&D investments that accounts for expert, design, and technology differences. This is a valuable parameter for both policy makers and modelers interested in uncertainty analysis, which can be compared with historical estimates of returns to RD&D (NRC 2001).

2. Data

We use responses from 67 experts about the future costs of nuclear power conditional on specified levels of RD&D investment obtained via expert elicitation included in the Harvard/FEEM (Anadon *et al* 2012) and CMU (Abdulla *et al* 2013) studies (25 experts in the Harvard elicitation, 30 in the FEEM elicitation, and 12 in the CMU elicitation). Table S1 in the supplementary material (available at stacks.iop.org/ERL/8/034020/mmedia) summarizes the key characteristics from these elicitation studies. Harvard and FEEM used online tools to elicit US and EU experts, respectively. In the CMU study experts completed a paper-based instrument during an in-person meeting.

For each expert, the three elicitations collected estimates of the 50th, 10th, and 90th percentile of expected overnight capital costs in 2030 for different types of reactors, conditional on levels of public annual RD&D funding. All elicited estimates are in 2010$. All experts provided estimates consistent with the business as usual (BAU) funding scenarios, where yearly public RD&D investment to 2030 would not significantly change from the present investment in the United States or in the European Union, depending on the study. Moreover, the FEEM and Harvard experts were asked about three additional RD&D scenarios: (1) a recommended budget scenario, with a yearly public RD&D investment level chosen by the experts (ranging between 1.5 and 20 times BAU investments); (2) a half recommended budget scenario, with a public RD&D investment equal to half the yearly amount in the recommended budget scenario; and (3) a 10× recommended scenario, with a public RD&D investment equal to ten times the yearly amount in the recommended budget scenario. Not all experts provided all estimates for all technologies, RD&D funding scenarios, and percentile values.

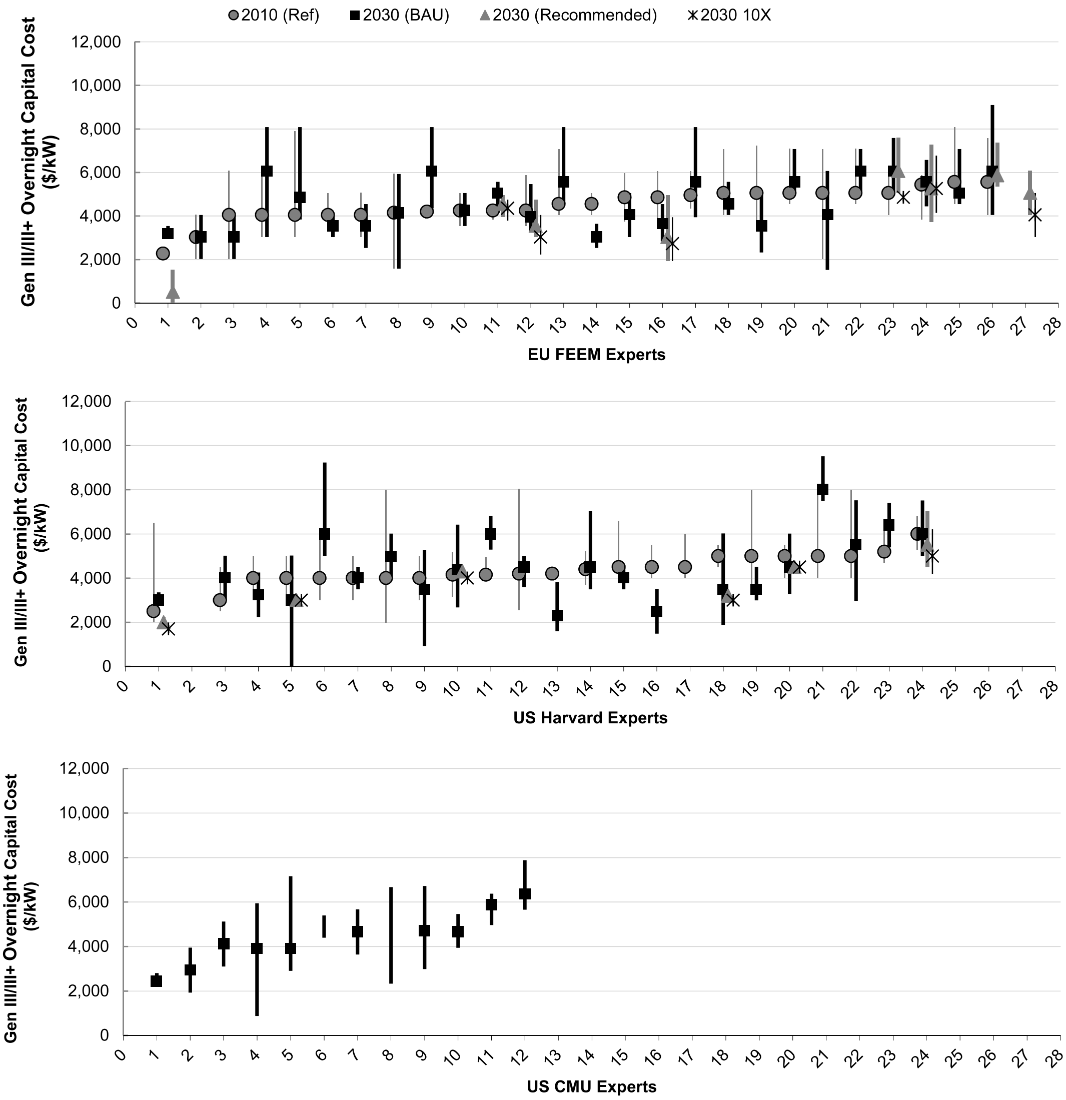

Figure 1. Elicitation results for large-scale Gen. III/III+ reactor systems for the FEEM, Harvard, and CMU studies (Abdulla *et al* 2013, Anadon *et al* 2012). The data points represent the 50th percentile estimates. The top and bottom error bars denote the 10th and 90th percentiles, respectively. The '2010 ref.' data point includes the experts' estimates of costs in 2010, of interest given the fact that there are few reactors being built in both the US and the EU. CMU experts 6 and 8 did not provide a 50th percentile estimate.

Figure 1 shows a wide range of estimates of future costs under different public nuclear RD&D investment scenarios for large-scale Gen. III/III+ reactor systems (Harvard in the upper panel, FEEM in the middle and CMU in the lower). Similar figures for the large-scale Gen. IV reactor systems and SMRs are reported in the SI (available at stacks.iop.org/ERL/8/034020/mmedia). 17 of the FEEM and Harvard experts also participated in a group meeting in which they discussed the rationale behind their answers and could potentially converge towards a consensus answer (Dalkey 1969). However, as documented in Anadon *et al* (2012), only a few experts made marginal changes to their estimates.

3. Approach

Our first objective is to understand how scenarios with different levels of potential public RD&D investment affect experts' central estimates (50th percentile) of the costs of nuclear technologies in 2030. Second, we assess whether the RD&D investment level also impacts the range of uncertainty surrounding these cost estimates. We define uncertainty here as the difference between the 90th and the 10th percentile of expected costs, normalized by the median (50th percentile). We thus use information on experts' responses for each technology in each RD&D scenario. Given that, as explained above, not all experts provided all cost estimates, we end up with 393 observations in the analysis of the central estimate and 389 observations in the analysis of the uncertainty range.

We draw on two strands of literature to choose a functional form for our specifications. First, the literature on learning-by-doing (LbD) finds that the accumulation of experience in manufacturing and/or project development, proxied by capacity, often leads to productivity improvements (Arrow 1962). In this 'learning curve' model, the rate of cost reductions in different technologies is a function

Table 1. Descriptive statistics. (Notes: the R&D rec. and the R&D high variables are dummy variables equal to 1 if the associated expert's cost estimate refers to the recommended and high R&D scenarios, respectively. The average values of the variables therefore represent the share of cost estimate referring to that specific R&D scenario within our sample.)

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variable, 2030 overnight capital costs ($ kW^{-1})					
Median ($p50$)	393	4872	1816	506	14 156
10th %tile	389	3781	1548	253	11 000
90th %tile	389	6463	2389	758	20 222
$p50/(p50_{2010})$	372	1.15	0.51	0.22	4.00
$(p90 - p10)/p50$	389	0.58	0.31	0.10	1.83
Investment					
RD&D ($m)	393	5324	10 386	400	80 000
RD&D rec.	393	0.22	0.41	0	1
RD&D high	393	0.21	0.41	0	1
Elicitation characteristics					
In person	393	0.03	0.16	0	1
Public	393	0.45	0.50	0	1
Industry	393	0.27	0.45	0	1
USA	393	0.55	0.50	0	1
PRONUKE	393	0.07	0.25	0	1
Gen IV	393	0.38	0.49	0	1
SMR	393	0.36	0.48	0	1

of the number of units installed or produced. LbD is investigated using a ln–ln specification linking technology costs and experience and has been applied to a wide range of technologies (Bodde 1977, Junginger *et al* 2005, Grubler *et al* 1999, Goldemberg *et al* 2004). The 'two factor learning curve' model augments the basic specification with a learning-by-searching factor accounting for the impact of RD&D investments on costs (Kouvaritakis *et al* 2000, Klaassen *et al* 2005, Soderholm and Klaassen 2007). We choose the ln–ln specification as our main model of the relationship between future costs and public RD&D investments. We however do not include a learning-by-doing variable because experts provided their cost estimates conditional on just RD&D investments (note that the CMU study only provides estimates consistent with a BAU public RD&D funding scenario in the US).

The second strand of literature focuses on returns to RD&D (Evenson and Kislev 1976, Evenson 1984, Segerstrom 1998, Popp 2002, Tassey 2003, Bosch *et al* 2005, Hall *et al* 2009). These contributions generally suggest that if too many resources are devoted to RD&D in a short time frame, technology cost improvements could exhibit diminishing returns (Kortum 1997, Popp *et al* 2012). Diminishing marginal returns are usually tested with the inclusion of a quadratic RD&D term or a negative exponential function (Blanford 2009). We thus also test a linear specification relating technology costs with RD&D and its squared term.

3.1. Dependent variable: experts' estimates of overnight capital cost

As explained above, we consider two different dependent variables to explore the impact of RD&D investment on expected nuclear costs: the 50th percentile estimate of overnight capital cost in 2030 and normalized uncertainty, defined as $(p90 - p10)/p50$. Descriptive on both variables are presented in table 1. The average expected cost of nuclear technologies in 2030 is around 4800 in $ kW^{-1}, with estimates as low as 506 $ kW^{-1} but also experts expecting costs as high as 14 156 $ kW^{-1}. Uncertainty ranges between 0.10 and 1.83, with an average value of 0.58. Table S2 in the SI (available at stacks.iop.org/ERL/8/034020/mmedia) contains a breakdown of the central estimate observations by RD&D scenario and technology type.

3.2. Independent variables: research design and experts' characteristics

The estimates of costs provided by the experts are conditional on RD&D investment but also on the type of technology included in the elicitations. Specifically, the assumed yearly public RD&D investment levels range from $2000 million to 80 billion dollars across the four different scenarios (BAU, recommended, half recommended and 10× recommended) (table 1). With respect to technology characteristics, our observations are almost equally divided between Gen. III/III+ technologies, Gen. IV technologies and small and medium sized reactors (SMRs). We define these technology categories in detail in the SI.

Among the observables that could potentially affect elicitation results we consider both variables capturing differences across studies (indicating differences in study design) and variables capturing differences across experts within studies (indicating individual characteristics). For example, studies suggest that selecting a diverse pool of experts can help avoiding anchoring to a usually conservative reference point (Meyer and Booker 2001). Table S3 in the supplementary material (available at stacks.iop.org/ERL/8/034020/mmedia) discusses and justifies the selection of the control variables.

Around 45% of our experts belong to public institutions (including supra-national European organizations), while 27% work in industry and the remaining 28% are academics (table 1). Moreover, around 55% of our expert pool work in the United States ('USA' variable), with the remaining 45% working in the European Union. Only 3% of the data in our sample (the CMU elicitations) was obtained through a face-to-face interview rather than online ('in-person' variable).

Omitting expert and technology subscripts, our main specification reads as follows:

$$\ln y = \alpha_0 + \beta \ln \mathrm{RD\&D} + \gamma' z + \varepsilon$$

where y is either the central estimate of future technology costs (50th percentile) or the uncertainty range ($p90 - p10/p50$), RD&D is the yearly public research and development budget in nuclear technologies associated with each cost estimate, z is the column vector of control variables as listed in table S2, and ε is an i.i.d. error component with mean zero and variance σ^2. The main shortcoming of the above specification is that there might be some unobservable individual characteristics that are likely to bias the estimates above and beyond what we can control for using our independent variables. We therefore check the robustness of our results also including experts' fixed effects.

4. Results

We present here the main results of the specifications for costs and the uncertainty range. Additional results are presented in the SI.

4.1. Predictors of median overnight capital costs

Table 2 presents the results of seven specifications focusing on the 50th percentile of expected overnight capital. Model 1 is a simple correlation in which we estimate the effect of (future) annual public RD&D investment on (future) cost without controlling for any other observable characteristics. The estimated coefficient is significant and indicates that a doubling of yearly public energy RD&D investment in nuclear technologies (equivalent to a 100% increase) is associated on average with 7% decrease in overnight capital costs by 2030. In model 2, we drop the continuous RD&D variable and use dummy variables associated with different RD&D levels. Specifically, the reference categories include BAU and half recommended RD&D budget level, while the dummy variables 'RD&D rec.' and 'RD&D high' indicate each expert's recommendation of RD&D investment and 10 times the expert's recommended level, respectively. The notion here is that using the actual RD&D levels provided in the elicitation may exaggerate the precision with which experts can be expected to understand the returns to RD&D. The hypothesis is that experts are better equipped to distinguish between low, medium, and high levels of RD&D. Both variables are significant and in the expected direction. The effects of high RD&D is twice that of recommended RD&D: high public RD&D investments are associated with costs that are on average approximately 21% lower than 'low' public RD&D investment scenario (which refers to the BAU and half recommended public RD&D scenarios). Note that approximate refers to the fact that this is a close approximation given that the dependent variables is in log form—we use this terminology throughout when interpreting the effect dummy coefficients. The elicitation questions on RD&D thrusts included in the FEEM and Harvard elicitations and the group workshop conducted by the FEEM and Harvard teams shed some light onto what technical issues experts thought public RD&D investments could address. Some of the key issues were additional work on modeling and demonstration projects to test the economics of Gen. IV designs, with a particular focus on sodium-cooled fast reactors, high-temperature reactors, and gas-cooled fast reactors, and also research to improve the safety and proliferation resistance of Gen. IV designs. Regarding SMRs, experts expressed the need for RD&D to safety test and demonstrate the viability and operability of light-water reactor designs, and to develop more advanced fuels and materials. Given that the full list of RD&D thrusts is too long to include here, the reader is referred to Anadon *et al* (2011a, 2011b) for a more comprehensive list.

The fit of models 1 and 2 is low but improves dramatically when the controls for experts' affiliation, the type of technology and the area of origin of the expert are added to the model (model 3 and model 4, respectively). In model 3, as a result of the inclusion of the additional controls, the coefficient on the RD&D variable is associated with a significant increase of roughly 25%, going from 0.0676 to 0.0843. Hence, a doubling of public RD&D yearly budget for nuclear technologies is associated with an 8% decrease of nuclear costs in 2030, on average and *ceteris paribus*. This indicates that any policy insight based on the correlation emerging from model 1 substantially underestimates the impact of public funding on nuclear cost reductions. Similar conclusions can be reached with respect to the RD&D levels as measured by dummy variables in models 2 and 4. Specifically, as a result of the inclusion of the additional controls, the central estimate of costs under the recommended RD&D scenario is approximately 14.7%, a significant increase from the approximate value of 10.8% in model 2 without the controls. Similarly, the effect of high R&D also increases with the controls.

Model 5 further explores the role of data acquisition method by including a dummy variable to control for face-to-face interview, but the estimated coefficient is not statistically significant. Finally, models 6 and 7 include experts' dummies in models 3 and 5, respectively, to account for unobservable expert characteristics that might be correlated with the elicited median costs. Adding expert fixed effects only slightly reduces the coefficient associated with the RD&D variable, but the estimate is still roughly 15% higher than in model 1.

The results for the other control variables (using model 3) show that experts from public institutions have estimates

Table 2. Estimates of expert's elicited 50th percentile of overnight capital cost. $Y = \ln(p50)$. (Note: robust p-values in brackets.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(RD&D)	−0.0676[b]		−0.0843[b]		−0.0852[b]	−0.0778[b]	−0.0778[b]
	[5.11×10^{-6}]		[1.73×10^{-9}]		[1.42×10^{-9}]	[0]	[0]
RD&D recommended		−0.108[a]		−0.147[b]			
		[0.0383]		[0.003 17]			
RD&D high		−0.213[b]		−0.249[b]			
		[1.40×10^{-5}]		[6.69×10^{-8}]			
Public			0.141[b]	0.125[b]	0.142[b]	0.857[b]	1.398[b]
			[0.000 150]	[0.001 02]	[0.000 140]	[2.58×10^{-8}]	[0]
Industry			0.312[b]	0.322[b]	0.317[b]	0.906[b]	1.570[b]
			[0]	[0]	[0]	[4.38×10^{-9}]	[0]
USA			−0.220[b]	−0.200[b]	−0.218[b]	−0.329[b]	−1.129[b]
			[0]	[5.72×10^{-9}]	[8.81×10^{-11}]	[0]	[0]
GEN IV			0.228[b]	0.232[b]	0.222[b]	0.227[b]	0.227[b]
			[8.30×10^{-7}]	[1.45×10^{-6}]	[5.30×10^{-6}]	[4.47×10^{-8}]	[4.47×10^{-8}]
SMR			0.240[b]	0.244[b]	0.233[b]	0.259[b]	0.259[b]
			[9.67×10^{-7}]	[1.64×10^{-6}]	[6.03×10^{-6}]	[2.62×10^{-8}]	[2.62×10^{-8}]
In person					−0.0723		−0.541[b]
					[0.476]		[7.68×10^{-6}]
Expert FE dummies	No	No	No	No	No	Yes	Yes
Constant	8.926[b]	8.488[b]	8.849[b]	8.294[b]	8.859[b]	8.225[b]	9.025[b]
Observations	393	393	393	393	393	393	393
Adjusted R-squared	0.052	0.044	0.233	0.218	0.232	0.619	0.619

[a] $p < 0.05$.
[b] $p < 0.01$.

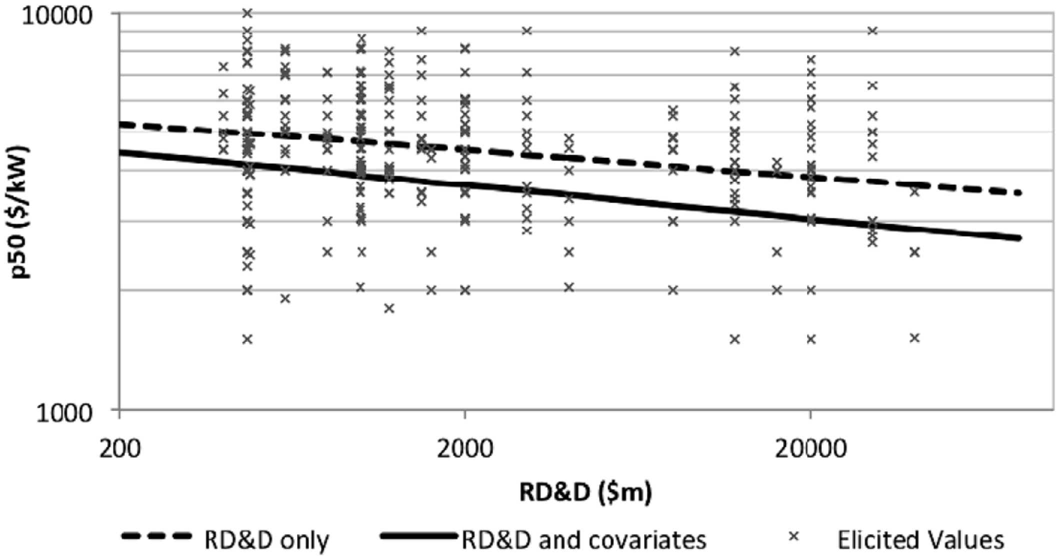

Figure 2. RD&D and technology cost with and without observable expert, technology and study characteristics. Axes in logarithmic scales.

of overnight capital costs that are about 14% higher on average than those of academics. Estimates for experts from industry are even higher, on average approximately 31% higher than academics. This difference could be explained by the fact that industry experts are generally more likely to think about potential escalations on labor, materials, licensing, and permitting costs than their academic counterparts, since academic experts may tend to be more detached from these less technical costs. Overnight capital costs are expected to be higher for both Gen. IV and SMR technologies with respect to Gen. III/III+ technologies by approximately 23% and 24%, respectively. Expected overnight capital costs are about 22% lower for experts in the USA when compared to experts in the European Union. All of the above controls are significant across all five models in table 2 in which they are included. The inclusion of the fixed effects in models 6 and 7 leads to increases in the magnitude of the coefficients for expert characteristics controls, although the sign and statistical significance remain the same. The in-person variable becomes negative and significant when expert fixed effects are included (model 7), although it is difficult to draw conclusions about this effect since it requires inclusion of unobserved expert characteristics for it to become significant. In-person effects will be a focus of future work assembling additional elicitation data so that more than the 3% of observations are in person. We focus our interpretation on models 1–5, without fixed effects. But the role of expert fixed effects does suggest that additional expert characteristics might be important to gather in future work.

Figure 2 shows how the estimated returns to public RD&D vary when accounting for observable expert, study and technology characteristics (models 1 and 3 compared). The x-axis shows public RD&D investment plotted in a log scale, while the y-axis shows the associated overnight capital costs in 2030, also plotted in a log scale. The lines in the graph represent the returns to RD&D estimated without controlling for other observable characteristics (discontinuous line—model 1) and including additional controls (continuous line—model 3). As already mentioned, not controlling for observable characteristics leads to a 25% underestimation of the effect of public RD&D investment on nuclear technology costs (meaning, the discontinuous line is 25% less steep than the continuous line). In addition, observable characteristics account for the distance between the two lines.

The SI includes additional specifications, all of which produced results in line with those above. These include: a normalized cost variable (calculated dividing the 2030 estimate by the 2010 estimate for the observations in the FEEM and Harvard studies) in both the linear, log–log and semi-log model; diminishing marginal returns to RD&D investments (RD&D^2); interacting dummies with RD&D and with each other; and Box–Cox transformation to further investigate the most appropriate functional form.

4.2. Predictors of dispersion in costs

Here we test whether dispersion in technology costs is affected by the level of RD&D funding and the observable expert, technology and study characteristics. Table 3 reports specifications in line with those included in table 2 but where the dependent variable is now the measure of the range of uncertainty, $(p90 - p10)/p50$.

We find that public RD&D investments are not statistically significant predictors of the uncertainty range provided by the experts. That is, higher or lower levels or investments are not systematically associated with narrower or wider uncertainty ranges under any of the seven specifications tested. US experts have significantly wider uncertainty ranges when compared to EU experts, approximately 16% larger according to model 5. In this case, the in-person variable is significant, and suggests that the uncertainty ranges for experts providing answers in person for the BAU RD&D scenario were about 40% lower, although the sign of this effect is not robust to the inclusion of expert fixed effects.

Table 3. Estimates of effects on variation in nuclear costs. $Y = \ln[(p90 - p10)/p50]$. (Note: robust p-values in brackets.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(RD&D)	0.0119		0.0207		0.0162	−0.001 28	−0.001 28
	[0.599]		[0.366]		[0.480]	[0.925]	[0.925]
RD&D recommended		0.0108		0.0189			
		[0.877]		[0.788]			
RD&D high		−0.0279		−0.0228			
		[0.717]		[0.766]			
Public			0.0629	0.0692	0.0689	−0.620[a]	−1.463[a]
			[0.371]	[0.323]	[0.328]	[6.62×10^{-11}]	[0]
Industry			0.0619	0.0601	0.0905	−0.883[a]	−0.993[a]
			[0.441]	[0.455]	[0.254]	[0]	[4.90×10^{-6}]
USA			0.154[b]	0.151[b]	0.163[a]	0.405[a]	−0.439[b]
			[0.0136]	[0.0152]	[0.009 14]	[0]	[0.0264]
GEN IV			−0.0433	−0.0335	−0.0793	−0.0544	−0.0544
			[0.551]	[0.649]	[0.278]	[0.247]	[0.247]
SMR			−0.101	−0.0925	−0.139[c]	−0.0821[c]	−0.0821[c]
			[0.163]	[0.209]	[0.0573]	[0.0876]	[0.0876]
In person					−0.398[c]		0.843[a]
					[0.0615]		[2.30×10^{-5}]
Expert FE dummies	No	No	No	No	No	Yes	Yes
Constant	−0.770[a]	−0.678[a]	−0.913[a]	−0.765[a]	−0.857[a]	−0.0648	0.778[a]
Observations	389	389	389	389	389	389	389
Adjusted R-squared	−0.002	−0.005	0.009	0.005	0.018	0.694	0.694

[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

The uncertainty range for SMRs is around 14% smaller than that for large-scale Gen. III/III+, suggesting that experts are relatively confident about their cost estimates on these systems, which are expected to be delivered to the site fully constructed from the manufacturing facilities, even though the current experience is limited and no operating licenses have been issued in the United States or the EU. The group workshop conducted by the FEEM and Harvard teams also shed some light regarding the uncertainties they considered when making their estimates, which included the costs of materials, increased safety requirements, differences in contract structures, and the outcomes of RD&D on materials and fuel fabrication. As shown in the SI, the results on the uncertainty range are generally robust to changes in the functional form used in the empirical estimation.

5. Conclusion

Because nuclear power is one of the few large-scale low-carbon power technologies available, understanding its future cost is important for the design of climate change mitigation efforts. As expert elicitations and models relying on expert elicitation data are increasingly used in science policy contexts, scrutiny of their reliability is certain to increase. But at present, knowledge about the impact of design factors on the probabilistic estimates emerging from these studies is scarce. In this letter we combined three recent elicitations on the future (2030) cost of three types of nuclear power reactor types: large-scale Gen. III/III+ systems, large-scale Gen. IV systems, and small modular reactors. We provide insights about: (a) how the design of the elicitation and the selection of the experts affect nuclear elicitation results—thereby providing guidance for future elicitations; and (b) the expected returns to government nuclear RD&D. The results show that sector and geographic location of the expert, reactor type, and RD&D investment are statistically significant factors affecting experts' estimates of overnight capital cost and are robust to the two specifications supported by the literature: a ln–ln specification and a linear specification with a quadratic term.

Controlling for expert characteristics increases the estimated public RD&D elasticity of expected costs by 25%. We also show that academic experts are the most optimistic about the future costs of nuclear reactors. On average public and industry experts expect costs to be approximately 14% and 32% higher, respectively than academics. Since academic experts are typically more removed from technology commercialization than their counterparts, this may be expected, although the significance and magnitude of the effect had never been estimated. US experts were more optimistic than their EU counterparts, with expected costs that were on average about 22% lower. This could be related to the fact that the EU has more recent experience building nuclear power plants than the USA, and that these projects have suffered from cost overruns. Both of these findings indicate that expert selection has a large impact on elicitation results.

This result applies beyond expert elicitations to other efforts to estimate the cost of meeting climate change targets, which inevitably rely on assumptions about technology costs. It suggests that more transparency about the source of the estimates in integrated assessment models and other policy analysis models may be necessary. If academic experts are indeed more optimistic about future costs, current efforts that emphasize academic assessments could underestimate costs. Sensitivity analysis thus becomes paramount.

In the elicitations included in this study, the normalized uncertainty range—defined by the difference between the 90th and 10th percentile estimates divided by the 50th percentiles—is on average 58% of the experts median estimates, highlighting the large uncertainty around future nuclear costs. Further, public RD&D investments do not affect uncertainty ranges, but experts provided lower uncertainty ranges for SMRs when compared to Gen. III/III+ and Gen. IV reactors. This seems somewhat surprising given the greater level of experience with Gen. III/III+ systems, but could be explained by a greater confidence of experts in the ability of centralized manufacturing of SMRs to deliver reactors on time and on budget when compared to large-scale projects, which have had widely varying costs in the past. Gen. III/III+ systems are expected to still be cheaper than Gen. IV and SMRs by 2030. In fact, even though the uncertainty around future SMR costs is lower, overnight capital costs are expected to be on average about 23% greater than that of Gen. III/III+ systems and only a little above large-scale Gen. IV systems.

These differences indicate that the specificity with which technologies are defined is an important elicitation design characteristic to consider. We find no evidence that the method of administering the survey (in person) has a significant impact on costs, although our analyses have low power since so few observations involved in-person interviews. We do see that the uncertainty range decreases when the elicitation was administered in person when compared to online, although it is possible that differences in the background information of the survey or the online displays have contributed to this. Finally, even though academic experts had lower estimates of costs, their uncertainty ranges were not different from those of industry and public institution experts.

We also find strong evidence that public RD&D investments present decreasing marginal returns. This indicates that when experts assess the impact of RD&D on cost their mental model includes considerations of depletion of improvement opportunities within a limited period of time.

Overall, this study shows quantitatively the importance of expert selection and elicitation design and of the need to increase transparency in modeling and policy analysis exercises about the source of technology assumptions. More precise estimates are likely to become available as a larger body of elicitation study results is included into this type of analysis. The RD&D elasticity estimates condense the literature available and could be used in modeling exercises. This work also provides a condensed view of central estimates that may be useful directly for research program managers and policy makers. On average, a doubling of public RD&D is expected to result in cost reductions around 8% in 2030, but uncertainty is very large. Overall, these insights regarding future costs, their uncertainty, the expected returns to public RD&D, and the importance of the source of estimates are important for more efficient and transparent analysis about technology strategies to meet climate challenges.

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