Low carbon energy R&D portfolios that are robust when models and experts disagree

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Abstract

Crafting energy policy in the face of climate change is daunting due to significant disagreement over technological uncertainty and the ultimate societal consequences of climate change. We address the challenge of designing energy technology Research and Development (R&D) portfolios, accounting for both parametric uncertainty about technological change and structural uncertainty about damages from climate change. We synthesize these conflicting beliefs to develop a set of plausible R&D portfolios, which are robust to multiple expert studies on technological change and multiple models of climate damages. This approach accounts for the best available information and allows policy makers to negotiate over qualitative issues. We identify common ground, with a high investment in Solar and Bioelectricity robust under all beliefs and models when the climate policy is ambitious. We find investment into Nuclear R&D the most sensitive, with stark disagreement among the models. Finally, the structure of investment portfolios is less sensitive to uncertainty and disagreement under more ambitious climate policies.

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Strategic R&D investment in low carbon energy technology is a critical path to decarbonizing the energy sector[1,2]. Allocating investment across portfolios of low carbon energy technologies while adhering to budget constraints and the requirement to reach climate targets is a tough task that requires handling enormous uncertainty. These uncertainties are related to the evolution of technologies and of the climate; the economic and societal consequences of long-term investments in the context of this change; and the role of climate policies[2]. Analyzing investment in low carbon energy technologies under these uncertainties is a growing research area[2]. Most work in this area has focused on analyzing portfolios of investment under *parametric uncertainty*[2,3]. Parametric uncertainty refers to uncertainty over the values of key model parameters; for example, the evolution of the costs and efficiency of energy technologies in response to investment in research and development[4] (R&D).

Many techniques have been used to investigate parametric uncertainty around climate and energy technology, including sensitivity analysis, uncertainty analysis, and sophisticated models of decision making under uncertainty[2]; many employing Integrated Assessment Models (IAMs). Sensitivity analysis, for instance, takes energy R&D investment as a given and examines the potential consequences of a range of technology assumptions[5]. Uncertainty analysis goes a step further, employing Monte Carlo or other similar methods to explore probability distribution over IAM outputs of interest (see for example Kanyako and Baker[6].) Finally, a number of papers have used stochastic dynamic programming to identify optimal R&D portfolios under a wide range of assumptions or models[2,7,8].

When it comes to climate change, however, it is not easy to derive probability distributions around the uncertain parameters: there is significant disagreement among experts and forecasting methods over these distributions[9]. This disagreement is of particular importance as there is no single decision maker poised to solve climate change, but rather a wide range of stakeholders with oft-conflicting criteria. Approaches to address such disagreement have included robust optimization[10], ambiguity aversion[11,12], and bottom-up exploratory methods, such as Robust Decision Making[13].

There has been a different approach to another kind of disagreement, often called *structural uncertainty*. Structural uncertainty refers to uncertainty about casual chains[4], implicit assumptions, and worldview; and is reflected by the wide range of models seen in the literature[14]. Structural uncertainty, which we will refer to as model uncertainty from now on, has been addressed qualitatively, through multi-model intercomparison studies[5,15]. These studies compare results side by side and provide qualitative analysis of what drives the differences in the model outputs. For example, Bosetti et al[4] used distributions over technological costs in three global IAMs to investigate the impact that technology assumptions have on environmental and economic metrics across the models. Similarly, Gillingham et al[16] combined parametric and structural uncertainty in their analysis. They performed uncertainty analysis using probability distributions over population, total factor productivity and climate sensitivity and compared these results across multiple IAMs. They found that for most model outputs, parametric uncertainty was more important than model uncertainty, in the sense that the outputs varied more within models than between them.

In this article, we present an integrated analytical approach to addressing parametric and model uncertainty simultaneously, going beyond sensitivity analysis and qualitative comparisons. We synthesize multiple expert elicitations and multiple models *without losing information*, a key criticism of both traditional methods[17] and non-expected utility or robust optimization methods[10,18,19]. These previous methods mathematically resolve conflict (through averaging or eliminating information) and result in a fully ordered set, masking disagreement and limiting decision maker flexibility.

We synthesize multiple cost-benefit IAMs and multiple expert elicitation studies using the concept of belief dominance[20] to derive specific insights into portfolios of low carbon energy R&D investment that are robust to both parametric and model uncertainty. This is a dominance concept (similar to Pareto and stochastic dominance) that exists in the literature under a range of names[21–24]. Under belief dominance, one alternative dominates another if it performs better under all plausible "beliefs" about the state of the world, where 'beliefs" include models as well as probability distributions over parameters. We use belief dominance to identify non-dominated portfolios of investment in energy technology (See Methods). Applying the framework of Robust Portfolio Decision Analysis[20] (RPDA), the non-dominated portfolios are analyzed further to get insight into robust individual investments within the portfolios.

We consider portfolios made up of investments in five low carbon energy technologies: electricity from biomass, liquid biofuels, Carbon Capture and Storage (CCS), nuclear, and solar; and three possible levels of investment in each technology, making a total of 3^5 possible portfolios of investment. We used three probability distributions of future costs and efficiencies of energy technologies derived from three large-scale expert elicitation studies[11] to represent input uncertainty. We combine this with three prominent cost benefit IAMs to represent model uncertainty, leading to a total of nine beliefs. We identify all non-dominated portfolios of R&D investment in low carbon energy technologies across these beliefs. A portfolio is non-dominated if no other portfolios outperform it across all models and probability distribution.

The expert elicitation studies provide forecasts of the costs and efficiencies of the five technologies, conditioned on R&D investments[11]. The studies were undertaken independently by three teams (Harvard, UMass, FEEM) in 2008-2013 and harmonized in Baker et al. 2015 [25]. For model uncertainty we use the three cost-benefit models, DICE [26], FUND [27], and PAGE [28]. The technologically detailed Global Change Analysis Model (GCAM)[29], with its detailed energy module, is used to estimate the impact of assumptions about technology cost and efficiency on emission abatement costs, temperature, and CO2 emissions and concentration. GCAM does not model climate change damages; instead, we estimate damages using the cost-benefit IAMs by soft linking GCAM to DICE, PAGE, and FUND (See supplementary S1 for descriptions of the models). Finally, we perform this analysis under three global climate policies: a USD 125/tCO2 carbon tax, a USD 50/tCO2 carbon tax (both growing by 3% per year starting in 2025), and a business-as-usual scenario with no global policy (See Method).

Results

Non-dominated portfolios under a stringent carbon tax

Under the \$125/tCO2 tax policy, we find that, out of the 243 possible portfolios, 16 portfolios are non-dominated across the probability distributions and the models. Figure 1 represents the normalized objective values under each of the nine combinations of probability distributions and IAMs. The objectives in this case are the sum of the expected value of the cost of abatement, the cost of damages, and the opportunity cost of the R&D portfolio. The values have been normalized, with zero being the portfolio that performs worst (i.e., has highest total cost) under the specific combination of models and elicitations, and one being the best (lowest cost). We have highlighted the eight portfolios that appear to be good compromises among the complete set of beliefs: They are never below 70% of the highest possible value for any of the combinations. See Table 1 below for the 16 portfolios ranked in ascending order of the R&D expenditure, where each row represents one portfolio.

The importance of model uncertainty can be seen by looking at the variation of the objective values within an elicitation team. For example, we see that when using the UMass elicitations, the DICE model can lead to very different objective values than the other two models. The importance of disagreements over parametric uncertainty can be seen by comparing across the teams. For example, we see some portfolios, such as Portfolio 2 and 6, consistently at the top under the FEEM elicitations but toward the bottom of the non-dominated group for UMASS.

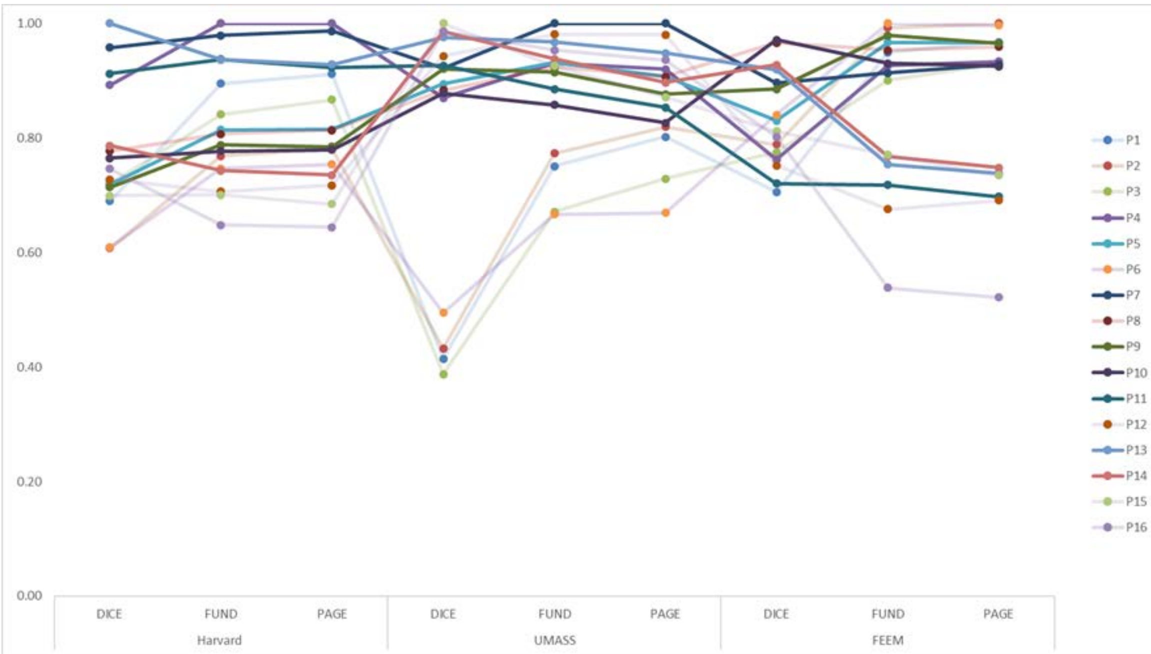

Figure.1. Normalized objective values of the non-dominated portfolios across nine combinations of probability distributions and IAMs, Harvard-DICE/FUND/PAGE, UMASS-DICE/FUND/PAGE, FEEM-DICE/FUND/PAGE. P1-P16 correspond to the different portfolios. The values are normalized with 1 being the best objective value, that is the lowest total cost and 0 the worst, i.e., highest cost.

Insights into individual Technologies

Looking at Table 1, we see that under the \$125/tCO2 tax policy, it is robust to invest in R&D at a high level in both Solar and Bioelectricity, regardless of the elicitation team, the damage model, or the investment in other technologies. On the other hand, we see investments at all levels (Low, Mid, and High) for Nuclear, CCS, and Biofuel among the non-dominated portfolios, suggesting that disagreement across elicitation teams and models is more relevant for these technologies under this policy. We note some relationships between technologies. For example, there are no non-dominated portfolios that recommend a high investment in both CCS and

Biofuels, and in fact a high investment in CCS is always accompanied by low investment in Biofuels, and a high investment in Biofuels is accompanied by low to medium investment in CCS, suggesting a kind of substitution between them.

We explore to what degree the disagreement is driven by the structure of the models or by disagreement over the distributions from the elicitation teams. Figure 2 provides a visualization of how the different models and elicitation teams lead to different investments in individual technologies through a ternary diagram for each technology under each model. Each ternary shows the optimal level of investment for each weighting of the elicitation teams.

Table 1: Table 1: Non-dominated portfolios. Columns 2-6 indicate the level of R&D investment for each technology, classified as Low, Mid, or High. Column 7 shows the total annual investment in R&D for each portfolio.

Portfolio	Technologies					Total R&D (In million USD $2019)
	Solar	Nuclear	Biofuels	Bio-elec	CCS	
1	High	Low	Low	High	Low	80.75
2	High	Low	Mid	High	Low	83.66
3	High	Low	Low	High	Mid	95.88
4	High	Mid	Low	High	Low	97.42
5	High	Mid	Mid	High	Low	100.33
6	High	Low	High	High	Low	105.02
7	High	Mid	Low	High	Mid	112.55
8	High	Mid	Mid	High	Mid	115.47
9	High	Mid	High	High	Low	121.69
10	High	Mid	High	High	Mid	136.82
11	High	High	Low	High	Low	301.69
12	High	Mid	Low	High	High	306.56
13	High	High	Low	High	Mid	316.82
14	High	High	Mid	High	Mid	319.73
15	High	High	High	High	Low	325.96
16	High	High	Low	High	High	510.82

To explore the importance of model uncertainty, read each row from left to right. Here we see the most striking difference between the models for Nuclear. Almost all combinations of elicitation teams lead to a high investment in Nuclear under DICE, whereas almost all combinations of beliefs point to a mid-investment under PAGE and FUND. This is somewhat surprising, as DICE is often considered to be in between the other two models. However, we note that below 2.5C warming, DICE has the highest damages, as the DICE damages are a quadratic function of temperature that increases smoothly with warming. PAGE responds much stronger to warming above 3℃, "when the risk of a discontinuity is present, and adaptation capacity is reduced. FUND projects net *benefits* below 2.5 °C, and impacts increase only gradually with temperature" [30]. The $125/tCO2 tax policy implemented here limits temperature change to less than 2.5℃ under all the portfolios. This, combined with the fact that GCAM considers nuclear energy to be particularly effective at reducing emissions, may explain why the DICE results lead to more aggressive R&D investment in Nuclear energy than the other models.

In the case of biofuels and CCS, a different narrative unfolds. There is a great deal more agreement between the models regarding R&D expenditure on these technologies. While there are some non-dominated portfolios with moderate or high investment in Biofuels, most combinations of models and elicitation result in a low-level investment in Biofuels. Similarly, the majority of possible combinations of beliefs and model result in a mid-level investment in CCS.

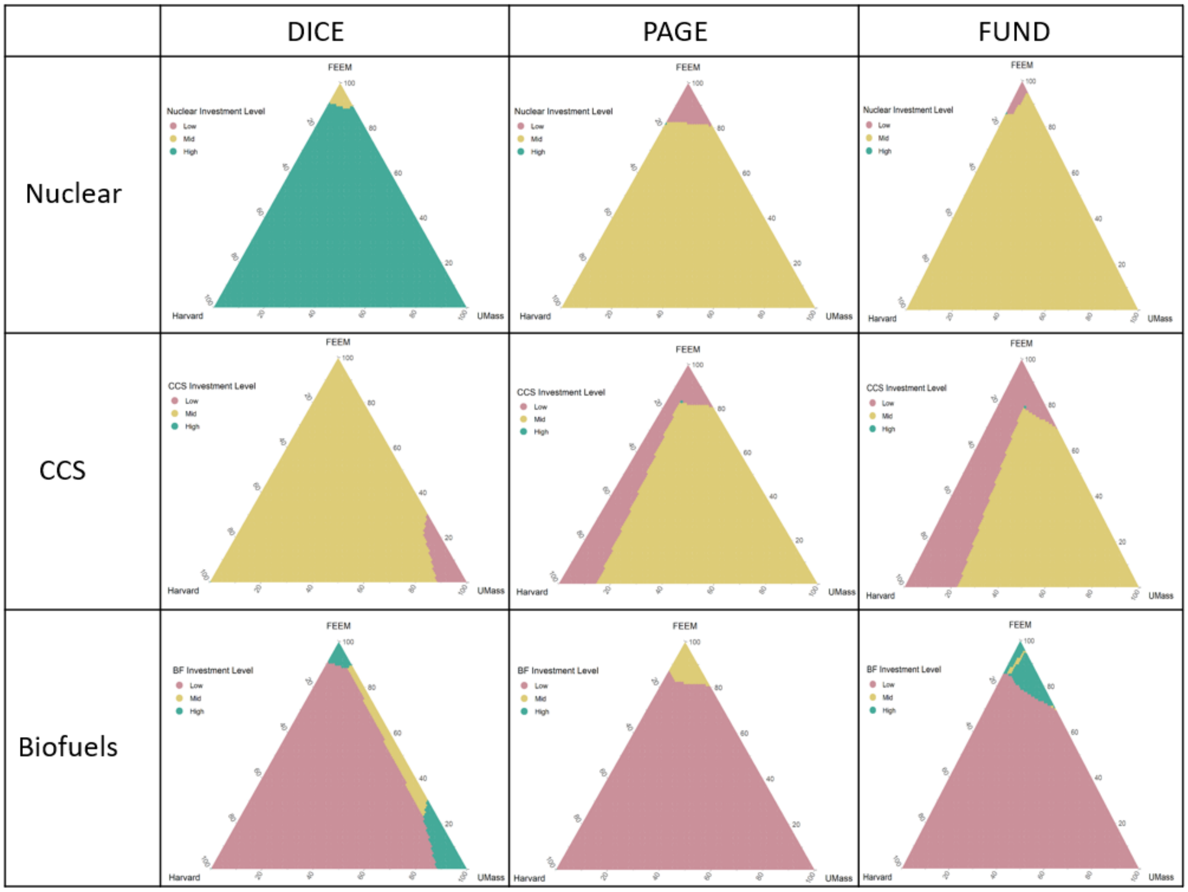

Figure 2. Each ternary diagram for DICE, PAGE and FUND across the three elicitations Harvard. UMASS and FEEM shows the optimal investment level in Nuclear, CCS and Biofuels, respectively, for each combination of elicitation teams and models, given the specific technology and model.

Disagreement is more important under less stringent policies

Less stringent policies result in a larger number of non-dominated portfolios across all elicitation teams and models (See Supplementary table S3). For instance, under the \$125/tCO2 tax policy, 16 portfolios are non-dominated, whereas there are 37 and 56 non-dominated portfolios, respectively, under the \$50/tCO2 tax policy and under the BAU assumption. This happens because as policy gets less stringent, emissions increase, and damages become more significant. This creates more space for model disagreement about the damages.

We identified four portfolios that are present in the non-dominated groups for each of the three policies: portfolios 5, 7, 13, and 15. We highlight portfolios 7 and 13 in particular because they contain the investment levels that are most prevalent across all teams and models as seen in Table 1, namely high investments in solar and bioelectricity; low investment in biofuels; moderate investment in CCS; and either moderate or high investment in nuclear. This finding suggests that independent of policy stringency, these portfolios and investment levels in these individual technologies reflect reasonable agreement among experts, models and policies.

Investment tends to increase with the severity of the climate policy, albeit this relationship is not consistent. Figure 3 depicts the proportion of each investment level in the optimal portfolio for each technology based on the elicitation teams' weightings. This is demonstrated over three policies and three damage models. Each bar is identical to the ternary diagrams above but emphasizes the aggregate share. We see a general trend toward increased investment as we increase the stringency of the climate policy. One notable exception is biofuels, which is dominated by a low investment under the most stringent policy under all three models. At very high price, biofuels become less competitive in GCAM and hence the technology's impact on mitigation is gradually reduced.

We observe several areas of consistency across policies and models, such as a lack of "high" investment in CCS and constant high investment in solar and bioelectricity under the \$125/tCO2 tax policy. The upshot from this analysis is that, while the stringency of policy objectives is crucial for the level of investment in specific technologies, we can still discover areas of agreement across all policies and models, as illustrated in portfolios 5,7,13, and 15. These portfolios are non-dominated across all policies, models, and expert elicitation, and can serve as a starting point for stakeholder discussions about R&D investment in low carbon energy technologies.

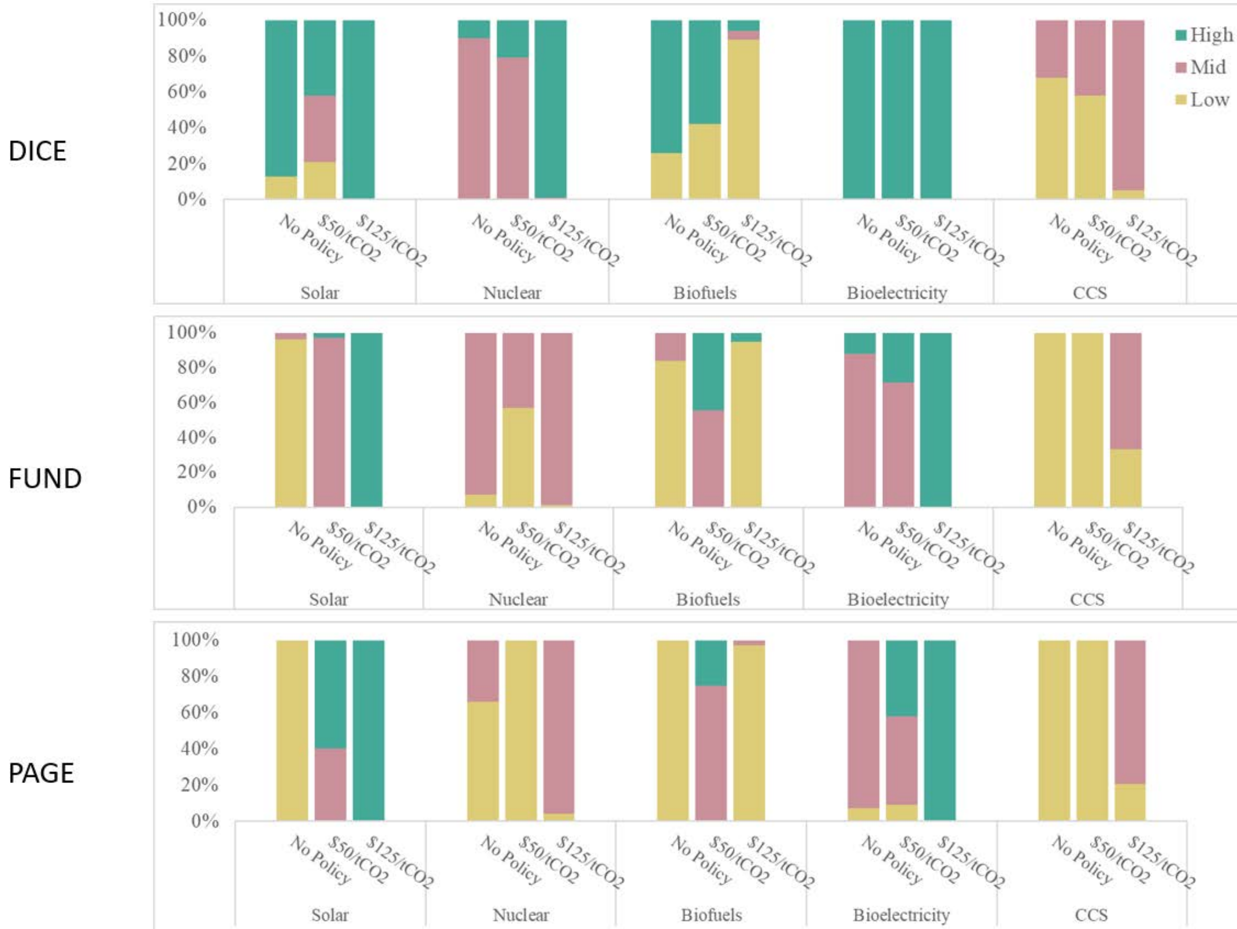

Figure 3: Non-dominated portfolios across different policies for all combination of models and elicitation.

Discussion

Over the last decade, expert elicitation and integrated assessment models have become integral to analysts and decision-makers as they formulate policy responses to climate change. For example, the IPCC AR5 [31] recommends expert elicitation to characterize uncertainty to provide insights into specific risks and understand and create effective strategies and policies to address climate change. The US government calculates the social cost of carbon, a monetary estimate of the societal costs of the climate damage caused by an extra unit of carbon dioxide (CO2) emitted into the earth's atmosphere, by averaging the three highly aggregated, integrated assessment models we use here. These models have long histories and have produced most of the SCC estimates in the recent scientific literature. However, while averaging is perfect for capturing central tendency, according to the flaw of averages by Savage [32], "decisions based on the assumption that average conditions will occur are wrong on average."

In this paper, we combined multiple representations of parametric uncertainty, as captured in three expert elicitation studies about the future cost and efficiency of energy technologies, with structural uncertainty, as captured in three cost-benefit IAMs, to address the problem of designing a portfolio of publicly funded R&D investment in low carbon energy technologies. We expanded on the RDPA[20] approach, identifying all non-dominated portfolios of R&D investment across all beliefs and models. Under a $125/tCO2 tax on emissions, we find common ground among the expert beliefs and the models, indicating that high investment in Bioelectricity and Solar are robust to all beliefs and the models given the climate policy.

We did not see the same level of consensus about investment in Nuclear, Biofuels, and CCS. We investigate the technologies individually across the models and beliefs to identify the source of the disagreement. We find that the disagreement about investment in Biofuels and CCS are largely parametric, while Nuclear is largely structural. For Biofuels and CCS, even though each investment level shows up in some non-dominated portfolios, most combinations of the beliefs lead to low investment in Biofuels and mid investment in CCS across the three models. For Nuclear, the damage models play an important role. Almost all combinations of beliefs lead to a high investment in Nuclear under DICE and mid investment under PAGE and FUND. The implication here is that our understanding of the structure of damages is particularly important for allocating investment into Nuclear, especially under stringent climate policies. If we believe that the DICE damage formulation is more relevant than the formulations of PAGE and FUND, at least at lower temperatures, then a high investment in nuclear is warranted; if PAGE or FUND are better representations, then this investment does not pay off since they are mainly allocating mid-investment. Finally, we find that the disagreement between expert beliefs and models is less important for more stringent climate policy.

Methods

We employ a multi-model framework comprised of four IAMs and the RPDA[20] framework to uncover non-dominated R&D portfolios across cost-benefit IAMs. Figure 4 is a schematic diagram representing the decision framework. The main decision, shown by the rectangular node, is the amount of R&D to allocate to each technology. The oval node represents the uncertainty around the performance of technologies in 2030. As illustrated by the arrow leading into the oval node, the probability distributions over technological performance are conditional on R&D spending. For each set of technology performance metrics and climate policy, the technologically detailed GCAM selects technology deployment and estimates abatement costs and climate variables. The cost-benefit IAMs (DICE, PAGE, and FUND) take the GCAM climate variables as input and estimate the climate damages (See supplementary Table S1 for damage description). Despite their similarities, the models significantly differ in their input assumptions and structure, most notably in their degree of regional and sectoral disaggregation, damage function, and the management of adaptation and uncertainty.

The main objective is to minimize the cost of abatement, the cost of climate damages, and the cost of R&D investment. We implement RPDA framework previously employed by Baker and colleagues [20] to identify the non-dominated portfolios for each of three policies: BAU and the two-carbon tax policy cases (USD 125/tCO2 and USD 50/tCO2) each increasing at 3% annually beginning 2025. Below we discuss how expert elicitations are implemented into GCAM and provide more detail on the objective and decision framework.

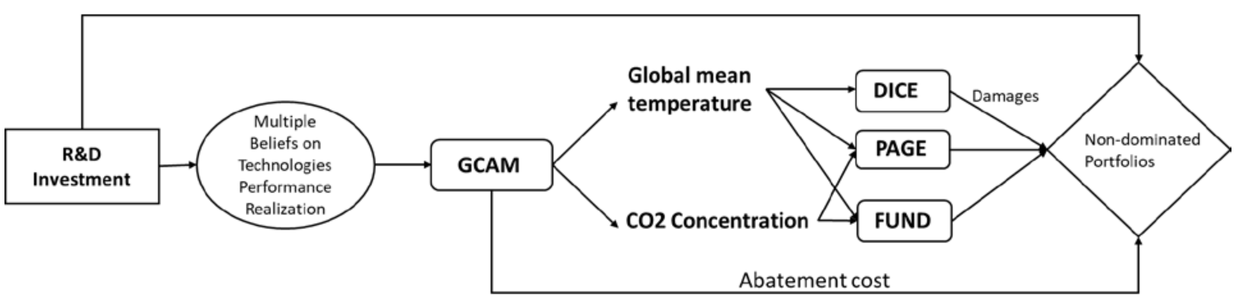

Figure. 4. A schematic diagram representing the decision framework. Rectangle nodes represent decisions; oval nodes represent uncertainties; rounded rectangles represent model calculations and the diamond represent the objective values.

Implementing the Expert Elicitation into GCAM

Technology competition in GCAM is based on the performance metrics of each technology, i.e., cost and efficiency of the technology (See supplementary S1 GCAM description and technology competition). The performance metrics used as inputs are sampled from the harmonized probability distribution from Baker et al.[25] There is one distribution for each uncertain performance metric: solar PV Levelized cost of electricity, nuclear power overnight capital cost, liquid biofuels

Levelized non-energy cost and conversion efficiency, bio-electricity non-energy cost and conversion efficiency, and CCS capital cost and energy penalty. In total, these eight independent probability distributions represent the cost and efficiency of the technologies in the year 2030.

We generated 1000 samples from each of the eight probability distributions using the Latin Hypercube sampling method, making a total of 8000 sample points to be evaluated. Each of the 1,000 samples reflects a potential future state of the world in 2030, comprising a unique value for each of the eight parameters. We implement each of the 1000 states of the world, one at a time, in GCAM, repeated for all three policy cases: business-as-usual case, with no climate policy in place, and the two carbon tax policy cases. The elicitation data set contains static values representing the states of the world of technology in 2030. To run a state of the world in GCAM, spanning from 2015 to 2100, we account for the change in the performance metrics every five years between 2015 and 2030 and subsequent years after 2030 using a slight modification of Moore's law, shown in equation (1) and (2). See Kanyako and Baker[6] for more detail.

$$m_{ij} = -\frac{1}{2030-2015} ln\left[\frac{z_{ij}(2030) - z_j{}^{min}}{z_j(2015) - z_j{}^{min}}\right] \quad (1)$$

$$z_{ij}(t) = z_j{}^{min} + \left(z_j(2015) - z_j{}^{min}\right)e^{-m_{ij}(t-t_{2015})} \quad (2)$$

Let m_{ij} be Moore's constant associated with sample i and metric j. The constant is calculated based on the elicitation data for year 2030. $z_{ij}(t)$ is metric j (cost or efficiency) for sample i, at time t. Each metric j has one lower, and one upper bound, $z_j{}^{min}$, and $z_j{}^{max}$. The lower bound is the cost or efficiency with cumulative probability of 10^{-6} ; the upper bound is the opposite tail. We use the lower bound $z_j{}^{min}$ for sample ij, when the sample indicates cost decreasing after 2015; and an upper bound $z_j{}^{max}$ if the sample indicates cost increasing after 2015. The base year value for each metric j for 2015, $z_j(2015)$ is constant across all samples; this value is taken from GCAM default assumptions for all the performance metrics [33]. Note, Equation (1) & (2) represent a case where the metric decreases in value approaching 2030, i.e., the metric's value is lower in 2030 than in 2015. The approach is similar in the case where metrics are higher in 2030, with a ceiling in the place of a floor.

Decision Framework

Here we describe the variables, objectives, and constraints of the decision problem. We note that we extend the original RPDA framework by including model disagreement. Let $h = \{1,2,..,5\}$ index the five technologies (note there are five technologies, indexed by h, and eight performance metrics, indexed by j) and d funding level. We define portfolio x as a vector of binary variables such that $x_{hd} = 1$ if technology h is invested in at the d^{th} funding level, and 0 otherwise. Each technology in portfolio x can be invested in at one of the three levels of investment ($d = low, mid, high$). Therefore, for the five technologies with three levels of investment, we have a total of $3^5 = 243$ possible portfolios. The total cost of R&D investment $B(x)$ for portfolio x is the sum of the individual R&D investments in each technology in the portfolio, multiplied by the opportunity cost multiplier $k = 4$ (See Baker et al. 2020 [20] for details on the opportunity cost multiplier). Table 2 shows the R&D cost assumptions for different levels of investment.

Let $md = \{1,2,3\}$ be the index for the three cost-benefit models: DICE, PAGE, and FUND and $\tau = \{Harvard, UMass, FEEM\}$ index the individual elicitation teams. For a sample $z_i = \{z_{i1}, z_{i2}, \dots, z_{i8}\}$, the probability of realization is $f_\tau(z_i|x)$, based on elicitation team τ given the portfolio x [25]. The damages depend on the model $md = \{1,2,3\}$. The overarching objective, represented by $H(x; md; \tau)$ is to minimize the expected cost of abatement (TAC) plus the climate damages (D_{md}) and the cost of R&D investment in portfolio x, given a policy scenario s:

$$H(x; md; \tau) \equiv \left[\sum_{i=1}^{1000} f_\tau(z_i|x)\{TAC(z_i, s) + D_{md}(z_i, s)\}\right] + kB(x) \quad (3)$$

$$s.t. \sum_d x_{hd} = 1 \; \forall t$$

The constraint assures that each technology is only invested in once. In order to find the non-dominated set across all models and teams, we begin by calculating the total expected cost, H, for each of the 243 portfolios using equation (3). Then, using Yukish's simple cull method [34], we find the non-dominated sets. A portfolio x belief dominates x' if $H(x; md; \tau) \le H(x'; md; \tau) \; \forall md, \tau$ with strict inequality for at least one of the beliefs. A portfolio x is non-dominated if it is not dominated by any other feasible portfolio.

Table 2: Annual R&D expenditures cost of each project, in millions of dollars, assumed constant over a 20-year period.

Investment Level	Nuclear	Solar PV	Bioelectricity	Bioliquids	CCS
Low	6.2	1.7	1.4	1.4	5.3
Mid	19.2	4.0	3.0	3.7	17.1
High	178.3	33.0	16.9	20.3	168.1

Total Abatement cost (TAC)

The cost of reducing CO2 emissions below the BAU level is the abatement cost in the objective function above. The cost of abatement is calculated by GCAM as the area under the marginal abatement curve (MAC). The cost of reducing emissions by one ton is referred to as the MAC [35]. By applying a real discount rate of 5% per year to future values, the discounted sum of the annual abatement costs from 2020 to 2100 equals the total present value of the total abatement costs $TAC(z_i, s)$ under policy s and scenario z_i

$$TAC(z_i, s) = \sum_t \delta^t \, AC(z_i, s)_t \quad (4)$$

Where $AC(z_i, s)_t$ is the annual abatement cost (in trillions of 2015 USD) under policy s and state scenario z_i at time t, and δ is the discount factor. Note in the BAU case, the cost of abatement is, by definition, zero. Hence in Equation (4) above, $TAC(z_i, BAU) = 0$.

Damages (D_m)

Each of the 1000 states of the world implemented in GCAM leads to different emissions and temperature paths and hence different estimates of damages in each IAM. Therefore, the climate variables that drive damage estimation in each IAM are replaced with the GCAM output for each scenario to account for the impact of technological change on these variables. For example, the global mean temperature estimate in DICE and PAGE is replaced by the global mean temperature change estimated from GCAM from 2010 to 2100 for each scenario. FUND is slightly more complicated. For each of the 14 sectors in FUND, the main drivers for each sector are replaced by either the global mean temperature change or the CO2 concentration from GCAM, depending on the variable that drives the damage estimate for that sector. For each climate policy: USD 125/tCO2 and USD 50/tCO2 (each increasing at 3% annually beginning 2025) and a business-as-usual case, damages are estimated for all 1000 scenarios for each IAM. The damages calculated from the cost-benefit IAMs, and the abatement cost estimated from GCAM are used as inputs into the decision framework.

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Author Contributions

F.K and E.B designed the research. F.K and D.A developed the modelling framework and performed the numerical simulations. F.K and E.B conducted the analysis, made figures and wrote the manuscript. All authors discussed the results and implications and provided critical feedback that helped shape the final manuscript.

Data availability

The specific model runs and expert elicitation data for this study are archived under https://doi.org/10.5281/zenodo.5748125 under a CC-BY-4.0 license.

Code availability

The code for the integrated assessment modelling framework used in this study, Mimi-DICE, Mimi-FUND and Mimi-PAGE and documentation are available in a public GitHub repository at https://github.com/mimiframework/Mimi.jl. The technical documentation is available at https://www.mimiframework.org/. The source code and documentation for the global change analysis model (GCAM) are publicly available at https://github.com/JGCRI/gcam-core and http://jgcri.github.io/gcam-doc/ respectively.

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