Energy xxx (2013) 1–11

Contents lists available at SciVerse ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

# Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios

Gregory F. Nemet [a,b,*], Erin Baker [c], Karen E. Jenni [c,d]

[a] La Follette School of Public Affairs, University of Wisconsin, 1225 Observatory Drive, Madison, WI 53706, USA
[b] Nelson Institute Center for Sustainability and The Global Environment, University of Wisconsin, Madison, USA
[c] University of Massachusetts, Amherst, USA
[d] Insight Decisions, USA

A R T I C L E I N F O

*Article history:*
Received 20 February 2013
Received in revised form
17 April 2013
Accepted 20 April 2013
Available online xxx

*Keywords:*
Carbon capture
Expert elicitation
Marginal abatement cost

A B S T R A C T

We use expert elicitations of energy penalties and literature-derived estimates of basic cost parameters to model the future costs of 7 types of carbon capture technology applied to coal power plants. We conduct extensive sensitivity analysis to assess the effects of various parameters on additional levelized electricity costs ($/MWh) and costs of avoided $CO_2$ emissions ($/t$CO_2$) in 2025. Although the expert elicitation of energy penalties under various policy conditions spans a considerable range, we find that costs are more sensitive to assumptions about overnight capital costs and discounting. We run Monte Carlo simulations to specify a distribution of the minimum costs of capture across these 7 technologies and find that in 74% of cases, the minimum cost of capture is determined by one of three technologies. Despite these concentrated outcomes, we see benefits to technology portfolio diversification in that a full portfolio of technologies approximately doubles the likelihood of achieving a $60/t$CO_2$ cost target versus focusing on a single capture technology.



## 1. Introduction

CCS (carbon capture and storage) is potentially one of the most important energy technologies to address climate change [1,2]. Modeling exercises frequently produce results with CCS accounting for 10% or more of global 21st century emissions reductions. However, CCS is only likely to play such a large role in climate change mitigation if its costs are near or below the marginal cost of abatement. As of April 2013, only 15 pilot-scale plants had been built worldwide, and no large-scale CCS plants (>60 MW) were operating [40]. The cost of pilot plants provides limited information about future costs of full-scale plants and thus the performance and total cost over time remain highly uncertain.

In general, the future costs of pre-commercial technologies are difficult to model, although methods have been developed that characterize the sources of uncertainty [3,4]. Representing future technological change is one source of considerable uncertainty. We know from past data that energy technologies have been dynamic, and that these changes have had substantial effects on the entire energy system, the economy, the environment, and society [5]. Private sector and public policy actors that make decisions assuming static technology in the future are almost certain to be wrong. The future performance of CCS also depends on government actions, such as funding research, subsidizing demonstration plants, and pricing pollution externalities [6,7]. The characteristics of future public policies involving these items are a second major source of uncertainty [8]. Moreover, the effects of any of these specific policies on technology performance are also uncertain. For example, whether and how much increased R&D funding will improve the performance of a specific technology is unknown, in part due to the inherent ex-ante ignorance about the outcomes of investing in technology development and the concentration of payoffs among a small number of development paths [9]. However, even though future change is uncertain, we are not completely ignorant; recent research has developed tools and produced data that, in combination, provide the basis for probabilistic estimates of future improvements in technology.

Our approach in this paper is to address these uncertainties in several ways. First, we represent uncertainty over future public policies by defining three distinct policy scenarios and evaluating the potential performance of capture technologies under each scenario:

* Corresponding author. La Follette School of Public Affairs, University of Wisconsin, 1225 Observatory Drive, Madison, WI 53706, USA.
*E-mail address:* nemet@wisc.edu (G.F. Nemet).

0360-5442/$ – see front matter 
http://dx.doi.org/10.1016/j.energy.2013.04.047

**S1 (Scenario 1)**: No further US government funded R&D (research and development) in CCS (i.e., zero public investments in future years), current worldwide carbon price ($\sim$\$5/t$CO_2$) is unchanged;

**S2 (Scenario 2)**: No further US government funded R&D in CCS, worldwide carbon price equivalent to \$100/t$CO_2$ starting in 2015 and continuing indefinitely;

**S3 (Scenario 3)**: "High" US government investment in R&D (an annual investment level about five times the 2005 investment was defined for each technology) from 2015 through 2025; current worldwide carbon prices are unchanged.

To reduce the dimensionality of the results, we focus in this paper on comparing S3 to S1 and leave S2 for future work in which we model costs beyond 2025.

Second, we represent uncertainty in technical and cost performance under each of these scenarios probabilistically. The approach we use here is to combine the results of an expert elicitation on technical feasibility and performance with a bottom-up cost model for carbon capture. Both sets of inputs are uncertain, and we use expert elicitation to quantify that uncertainty where necessary, while relying on engineering cost models and existing work to quantify other uncertainties for which there is a more robust basis for estimates. Our objective is to generate insights on the effects of alternative policies on the marginal costs of $CO_2$ emissions abatement.

Through our extensive sensitivity analysis, we find that focussed, science-based R&D has a role to play in making CCS more cost effective through reducing the energy penalty, but it does not appear to be as important in determining the overall costs as a couple of other factors, namely overnight capital cost and the discount rate. Uncertainty in these two factors is the major contributor to uncertainty in the marginal abatement costs. This implies that policies that affect these factors—such as demonstration plants, subsidies, or loan guarantees—may be particularly important parts of the policy portfolio. Through modeling the entire range of uncertainty and explicitly positing technology competition within CCS, we are able to draw out some insights about the portfolio of CCS technologies. We find that among the suite of 7 technologies we consider, the three most mature end up setting the price in about three-quarters of the cases we simulate. On the other hand, there appears to be some value in keeping a diversified portfolio of technologies on the table: the probability of achieving a cost of \$60/t$CO_2$ or less is about double when all technologies are considered, versus just the best one.

Keeping in mind the potential for ambiguity and inconsistency in studies of the cost of CCS [10], we aim to be as explicit as possible about our assumptions and clear in our definitions. For example, comparisons are often made among studies that state costs in terms of \$/t$CO_2$ but use different conceptions of what is included in both costs and the amount of $CO_2$. There are at least 6 definitions of energy penalty, which can easily be conflated. Which costs are included in capital costs also vary across studies. Moreover, many studies are deterministic with only limited consideration of the effects of alternative assumptions. To help address these concerns, we conduct extensive sensitivity analysis, provide all the calculations used in our model in Section 2, and provide extensive documentation of the input values used in a Supporting information (SI) document.

In order to characterize the relationship between R&D investments and non-incremental technical change (the effects of scenario 3), we use the results of an expert elicitation. There has been growing interest in using expert elicitation to support important public policy problems [11]. The 2010 InterAcademy Council review of the climate change assessment of the IPCC (Intergovernmental Panel on Climate Change) suggested that "[w]here practical, formal expert elicitation procedures should be used to obtain subjective probabilities for key results" [12]. Similarly, the National Research Council recommends that the U.S. Department of Energy use probabilistic assessment based on expert elicitations of R&D programs in making funding decisions [13].

Expert elicitation is a formal process for obtaining expert judgments about uncertain values, and quantifying those judgments in terms of probabilities that can be used in further analyses [14,15]. The process is more intensive than surveys and more structured than simply collecting informed opinions. There have been a number of recent studies using expert elicitation to understand the prospects for advancement in CCS. We build on the work of Jenni et al. [16], who performed an expert elicitation on the EP (energy penalty) of eight different CCS technologies. Chung et al. [17] also considered EP, but only for three technologies. Rao et al. [18] considered more specific technological metrics, for only one specific technology. Baker et al. [19] did not differentiate between different post-combustion technologies. Chan et al. [20] focused on capital cost. The NRC (National Research Council) study assessed the additional cost of electricity [13]. Using elicitations of EP allows us to focus our questions on an area that is clearly within each expert's area of expertise; to simulate the effects of a range of other input assumptions (capital costs, discount rates), not just the ones the expert implicitly assumed; and to make those assumptions consistent across experts.

In this paper, Section 2 describes the methodology for estimating costs, with additional detail in the SI. Section 3 provides the initial results: probability distributions over the 2025 costs for each of 7 carbon capture technologies individually, under various assumptions on parameter values. In Section 4 we derive a combined distribution of the overall cost of CCS, considering the outcomes for all technologies. Section 5 discusses the results.

## 2. Modeling approach

We develop a model of the costs of carbon capture that allows us to characterize the full range of cost outcomes under various combinations of input assumptions. To determine the most influential parameters affecting costs, we ran a sensitivity analysis [21] on the IECM (Integrated Environmental Control Model) [18,22]. We then modeled those influential parameters explicitly in our own model, which is in a reduced form compared to IECM and other similarly detailed studies [23–25], but is more technologically detailed than characterizations of CCS typically used in integrated assessment models. We use a reduced-form model for three reasons. First, our elicitations of energy penalty provide one parameter that effectively summarizes the effects of a wide swath of technology-specific variables used in more detailed models, e.g. electricity used for pumps and blowers. Second, the availability of a recent and carefully calibrated survey of all major studies of the capital costs of CCS [26] enables us to use a broader range of assumptions on capital costs. Third, the reduced-form of our model makes extensive sensitivity analysis feasible. We run hundreds of thousands of iterations using various combinations of values for input parameters. The model described below estimates the costs of 7 types of CCS technologies and simulates the effect of R&D investments and carbon prices on technology costs in 2025.

### 2.1. Cost model structure

We calculate costs of carbon capture based on the additional costs associated with producing electricity using carbon capture compared to a pulverized coal reference plant. Capture technologies typically add capital costs, O&M (operation and maintenance) costs, as well as T&S (transport and storage) costs. In addition, parasitic energy consumption to power and heat the capture

Please cite this article in press as: Nemet GF, et al., Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios, Energy (2013), http://dx.doi.org/10.1016/j.energy.2013.04.047

process reduces energy output. Since our analysis is intended to add insight on the effects of policy on the marginal costs of $CO_2$ emissions abatement, we use two outcome metrics: (1) the additional levelized cost of electricity (\$/MWh) and (2) the cost of avoided $CO_2$ emissions (\$/t$CO_2$).

Fig. 1 provides an overview of the model approach and the sources for the input parameters used. Sources include the IECM model [22], a survey by the IEA (International Energy Agency) [26], and an expert elicitation [16]. The model is flexible, allowing us to explore various configurations of the model inputs to propagate multiple distributions of values through the model. Each input shown in Fig. 1 includes the type of distribution used for the sensitivity analysis: binomial for feasibility, aggregated distribution from expert responses for energy penalty, and triangular for the others. The overlapping rectangles for feasibility and electricity produced indicate that input values are conditional on each of 3 policy scenarios described in the Introduction. This structure is repeated separately for each of the 7 technologies assessed. The rest of this section describes the parameterization of the cost model and the values used to populate it.

#### 2.1.1. Categories of carbon capture technology

We conducted interviews with industry experts and reviewed taxonomies of carbon capture in the literature [27,28] to define 7 areas of capture technology that are sufficiently distinct to elicit clear responses and aggregated enough that multiple experts are available to provide input for each technology:

1. **Absorption**: post-combustion using absorption via solvents, including MEA (monoethanolamine), ammonia, and novel solvents.
2. **Adsorption**: post-combustion using adsorption, including solid sorbents and metal organic frameworks.
3. **Membranes**: post-combustion using membranes, including ionic liquids.
4. **Other PC**: post-combustion using other approaches, including enzymes and cryogenics.
5. **Pre-combustion capture**: typically with IGCC (integrated gasification combined cycle).
6. **Oxyfuel**: alternative combustion using pure oxygen rather than air.
7. **Chemical looping combustion**: use of metals to transport oxygen.

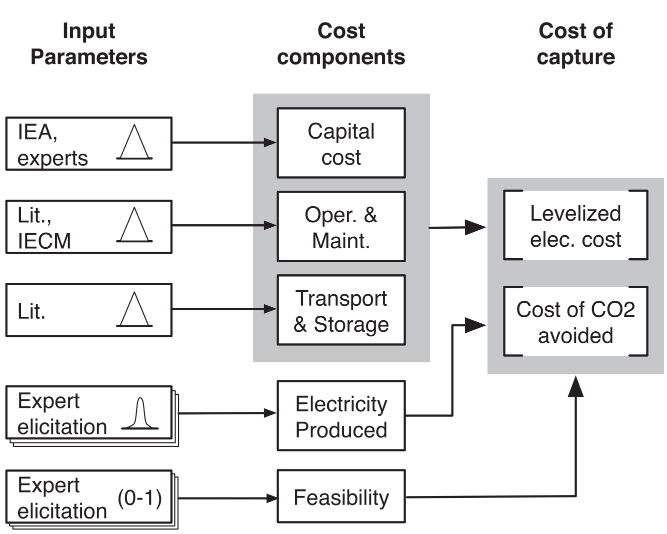


**Fig. 1.** Model approach showing sources of input parameter values, cost components, and outcome metrics.

We calculate costs for each of these technology categories separately.

#### 2.1.2. Electricity production

In our model, energy penalty (EP) reduces the net capacity of the power plant. We use a consistent definition of EP based on the effect of CCS on the plant's total efficiency ($\eta$), relative to that of a reference plant:

$$EP = 1 - \frac{\eta_{\text{with CCS}}}{\eta_{\text{reference}}} \tag{1}$$

We note that some CCS cost studies increase the size of the capture-equipped power plant to compensate for this parasitic energy loss. As a result, in these studies much of the increase in electricity costs due to energy penalty emerges as increases in capital cost, due to the upscaling of boilers, pollution controls, and other components of the reference plant needed to achieve the same net electricity production. Our strategy assumes that the 500 MW reference plant is already sized at optimal scale [29], so the net output of the capture plant is reduced by the addition of the capture technology. The impact of the EP thus appears as a reduction in AEP (annual electricity produced), thus increasing the unit cost of electricity from the plant. For data on energy penalty we use the results of the expert elicitation described below.

#### 2.1.3. Cost calculations

We use the following calculations to estimate the additional levelized cost of electricity and the costs of avoided $CO_2$ emissions [30].

*Levelized cost of electricity*: To calculate the additional LCOE (levelized cost of electricity) in \$/MWh, we calculate the LAC (levelized annual cost) of CCS (\$/year) and divide by the annual energy produced (AEP) by a reference plant with CCS. AEP in MWh/year is defined using:

$$AEP_{ccs} = NetCap_{ref}(1 - EP)\cdot CF\cdot H \tag{2}$$

where CF is capacity factor and $H$ is hours in a year (8766). The net capacity ($NetCap_{ref}$) in $MW_e$ is the electrical power output of the reference plant. For plants with capture, the net capacity is derated due to the energy penalty (eq. (1)). The LAC is calculated by summing the four basic components of cost:

$$i = Capital,\ O\&M,\ T\&S,\ PowerBlock$$

$$LAC_{ccs} = \sum LAC_i \tag{3}$$

Capital costs and PowerBlock costs dominate the O&M and T&S costs (see Fig. 10 in the Appendix) so we rely on the literature to obtain values for $LAC_{O\&M}$ and $LAC_{T\&S}$. The other two major cost components are calculated as shown below.

$LAC_{capital}$ is defined as: TCR•CRF, where TCR (total capital required) is the additional overnight cost of the CCS plant (compared to a reference plant) plus interest during construction plus preproduction costs, both of which are calculated as a percentage of the overnight cost. The CRF (capital recovery factor) is defined using the discount rate ($r$) and the amortization lifetime of the plant ($L$):

$$CRF = \frac{r}{\left(1 - (1 + r)^{-L}\right)} \tag{4}$$

In this case, we treat $L$ as the time period over which the owners can depreciate the value of the plant.

Please cite this article in press as: Nemet GF, et al., Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios, Energy (2013), http://dx.doi.org/10.1016/j.energy.2013.04.047

PowerBlock accounts for the increased cost of the reference plant electricity ($/MWh) due to parasitic energy loss for capture. Although we assume that the reference plant itself does not change with CCS, the electricity costs of each MWh ($LCOE_{ref}$) increase because some energy is used for capture.

$$LAC_{PowerBlock} = LCOE_{ref}\left(\frac{1}{1-EP} - 1\right)AEP_{ref} \tag{5}$$

We sum these four annual costs (eq. (3)) and use the resulting $LAC_{ccs}$ to calculate the additional levelized cost of electricity ($/MWh) due to capture.

$$LCOE_{ccs} = \frac{LAC_{ccs}}{AEP_{ccs}} \tag{6}$$

The $LCOE_{ccs}$ provides an indication of how much the costs of electricity from a reference plant will rise due to CCS.

*Cost of avoiding $CO_2$ emissions*: We calculate the cost of avoiding $CO_2$ emissions ($/t$CO_2$) as:

$$CO_2\ \text{cost} = \frac{LCOE_{ccs}}{CO_2\ \text{avoided}} \tag{7}$$

The amount of $CO_2$ avoided (t$CO_2$/MWh) is the difference between the emissions of the reference plant and emissions from the plant with carbon capture, per unit of electricity produced.

$$CO_2\ \text{avoided} = CO_2\ \text{emit}_{ref}\left(1 - \frac{1-\text{CaptureRate}}{1-EP}\right) \tag{8}$$

where $CO_2$ $\text{emit}_{ref}$ is the per unit emissions of $CO_2$ from the reference plant (t$CO_2$/MWh) and CaptureRate is the portion of $CO_2$ captured relative to that produced.

### 2.2. Parameter values

We next describe the data and process used to populate these model parameters. We also include justifications for ranges of alternative values that we use for sensitivity analysis.

#### 2.2.1. Energy produced, elicited energy penalties, and policy scenarios

To obtain values of EP, we interviewed 15 CCS experts and explicitly assessed their subjective probabilities over technological parameters for the 7 capture technologies, focusing on EP as a key metric of technological advance [16]. Interview duration ranged from 2 to 8 h and each expert evaluated between 1 and 7 of the capture technologies. We converted all expert responses into a consistent definition of EP based on eq. (1). Each expert provided probability distributions of EP in 2025 for one or more of the technologies under each of the 3 policy scenarios. Typically, experts identified challenges involved in each technology, areas in which improvements would lead to reductions in EP. They then worked through their assessment of how much of a reduction in EP would be likely under each scenario, eventually arriving at quantitative assessments of the EP. Jenni et al. [16] document the individual results of each expert assessment and describe how those individual assessments can be aggregated. In this paper we present results using only the aggregated distributions for EP, which represent the full range of elicited expert opinion on the future feasibility and performance of the technologies. The SI includes results based on each of the individual expert's assessments. Fig. 2 shows the aggregated results for each technology and scenario. We focus our analysis on the effects of increased R&D investment on technological advance, and consider primarily the S3 results, in comparison with the S1 results.

#### 2.2.2. Capital costs

Our capital cost data for carbon capture comes from a survey of 13 studies by the International Energy Agency (IEA). We supplement these data with expert judgments on the costs of those technologies not covered in the IEA survey: adsorption, membranes, and other post-combustion (see SI). We use the IEA data because they span a wide set of published estimates, carefully control for variation in study design to provide consistent estimates of costs, and explicitly report assumptions, e.g. which costs are excluded and what assumptions are used for characteristics of the reference plant [26,31]. They also reflect a more recent set of studies than those conducted in the mid-2000s [28,32]. These results provide us with a rather large distribution of capital costs for input data, as shown in Fig. 9.

We adjust the data from Finkenrath [26] in the following ways. First, because we are primarily concerned with the additional costs of capture in a broad climate change mitigation context, we calculate additional overnight capital costs for all technologies compared to a pulverized coal reference plant. Studies of pre-combustion capture often report additional capital costs above an IGCC reference plant, which for us provided an inconsistent baseline for comparison. Second, we use the detailed description of capital costs in the IECM model to include additional costs that are not present in the IEA estimates. Our capital costs thus add to the IEA values: (1) interest payments during construction or AFUDC (allowance for funds during construction), estimated at 7.25% of the overnight capital cost and (2) preproduction costs of 1 month's fixed and variable O&M cost, estimated at 4% of the overnight capital cost. Third, as described above, we recalculate the capital cost by taking energy penalty into account in AEP, rather than scaling up the plant to be equivalent in peak electricity output, as is done in other studies. This adjustment, shown in the SI, allows our recalculated $/MW$_e$ capital cost to be consistent with the capture plant's output, which we calculate in eq. (2).

#### 2.2.3. O&M costs

Carbon capture has non-energy costs involved in operating and maintaining the capture system. These process costs include the cost of materials, such as sorbents and reagents, water, waste disposal, and labor costs. We use the detail in the IECM model to estimate these costs. Sensitivity analysis conducted by Rasmussen [21] provides indications of ranges to use for high and low cost assumptions. We supplement these ranges with estimates from the literature that expand the possible range of best case and worst case process costs.

#### 2.2.4. $CO_2$ transport and storage costs

Costs to transport pressurized $CO_2$ from the capture plant to a storage facility and to store and maintain the $CO_2$ are highly location specific. Unknown evolution of the infrastructure as well as the importance of location and clusters in moving, storing, and maintaining pressurized $CO_2$ lead to large heterogeneity in these costs

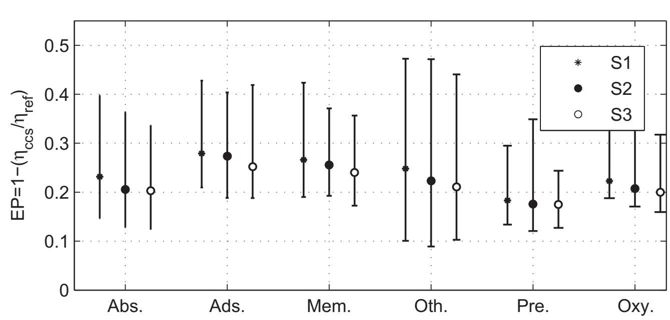


**Fig. 2.** Elicited energy penalty $(1 - \eta_{ccs}/\eta_{ref})$ in 2025 aggregated across experts. Bars indicate ranges of 5–95th percentile and markers indicate medians.

[33]. We use a base estimate of \$10/t$CO_2$ and a range of ±\$5/t$CO_2$ [34,35]. We note that many comparable estimates of the cost of carbon capture exclude these costs from their calculations, primarily due to uncertainty about their magnitude. Because we are ultimately interested in marginal abatement costs, we need the full cost of capture technology and thus include transport and storage in all our reported costs.

### 2.3. Additional parameter values

We also use elicited values for chemical looping and for the technical feasibility of each technology. We describe additional base case and alternative assumptions for other parameter values.

#### 2.3.1. Chemical looping combustion

Because chemical looping combustion is less mature than other technologies, we used a different structure for our elicitation questions. Instead of asking experts for energy penalties at given probabilities, we asked for the probabilities of attaining each of three endpoint outcomes in 2025. Feedback from experts allowed us to define these outcomes using multiple parameters:

**Outcome 1**: <10% energy penalty, <10% increase in capital costs, and can operate for at least 6000 h without need for a shutdown (1 planned shutdown per year).

**Outcome 2**: 10%–12% energy penalty, 10%–55% increase in capital costs, and ~4000 h without need for a shutdown (2 planned shutdowns per year).

**Outcome 3**: Does not work, or any performance lower than that described for Outcome 2.

Four experts provided assessments of chemical looping, each providing probabilities of achieving each outcome under the three scenarios (see SI). The outcomes are mutually exclusive and exhaustive so each expert's probabilities sum to one.

#### 2.3.2. Technical feasibility

We also asked the experts for their judgments of the likelihood that each technology would turn out to be technically unfeasible, independent of costs. They reported probabilities of feasibility from 0 to 1 (see SI). All experts expected that post-combustion, pre-combustion, and oxyfuel would be technically feasible in 2025. Each of the other four technologies had at least one expert who assigned a probability less than 1. For each technology, we average the responses across experts to provide aggregated estimates of the probability that each technology would be feasible under each of the 3 scenarios. As discussed above, expert judgments for chemical looping feasibility have three possibilities rather than two.

#### 2.3.3. Other parameters

Assumptions on other parameters include the following. We assume a reference plant efficiency of 43% representing a central value from our elicitations [16] and account for variation from 38% to 48%. Capacity factor for the capture plant is 75% and includes a range of 65%–85% [36]. Other studies have found that some energy systems would dispatch CCS plants at lower capacity factors, making these plants too expensive to justify construction [37]. The range we use is thus conditional on an energy system that would dispatch in this range. Reference plant output is 500 $MW_e$ and capture plant output is reduced from this value due to EP. $CO_2$ removal efficiency of each capture system is assumed to be 90%. Emissions of $CO_2$ from the reference coal plant are 0.751 t$CO_2$/MWh [31]. Our base case discount rate $r$ is 14% [36]. Sensitivity analysis includes values up to 25%, a high corporate 'hurdle' rate, and as low as 3%, a social discount rate [38]. Firms depreciate their capital investments over 30 years in the base case, which we vary from accelerated depreciation at 20 years to the lifetime of the plant at 50 years. All dollar values are reported at year 2010 price levels. Table 1 and the SI summarize these values.

### 2.4. Benchmarking

After populating our model, we compare our central estimates to those of other studies, ex-post. Finkenrath [31] surveys several studies of CCS costs by 8 organizations and harmonizes them so they use consistent assumptions, e.g. on price levels and discount rates. We reset our base case assumptions such that discount rate (10%), amortization period (40 years), reference plant efficiency (41.4%), and capacity factor (85%) match those in the survey. In addition we add to the surveyed studies the \$10/t$CO_2$ for transport and storage that is included in our results. If our central estimates for scenario 3 were included with the other studies, they would be at the 33rd percentile for post-combustion, 33rd for pre-combustion, and 50th for oxyfuel (Fig. 3). Scenario 1 values would be at the 47th, 33rd, and 75th percentiles. Our central estimates are consistently higher than those of a similar modeling effort from the mid-2000s [32].

## 3. Distributions of costs for individual technologies

In this section, we propagate distributions of input parameter values through our cost model to generate probability distributions of capture costs, considering one technology at a time. We start by presenting the distributions of the costs of each technology taking into account the variation in energy penalty while holding other parameters fixed at their base case values. We then provide some results on how the capture cost distributions are impacted by the assumptions on the 7 other model parameters we consider. Building on this, we then present the distributions that result from propagating distributions for all of the input parameter values through the model.

We calculate cost outcomes for both the cost of avoided $CO_2$ emissions (\$/t$CO_2$) and the additional levelized cost of electricity due to carbon capture (\$/MWh). To reduce the dimensionality of the results, we present only the cost of avoided $CO_2$ emissions in this paper; the SI includes results for both estimates of capture costs. Note that the results in this section are all conditional on each technology being feasible.

### 3.1. Cost distributions resulting from energy penalty distributions

Fig. 4 shows the costs of avoided $CO_2$ using the full distributions of energy penalties aggregated across experts. In this first stage, we hold other parameter values at their base case values. We do not include chemical looping because that technology was elicited as a multi-criteria endpoint rather than as an energy penalty. Gray areas show PDFs (probability density functions) of the cost of avoided $CO_2$ for scenario 3. Black lines show the corresponding PDF for

**Table 1**
Input assumptions for sensitivity analysis.

| | Low cost | Base case | High cost | Source |
|---|---|---|---|---|
| 1. Capital cost | See Fig. 9 | | | [31] |
| 2. Reference plant, $\eta$ | 0.38 | 0.43 | 0.48 | [16] |
| 3. Process costs | 0.7 | See SI | 1.3 | [36] |
| 4. Discount rate | 0.03 | 0.14 | 0.25 | [36,38] |
| 5. Depreciation life | 50.0 | 30.0 | 20.0 | [31] |
| 6. Capacity factor | 0.85 | 0.75 | 0.65 | [36] |
| 7. $CO_2$ transport & storage | 5.0 | 10.0 | 15.0 | [35] |

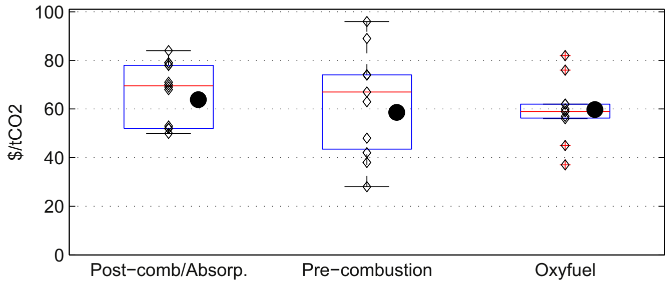


**Fig. 3.** Comparison of costs of avoided carbon emissions ($/t$CO_2$) using model central estimates for scenario 3 (circles) to results from other studies (diamonds). Boxes show interquartile ranges.

scenario 1. Median values for each distribution are included in the legends. The SI provides a comprehensive set of these results for all technologies and all experts, as well as additional metrics, including the levelized costs of capture, energy penalties, and scenario comparisons.

### 3.2. Sensitivity analysis of cost model assumptions

We next assess the sensitivity of technology cost outcomes to the input assumptions used in the cost model. Table 1 shows the base case values as well as the alternative values used. Here we look at the effects of the range of input values varied one at a time. Fig. 5 shows how alternative assumptions for each parameter, including energy penalty, individually affect the cost of $CO_2$ avoided for each capture technology under scenario 3. The horizontal solid line shows the cost of the technology in the base case. One can see that

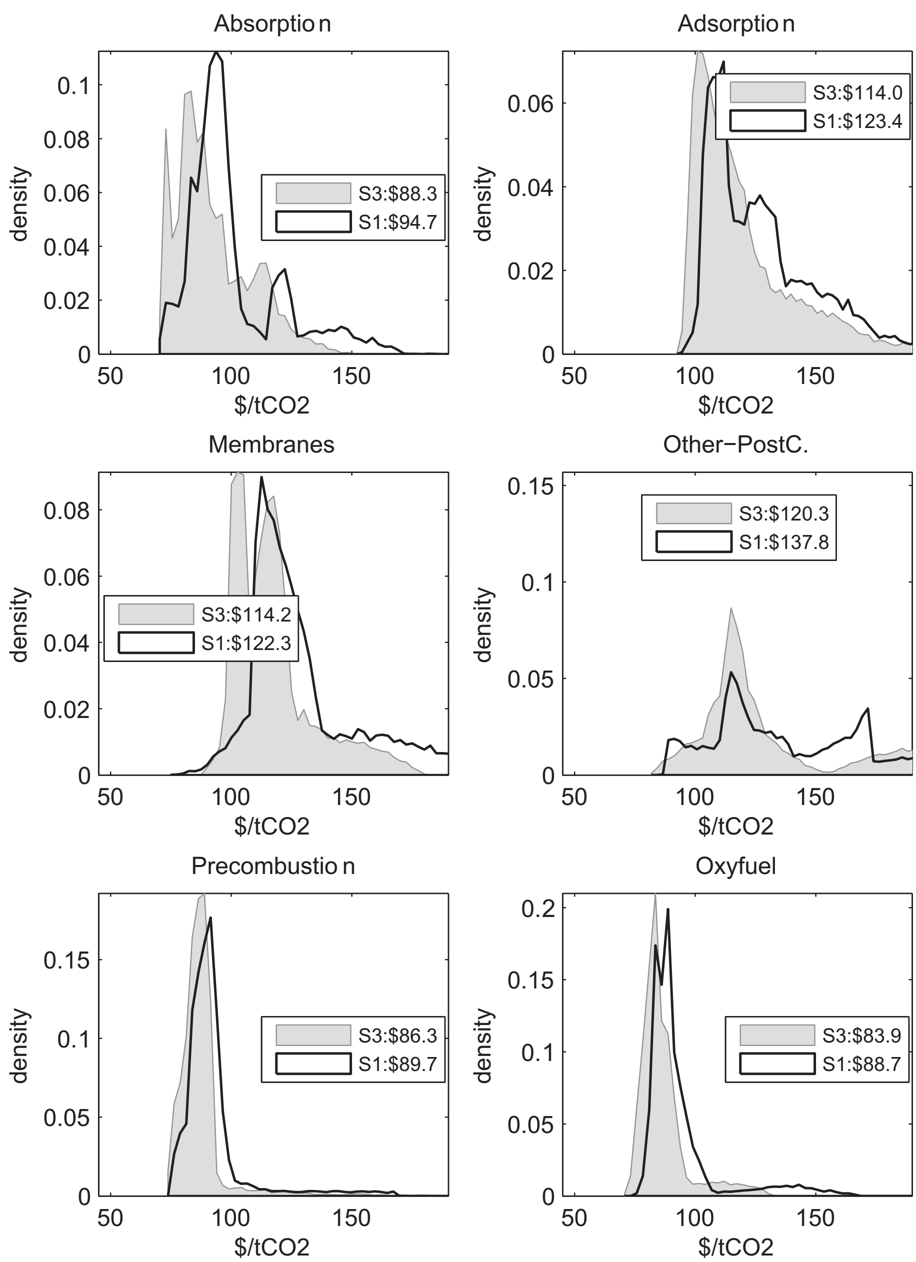


**Fig. 4.** Comparisons of probability distributions of cost of avoided $CO_2$ emissions ($/t$CO_2$) in 2025 for 6 technologies using distributions of energy penalties: scenario 1 (black line) and scenario 3 (gray area). Legend shows median values.

Please cite this article in press as: Nemet GF, et al., Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios, Energy (2013), http://dx.doi.org/10.1016/j.energy.2013.04.047

the largest effects are from assumptions about energy penalty, capital cost, and discount rates. There is a substantial variation in size and relative importance of each parameter across technologies.

### 3.3. *Cost distributions resulting from uncertainty on all parameters*

Here, we run simulations drawing values from the distribution for each parameter in the sensitivity analysis simultaneously. Each parameter, other than energy penalty, is assigned a triangular distribution using the values shown in Table 1 as minima, modes, and maxima (see SI). We assume that all 8 parameters are independent. Results remain conditional on each technology being technically feasible. Fig. 6 shows PDFs of costs for each technology under scenario 3 and under scenario 1. Median values for each distribution are shown in the legends and cumulative probabilities of costs ≤\$60/t$CO_2$ (a commonly mentioned target for CCS costs) for scenario 3 are indicated for each technology. The dispersion in costs in Fig. 6 is much larger than when restricting variation to energy penalty (Fig. 4). In addition, the ranges are all larger than those included in Fig. 5, a consequence of allowing all parameters to vary simultaneously. For each technology, the effects of R&D—the difference between scenario 3 and scenario 1—are small relative to the dispersion within each scenario. All distributions are noticeably right-skewed, which is primarily due to the skewness in energy penalties observable in Fig. 2. Low cost outcomes are bounded by thermodynamic limits, especially on compression energy, while higher cost outcomes are unbounded, which contributes to the skewness in the distributions.

As a further sensitivity analysis, we generated these same cost distributions but held one of the parameter values for capital costs, discount rate, and energy penalty constant, while allowing the

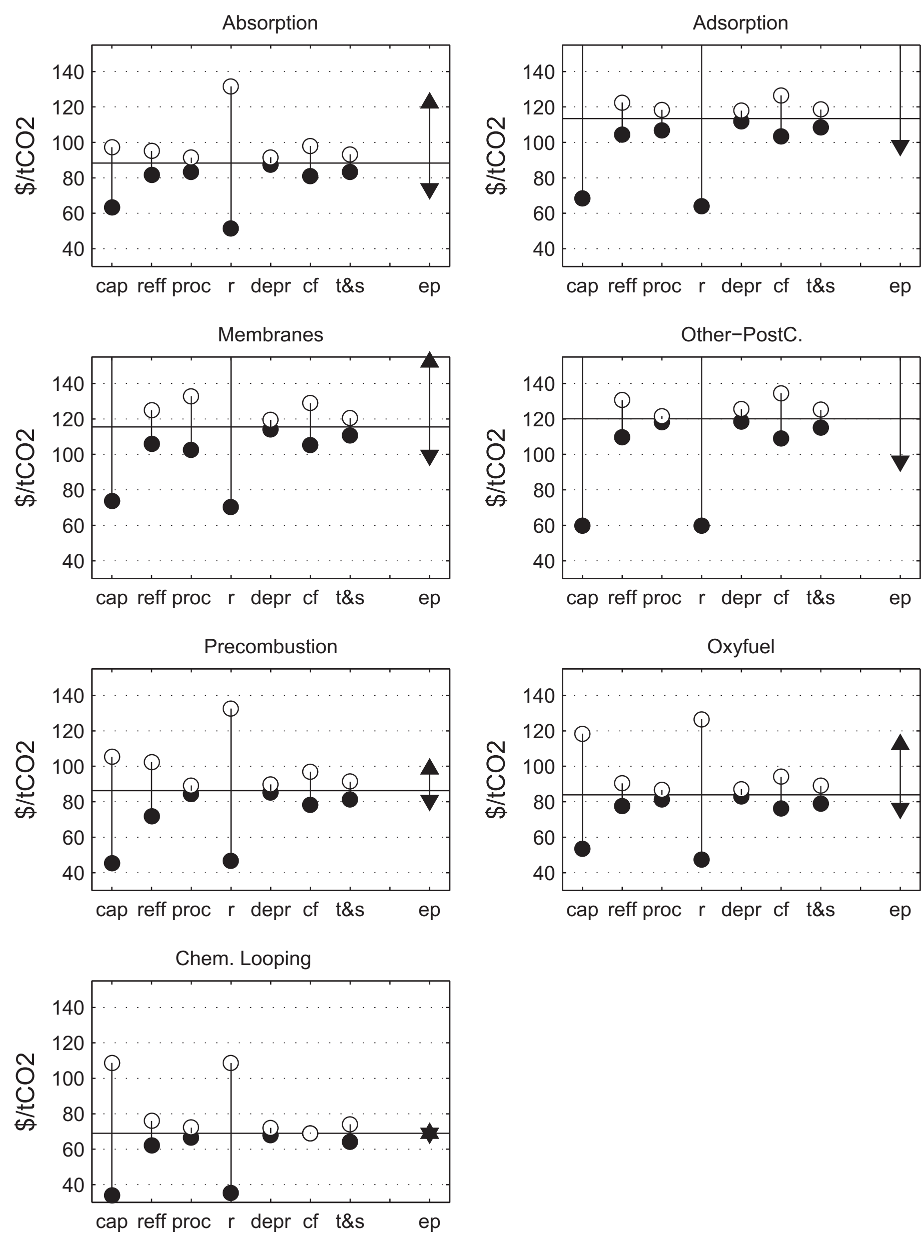


**Fig. 5.** Sensitivity of the cost of $CO_2$ avoided in 2025 under scenario 3 to alternative assumptions on input parameters: capital cost (cap), reference plant efficiency (reff), process costs (proc), discount rate (r), depreciation period (depr), capacity factor (cf), and transport and storage costs (t&s). Energy penalty (ep) is also displayed, but in different markers because range is 5–95th, rather than 0–100th percentile.

Please cite this article in press as: Nemet GF, et al., Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios, Energy (2013), http://dx.doi.org/10.1016/j.energy.2013.04.047

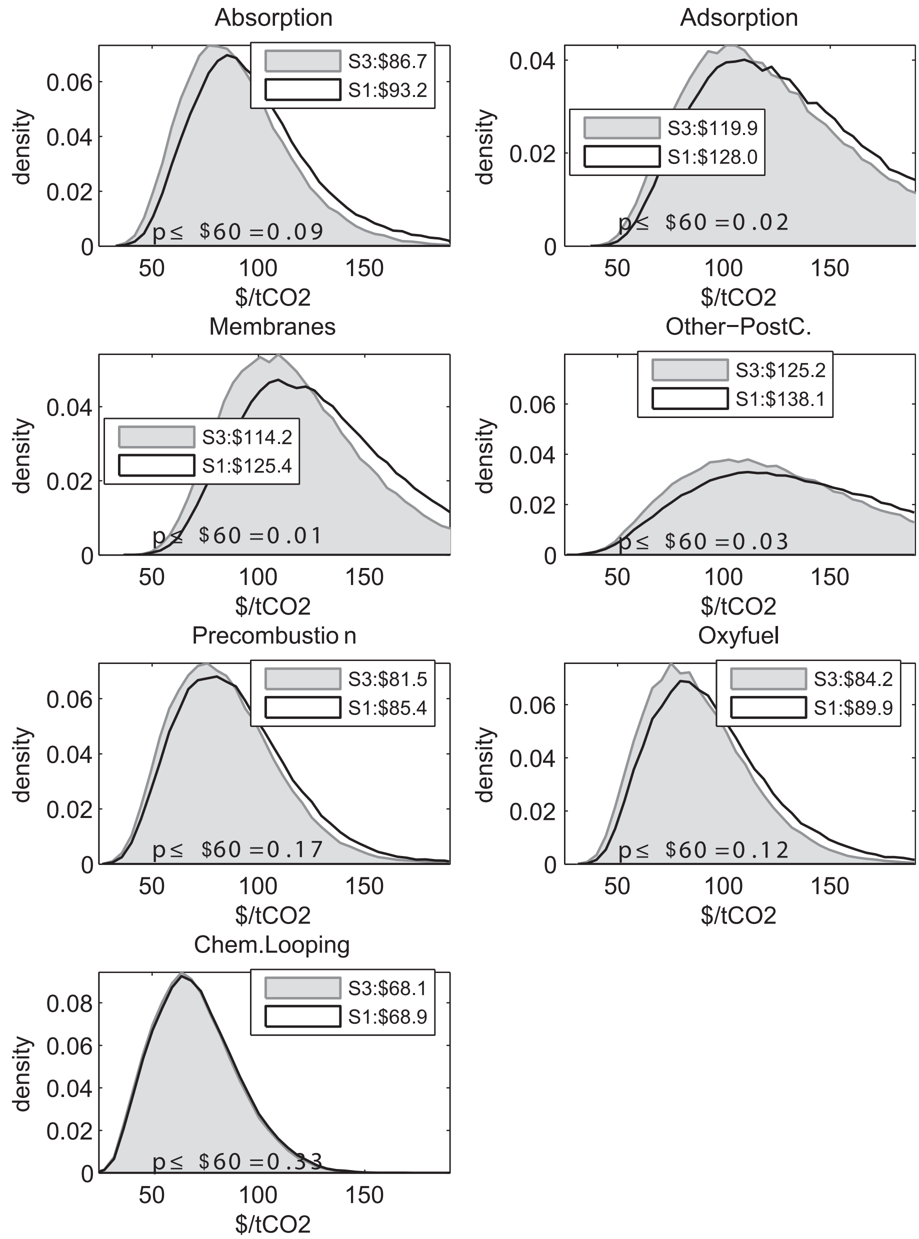


**Fig. 6.** Avoided cost of $CO_2$ in 2025 under scenario 3. The resulting distribution includes outcomes across all 7 sensitivities and energy penalty elicitations. Results do not reflect experts' assessments of feasibility. Legend shows median value for each technology.

other 7 parameters to vary (see SI for details). In almost every case, removing variation shrinks the left tail and thus reduces the cumulative probability of achieving a $60 target. Fixing discount rate has the largest effect, followed by capital cost, and then energy penalty. Because energy penalty is strongly right-skewed, fixing it can produce a small increase in cumulative probability as it precludes high cost outcomes.

## 4. Distributions of technology cost with technology competition

In this section, we assess the cost of carbon capture with all 7 technologies competing to set the lowest cost in each sample of a Monte Carlo simulation. As in the previous section, we first consider only the impact of EP, then of all parameters together. For each sample, we calculate a cost of capture for each of the 7 technologies, and then identify the minimum of those costs as the cost of CCS. We repeat this exercise over 100,000 samples to develop a distribution of carbon capture costs. In this section we incorporate experts' judgments about the technical feasibility of each technology, using the values shown in the SI.

### *4.1. Variation in energy penalty*

In Fig. 7, we present the distributions for the costs of capture that result when sampling over the distributions of energy penalties 100,000 times, holding all other cost model assumptions at their base case levels. We assume that energy penalties are independent across technologies. Because these distributions are based on the minimum costs across 7 technologies, they are shifted to the left relative to any of the distributions based on only one technology (Fig. 4). The left mode around $55 arises from the experts' aggregated expectations that the likelihood of Outcome 1 for

Please cite this article in press as: Nemet GF, et al., Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios, Energy (2013), http://dx.doi.org/10.1016/j.energy.2013.04.047

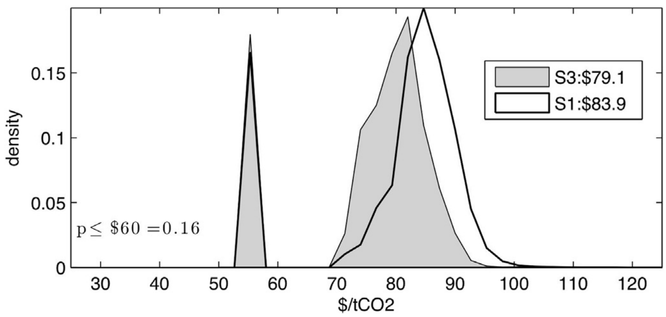


**Fig. 7.** Comparisons of probability distributions of minimum cost of $CO_2$ avoided ($/t$CO_2$) in 2025 across 7 technologies, including variation in energy penalties. Legend shows median values.

chemical looping is around 16%. One can also see the effect of R&D in shifting the gray area to the left of the black line.

### 4.2. Variation in all parameters

To simulate the full distribution of minimum costs, we calculate minimum cost outcomes, sampling across distributions of energy penalties and distributions of other model parameters. As before, we assume that the parameters are independent from each other. We also assume independence across technologies for energy penalties, capital costs, capacity factor, and O&M costs. Each of these parameters can take different values in different technologies within a sample. For example, in one draw, post-combustion–absorption may have capital costs at its 10th percentile while pre-combustion has capital costs at its 70th percentile.[1] In contrast, we assume that reference plant efficiency, discount rates, depreciation schedule, and costs for transport and storage are exogenous parameters, and therefore that these values are the same across technologies within each sample. One could make the case that technologies that involve more risk—at the time of construction—might require higher discount rates. However, we already incorporate differences in technical feasibility and probabilistic estimates of technology outcomes, so adjusting discount rates to reflect differences in risk would involve double-counting.

#### 4.2.1. Distribution of minimum cost among 7 technologies

The upper panel of Fig. 8 shows the distribution of the minimum cost of capture under scenario 3, with the black line showing the results for scenario 1. Median values are included in the legend, and the figure also shows the probability that the costs of $CO_2$ avoided will be ≤$60/t$CO_2$ under scenario 3. In the lower panel, we show which technology is determining the minimum cost in each sample under scenario 3. The PDFs for each technology are stacked so that the top line shown at a given cost level on the $x$-axis is the combined value for all technologies, i.e., the density is identical to that of the PDF for scenario 3 in the upper panel. The legend in the lower panel shows the portion of the 100,000 samples for which each technology sets the minimum cost.

This full accounting of uncertainty in input parameters provides a minimum capture cost of slightly less than $20/t$CO_2$ and maximum of around $130/t$CO_2$, when selecting the technology with the lowest cost in each sample. The median capture cost is $67/t$CO_2$ using the scenario 3 elicitations and $71 using the scenario 1 elicitations. For

[1] In reality, capital costs across technologies are probably partially correlated. Some of the variation may be technology specific, e.g. how complicated it turns out to be to construct each type of plant at scale. On the other hand, some of the variation in capital costs may be general across technologies, e.g. due to commodity prices or labor costs. See SI for detail.

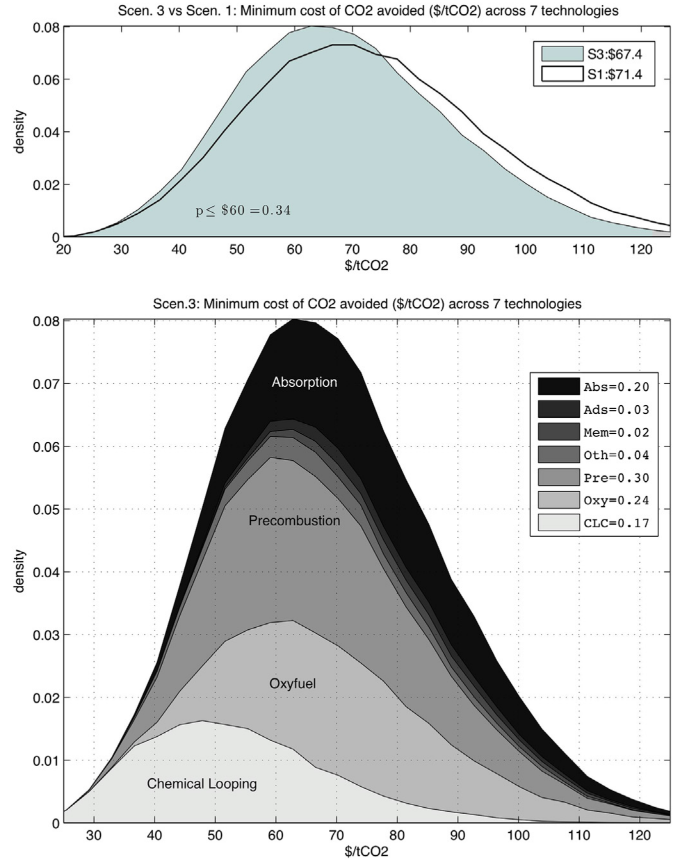


**Fig. 8.** Comparisons of probability distributions of minimum cost of $CO_2$ avoided ($/t$CO_2$) in 2025 across 7 technologies. Distribution of costs results from distribution of energy penalties and cost model assumptions. Legend shows portion of all instances in which each technology sets the lowest cost.

74% of 100,000 samples, the minimum cost of capture is determined by one of three technologies: pre-combustion (30%), oxyfuel (24%), and post-combustion–absorption (20%). Although even the least likely of the seven technologies (post-combustion/membranes) sets the minimum cost of capture in 2% of samples. The technology with the lowest expected value cost (chemical looping) in Fig. 4 sets the minimum cost in 17% of cases. This result is driven primarily by the experts' aggregated expectations of the feasibility of the best outcome for chemical looping, 18%. Chemical looping accounts for a large portion of the lowest cost outcomes, e.g. more than half of those cases in which the cost of CCS is below $40/t$CO_2$.

#### 4.2.2. Probability of meeting a target

We also assess the probability of capture costs below a target of ≤$60/t$CO_2$. Using all technologies, we find a cumulative probability of 28% under scenario 1 and 34% for scenario 3. Table 2 provides specificity on each technology by showing $p \leq$ $60/t$CO_2$ for each technology under these two scenarios. Pre-combustion has the highest probability among technologies in both scenarios. Three technologies with substantial probabilities of meeting that target—absorption, pre-combustion, and oxyfuel—all show improvement from R&D. Chemical looping, which has a probability above 0.1, shows only a modest improvement with R&D. Note that the probabilities for each technology reflect the frequency of each technology being below the threshold across all samples—not just the sample in which that technology sets the minimum cost. As a result the individual technology probabilities do not sum to the overall probability. We also considered the results of additional runs in which capital costs are fully correlated across technologies. This alternative

Please cite this article in press as: Nemet GF, et al., Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios, Energy (2013), http://dx.doi.org/10.1016/j.energy.2013.04.047

**Table 2**
Probability of capture costs $\leq$ \$60/t$CO_2$.

| | Scen. 1 | Scen. 3 |
|---|---|---|
| 1. Absorption | 0.06 | 0.09 |
| 2. Adsorption | 0.01 | 0.02 |
| 3. Membranes | 0.00 | 0.01 |
| 4. Other post-c. | 0.02 | 0.03 |
| 5. Pre-combustion | 0.13 | 0.17 |
| 6. Oxyfuel | 0.08 | 0.12 |
| 7. Chemical looping | 0.11 | 0.12 |
| All 7 techs | 0.28 | 0.34 |

assumption tends to concentrate the minimum cost outcomes among a smaller set of technologies and reduces the overall probability of reaching a \$60 target.

## 5. Discussion

We used an expert elicitation of energy penalties as an input to model the cost of CCS across 7 technologies. Our primary objective was to scope out the distribution of possible outcomes using the elicitation results and distributions of possible values for other model parameters. We ran Monte Carlo simulations to identify the lowest cost among all 7 capture technologies using the full distribution of input values.

### 5.1. Uncertain levelized capital costs

Our sensitivity showed that the uncertainty in levelized cost of capital is the dominant source of uncertainty in the future costs of CCS. This factor itself consists of two parameters: overnight capital cost and discount rate. Each has it own substantial uncertainty, but for different reasons.

#### 5.1.1. Overnight capital cost

Expectations about overnight capital costs are subject to a very large range of views, from \$600 to 2500/kW (Fig. 9). Reducing uncertainty in these ranges would decrease uncertainties about the overall cost of capture. A key open question in understanding future CCS costs is whether the factors affecting capital costs are primarily exogenous—having to do with exchange rates, labor costs, and material costs for example—or whether they can be targeted with purposive investment, such as with R&D, scaling up, or learning by doing. The experts we spoke with acknowledged uncertainty about capital costs, but they consistently rejected the hypothesis that these could be affected in any meaningful way by R&D funding. This consensus extended to a sentiment that the construction of some number of early plants would reduce uncertainty in capital costs for subsequent plants.

#### 5.1.2. Discount rates

A second parameter affecting capital costs is the rate used to amortize the overnight capital costs. The appendix Fig. 10 shows the effect of discount rates on both the total cost and contribution of cost components under different discount rates. Our base value of 14% is similar to those used in other CCS studies. It is perhaps representative of a corporate hurdle rate, in which the decision to invest in a CCS plant competes with other investment opportunities with expected returns at that rate. This rate could reasonably be as high as 25%, our high cost extreme value. It depends on several factors, such as the economy-wide interest rate, the firm's profit margins, and the degree to which firms account for risk by increasing their discount rate. Our low discount rate, 3% is not meant to represent a low corporate discount rate. Rather, it represents a social discount rate that takes into account a different but overlapping set of considerations, such as the returns on other government programs and consideration of future generations. It might also vary over time, providing opportunities for public investment when rates are especially low, e.g. reflecting low economic growth [39]. The choice of whether to use a social or private rate depends on the perspective we take: that of a policymaker accounting for citizen preferences or that of a company deciding how to allocate resources among capital investments. In the case of climate change and public policies to address it, we are probably most interested in the social discount rate, since we will ultimately be comparing mitigation costs to the social cost of carbon, which would never be assigned a corporate discount rate. Still, firms' decisions are crucial as we assume that they, not the government, will ultimately decide whether or not to build large numbers of CCS plants. Their opportunity cost is the returns on alternative investments, represented by a corporate discount rate. Using a social discount rate will underestimate the costs they face and thus bias estimates of adoption upward. Ultimately we face a situation in which mitigation costs are discounted at a high private rate while benefits are discounted at a lower social rate.

### 5.2. Effects of R&D

Consistent with the above, we find that energy penalty is an important factor in determining overall costs, but its role is not a dominant one. Moreover, the difference in energy penalty between R&D scenario 3 as compared to scenario 1, as elicited from the experts, leads to modestly, but consistently, lower cost of capture across all technologies (Fig. 6). These two findings lead to the conclusion that, while R&D aimed at reducing EP clearly has an effect, it does not appear very large. When the importance of capital cost and discount rates is taken together with the modest impacts of science-based R&D, it suggests that policies aimed at reducing these cost factors—such as demonstration projects, subsides for adopting and implementing CCS, or loan guarantees—may be more effective at reducing the overall costs of capture for CCS than R&D funding.

### 5.3. Benefits of portfolio diversification

One interpretation of the results in Section 4 is that they show the gains from portfolio diversification, excluding for now the costs associated with funding a diversified portfolio. We found that for 74% of 100,000 samples, the minimum cost of capture is determined by one of three technologies (Fig. 8). However, even the least likely of the seven technologies sets the minimum cost of capture in 2% of samples. Despite these concentrated outcomes, we see benefits to technology portfolio diversification. If a mitigation cost target such as \$60/t$CO_2$ exists, then picking the technology with the best chance of meeting the threshold has a substantially lower chance of success (17%) than expanding investment to a portfolio of technologies that includes technologies that have lower chances of success in meeting the target. In this study, the probability of meeting that target given a full portfolio increased substantially, to 34%. This result establishes that benefits to diversification exist and are non-negligible. In fact, they may be substantial. Ultimately, for decisions about how much to diversify, the costs of expanding the portfolio need also be taken into account, as would the benefits, e.g. in terms of reduced climate damages or abatement costs. Our subsequent work will address these costs, as well as the benefits, of R&D using integrated assessment modeling.

## Acknowledgments

Thanks to Samuel Harms, Santosh Lamichane, and Peter Rasmussen for assistance with this research. This project was partially supported by the NSF program on the Science of Science and Innovation Policy under awards No. SMA-0960993 and SMA-0962100.

## Appendix A

Fig. 9 shows the estimates used for capital costs and Fig. 10 shows components of costs calculated by the model.

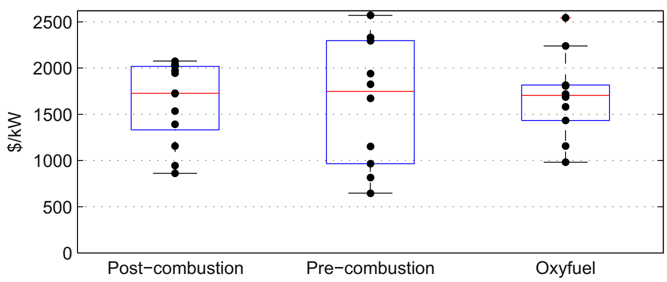


**Fig. 9.** Range of estimates of the capital costs of carbon capture [31,34–36]. Costs are the difference between overnight capital costs of a new plant including capture minus the cost of a new pulverized coal power plant. Central estimates are used to define base case values. Ranges are used to define low and high cost alternative assumptions for sensitivity analysis (Table 1).

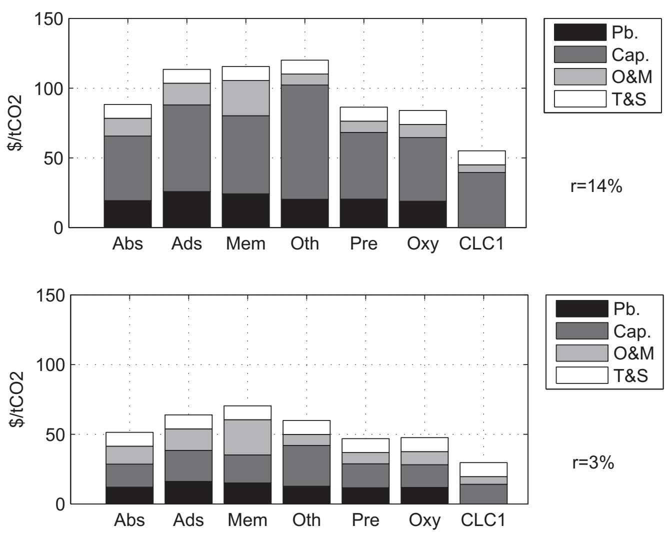


**Fig. 10.** Components of cost of $CO_2$ avoided for each technology using base assumptions, scenario 3, and median energy penalties. Lower panel shows results using alternative social discount rate, $r = 0.03$.

## Appendix B. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.energy.2013.04.047.

## References

[1] Bennaceur K, Gielen D. Energy technology modelling of major carbon abatement options. International Journal of Greenhouse Gas Control 2010;4:309–15.
[2] Clarke L, Edmonds J, Jacoby H, Pitcher H, Reilly J, Richels R. Scenarios of greenhouse gas emissions and atmospheric concentrations. Final Report. U.S. Climate Change Science Program, http://www.climatescience.gov/Library/sap/sap2-1/finalreport/sap2-1a-final-all.pdf; 2007.
[3] Nemet GF, Baker E. Demand subsidies versus R&D: comparing the uncertain impacts of policy on a pre-commercial low-carbon energy technology. The Energy Journal 2009;30:49–80.
[4] Nemet GF, Brandt AR. Willingness to pay for a climate backstop: liquid fuel producers and direct $CO_2$ air capture. The Energy Journal 2012;33:53–82.
[5] Grubler A, Nakicenovic N, Victor DG. Modeling technological change: implications for the global environment. Annual Review of Energy and the Environment 1999;24:545–69.
[6] Popp D. Innovation and climate policy. Annual Review of Resource Economics 2010;2:275–98.
[7] CBO. Federal efforts to reduce the cost of capturing and storing carbon dioxide. Technical Report. Congress of the United States, Congressional Budget Office, http://www.cbo.gov/publication/43357; 2012.
[8] Finon D. Efficiency of policy instruments for CCS deployment. Climate Policy 2012;12:237–54.
[9] Scherer FM, Harhoff D. Technology policy for a world of skew-distributed outcomes. Research Policy 2000;29:559–66.
[10] Rubin ES. Understanding the pitfalls of CCS cost estimates. International Journal of Greenhouse Gas Control 2012;10:181–90.
[11] Baker E, Keisler JM. Cellulosic biofuels: expert views on prospects for advancement. Energy 2011;36:595–605.
[12] IAC. Climate change assessments: review of the processes and procedures of the IPCC. Report. InterAcademy Council (IAC) Committee to Review the Intergovernmental Panel on Climate Change, http://reviewipcc.interacademycouncil.net/report.html; 2010.
[13] NRC. Prospective evaluation of applied energy research and development at DOE (phase two). Washington: The National Academies Press; 2007.
[14] Cooke R. Experts in uncertainty: opinion and subjective probability in science. New York: Oxford University Press; 1991.
[15] Meyer M, Booker J. Eliciting and analysing expert judgment: a practical guide. London: Academic Press Ltd; 1991.
[16] Jenni KE, Baker ED, Nemet GF. Expert elicitations of energy penalties for carbon capture technologies. International Journal of Greenhouse Gas Control 2013;12:136–45.
[17] Chung TS, Patio-Echeverri D, Johnson TL. Expert assessments of retrofitting coal-fired power plants with carbon dioxide capture technologies. Energy Policy 2011;39:5609–20.
[18] Rao AB, Rubin ES, Keith DW, Granger Morgan M. Evaluation of potential cost reductions from improved amine-based $CO_2$ capture systems. Energy Policy 2006;34:3765–72.
[19] Baker E, Chon H, Keisler J. Carbon capture and storage: combining economic analysis with expert elicitations to inform climate policy. Climatic Change 2009;96:379–408.
[20] Chan G, Anadon LD, Chan M, Lee A. Expert elicitation of cost, performance, and RD&D budgets for coal power with CCS. Energy Procedia 2011;4:2685–92.
[21] Rasmussen PG. The economic impacts of technical change in carbon capture. Masters thesis 2011.
[22] Rao AB, Rubin ES. Identifying cost-effective $CO_2$ control levels for amine-based $CO_2$ capture systems. Industrial & Engineering Chemistry Research 2006;45:2421–9.
[23] Hammond G, Akwe S, Williams S. Techno-economic appraisal of fossil-fueled power generation system with carbon dioxide capture and storage. Energy 2011;36:975–84.
[24] Cormos C-C. Integrated assessment of IGCC power generation technology with carbon capture and storage (ccs). Energy 2012;42:434–45.
[25] Pettinau A, Ferrara F, Amorino C. Combustion vs. gasification for a demonstration ccs (carbon capture and storage) project in Italy: a techno-economic analysis. Energy 2013;50:160–9.
[26] Finkenrath M. Carbon dioxide capture from power generation status of cost and performance. Chemical Engineering & Technology 2012;35:482–8.
[27] Figueroa JD, Fout T, Plasynski S, McIlvried H, Srivastava RD. Advances in $CO_2$ capture technology – the U.S. department of energy's carbon sequestration program. International Journal of Greenhouse Gas Control 2008;2:9–20.
[28] IPCC. IPCC special report on carbon dioxide capture and storage. Prepared by Working Group III of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press, http://www.ipcc.ch/publications_and_data/_reports_carbon_dioxide.htm; 2005.
[29] Wilson C. Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. Energy Policy 2012;50:81–94.
[30] Baker E, Nemet G, Rasmussen P. Modeling the costs of carbon capture, handbook of $CO_2$ in power systems. Springer; Berlin, Heidelberg: p. 349–72.
[31] Finkenrath M. Cost and performance of carbon dioxide capture from power generation. Working Paper. International Energy Agency (IEA); 2011.
[32] Davison J. Performance and costs of power plants with capture and storage of $CO_2$. Energy 2007;32:1163–76.
[33] Li J, Liang X, Cockerill T. Getting ready for carbon capture and storage through a 'ccs (carbon capture and storage) ready hub': a case study of Shenzen city in Guangdong province, China. Energy 2011;36:5916–24.
[34] Hamilton MR. An analytical framework for long term policy for commercial deployment and innovation in carbon capture and sequestration technology in the United States. Ph.D. thesis 2009.
[35] Herzog HJ. Scaling up carbon dioxide capture and storage: from megatons to gigatons. Energy Economics 2011;33:597–604.
[36] Versteeg P, Rubin ES. A technical and economic assessment of ammonia-based post-combustion $CO_2$ capture at coal-fired power plants. International Journal of Greenhouse Gas Control 2011;5:1596–605.
[37] Lund H, Mathiesen BV. The role of carbon capture and storage in a future sustainable energy system. Energy 2012;44(1):469–76.
[38] Moore MA, Boardman AE, Vining AR, Weimer DL, Greenberg DH. Just give me a number! practical values for the social discount rate. Journal of Policy Analysis and Management 2004;23:789–812.
[39] Lund H, Hvelplund F. The economic crisis and sustainable development: the design of job creation strategies by use of concrete institutional economics. Energy 2012;43:192–200.
[40] Carbon Capture and Sequestration Technologies at MIT. Carbon capture and sequestration project database, http://sequestration.mit.edu/tools/projects/; 2013 [accessed April 2013].

Please cite this article in press as: Nemet GF, et al., Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios, Energy (2013), http://dx.doi.org/10.1016/j.energy.2013.04.047