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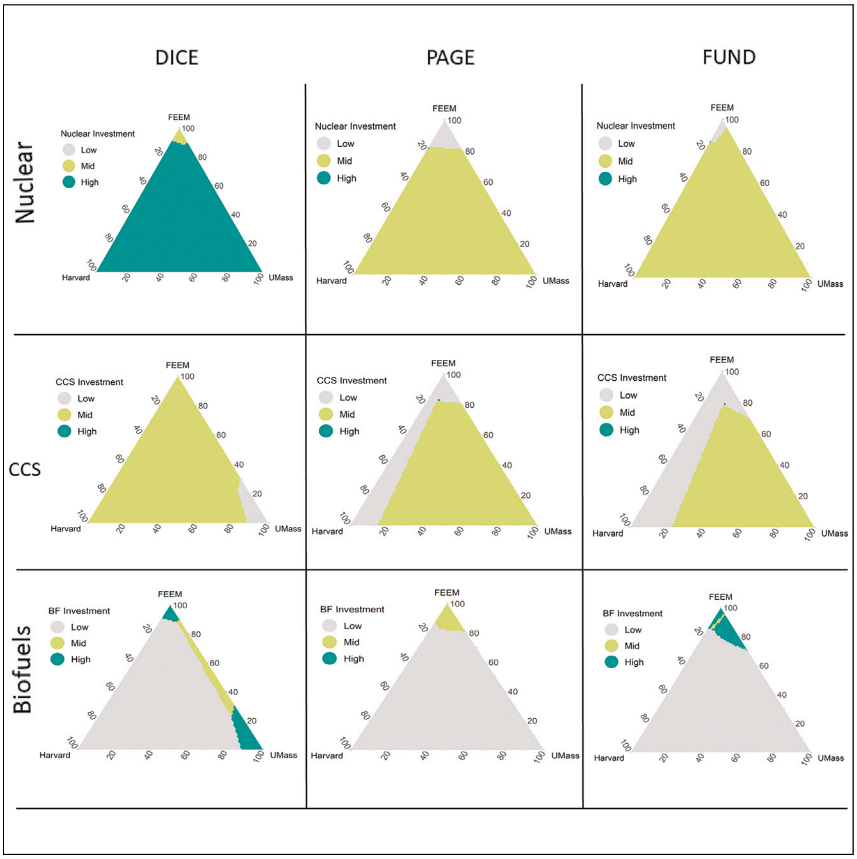

This paper introduces an innovative approach that addresses uncertainties in both technology costs and in integrated assessment models to design robust energy investment portfolios of low-carbon energy technologies. The method facilitates decision making by identifying common ground and disagreements, offering valuable insights for crafting energy policies considering diverse perspectives and uncertainties.

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Highlights

Synthesize multiple expert beliefs and climate models to inform policy

The decision framework addresses both structural and parametric uncertainties

Uncover areas of consensus and disagreement between models and experts

More stringent climate policy leads to less disagreement across models and experts

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Identifying low-carbon energy R&D portfolios that are robust when models and experts disagree

Franklyn Kanyako,[1,3,*] Erin Baker,[1] and David Anthoff[2]

SUMMARY

Crafting energy policy in the face of climate change is daunting due to disagreement over technological uncertainty and societal consequences of climate change. We present an approach accounting for structural and parameter uncertainty. We provide proof of concept for designing energy R&D portfolios, accounting for uncertainty and disagreement around technological change and climate impact. We synthesize conflicting beliefs by combining expert elicitation studies on technological change and climate impact models into one decision framework. We identify plausible R&D portfolios that are robust to expert studies and climate impact models using the best available information. In this proof of concept, the method successfully narrows portfolios and identifies common ground on some technologies, allowing policymakers to negotiate over qualitative issues. We illustrate how this method can identify where the disagreement is most important. In this case, the different damage models resulted in starkly different investments in nuclear energy R&D.

CONTEXT & SCALE

Low-carbon energy R&D investment is complex, involving a wide range of stakeholders with conflicting beliefs and priorities, making it difficult to arrive at a single best solution. We propose an integrated approach beyond typical model intercomparison studies, synthesizing information from different cost-benefit models and expert beliefs on technology costs to identify low-carbon energy portfolios robust to both models and expert beliefs. For instance, we found common ground for high investments in solar and bioelectricity across all models and experts under a \$125/ tCO_2 tax on emissions. However, there is disagreement about nuclear, biofuels, and CCS investments. Furthermore, stringent climate policies lead to more consensus among the models and experts in contrast to less stringent policies. Our approach can provide valuable insights into robust investment decisions and identify areas of consensus and disagreement between models and experts.

INTRODUCTION

Strategic research and development (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 to reach climate targets in a cost-effective way is a tough task that requires handling enormous uncertainty. These uncertainties are related to the evolution of technologies and climate change, the economic and societal consequences of long-term investments in the context of this change, policy uncertainty,[2] and the modeling tools used to analyze technology interaction and climate impact. 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] We present a methodological contribution with an illustrative exercise as a proof of concept with an integrated analytical approach that simultaneously addresses parametric and model (structural) uncertainty. 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 R&D.[4] Structural uncertainty refers to uncertainty about causal chains,[5] implicit assumptions, and worldview and is reflected by the wide range of models seen in the literature.[6] Going beyond sensitivity analysis and qualitative comparisons, we synthesize multiple expert elicitations and multiple models into a single decision framework to derive outcomes that are robust to both expert elicitation and model uncertainty. These robust outcomes can enable decision makers to find common ground on investments in different energy technologies that are not only resilient to variations in key model parameters and implicit assumptions but also account for diverse beliefs of the decision-makers and expert opinions.

Some of the techniques that have been employed to investigate parametric uncertainty in climate and energy technologies include sensitivity analysis,[7] uncertainty analysis,[8] and sophisticated models of decision making under uncertainty.[9] Sensitivity analysis, for instance, takes energy R&D investment as a given and examines the potential consequences of a range of technology assumptions. Uncertainty analysis goes a step further, employing Monte Carlo or other similar methods to explore probability distributions over integrated assessment model (IAM) outputs of interest.[8] Finally, a number of papers have used stochastic dynamic programming to identify optimal R&D portfolios under a wide range of assumptions or models.[2,10,11] For climate change policy, however, deriving probability distributions around the uncertain parameters can be difficult due to the significant disagreement among experts and forecasting methods over these distributions.[12] This disagreement is of particular importance because 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,[13] ambiguity aversion,[9,14] and bottom-up exploratory methods, such as robust decision making.[15]

On the other hand, structural uncertainty, which we will use interchangeably with model uncertainty, has been addressed qualitatively through multi-model intercomparison studies.[7,16] 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.[7] 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 overpopulation, 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.[4] A recent study by Xexakis et al.[17] underscores the necessity of incorporating citizens' perspectives in energy transition scenarios, emphasizing that energy transition scenarios should not solely rely on model-based scenarios but also incorporate the varying citizens' beliefs that may not always be aligned with the model-based scenarios.

In this article, we introduce a method that combines multiple expert beliefs and multiple models while respecting the full range of information. A key criticism of both traditional methods[18] and non-expected utility or robust optimization methods[13,19,20] is that they do not reflect the full range of beliefs. 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. The approach illustrated here provides a way of accounting for multiple contrasting beliefs and models in a concise framework to provide a set of plausible alternatives. These alternatives can initiate a discussion among agents and policymakers without having to choose a priori a specific decision rule, model, or beliefs, thus avoiding challenges before the analysis begins.

Objectives and overall approach

We use a multi-model framework to combine multiple cost-benefit IAMs' climate damage modules and multiple expert elicitation studies on the future cost of

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Table 1. 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

See Baker et al.[4] for more details about Table 1.

low-carbon energy technologies. We implement robust portfolio decision analysis (RPDA) and belief dominance,[21] expanding this decision framework to account for model uncertainty. In our proof of concept, we derive specific insights into portfolios of low-carbon energy R&D investment that are robust to both parametric and climate damage uncertainty. Belief dominance is a dominance concept (similar to Pareto and stochastic dominance) that exists in the literature under a range of names.[22–25] Under belief dominance, one alternative dominates another if it performs better under all plausible "beliefs" about the state of the world, where we allow beliefs to include models, as well as probability distributions over parameters. We use belief dominance to identify non-dominated portfolios of investments in energy technology (see experimental procedures). A portfolio is non-dominated if there is no other portfolio that performs better under all models and elicitation combinations. We investigate the set of portfolios that are non-dominated in order to get insight into individual investments within the portfolios that are robust to the full range of beliefs and models.

For the proof of concept, we rely on available data and existing expert elicitations derived from three large-scale expert elicitation studies.[4] Thus, we consider portfolios made up of R&D 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 (see Table 1 in experimental procedures for the definitions of the investment levels, which vary by technology). We note that this represents four generation technologies and one transportation. We construct three sets of probability distributions from the three large-scale expert elicitation studies,[4] one for each study to represent parametric uncertainty. The expert elicitation studies provide forecasts of the costs and efficiencies of the five technologies, conditioned on R&D investments.[4] The studies were undertaken independently by three institutions (Harvard, UMass, and Fondazione Eni Enrico Mattei [FEEM]) and harmonized in Baker et al.[4] We note that these elicitations were published between 2008 and 2014 and that they are limited in the technologies they consider. As such, we interpret the strength of this article not as statements of fact about technology investment portfolios but rather as the presentation of a consistent framework for synthesizing different assumptions about technology investment and modeling framework into a single decision framework for identifying robust pathways. We briefly discuss alternative methods for characterizing parametric uncertainty. An advantage of our approach is that it facilitates the discovery of robust alternatives that would not have been discovered if only one model or set of cost assumptions were used.

The costs and efficiencies in the elicitation datasets are propagated through the technologically detailed global change analysis model (GCAM).[26] GCAM, with its detailed energy module, selects technology deployment and estimates the impact of technology cost and efficiency assumptions on emission abatement costs and climate variables such as temperature and carbon dioxide (CO_2) emissions and concentration. We soft link the climate variables from GCAM with the damage function modules of three prominent cost-benefit models, DICE (Dynamic Iintegrated Cclimate-Eeconomy),[27] FUND (Climate Framework for Uncertainty, Negotiation and Distribution),[28] and PAGE (Policy Analysis of the Greenhouse Effect)[29] (see supplemental information section "overview of the global integrated assessment models (IAMs) used in this study" for detail), to account for the impact of clean energy technology cost and efficiency from the three expert elicitation studies on climate change, through climate damages. In cost-benefit IAMs, climate change damages are represented by a damage function that relates climate variables, such as temperature, CO_2 concentrations, and sea-level rise, to economic welfare.[30]

Combining the three large expert elicitations, which represent parametric uncertainty, with the three-cost-benefit IAMs to represent model uncertainty related to climate damages, leads to a total of nine possible beliefs. Synthesizing all of these parts into a single decision framework, the overall objective is to minimize the sum of the expected value of the cost of abatement (from GCAM), the cost of damages (from DICE/PAGE/FUND), and the opportunity cost of the R&D portfolio. We identify all non-dominated portfolios of R&D investment across these beliefs. Finally, we perform this illustrative analysis by running GCAM under three global climate policies: a \$125/tCO_2 carbon tax, a \$50/tCO_2 carbon tax (both growing by 3% per year starting in 2025 to 2100), and a reference scenario with no constraint on emissions termed BAU (business as usual) (see experimental procedures). In each scenario, we used the shared socioeconomic pathway (SSP2), which follows a trajectory in which social, economic, and technological trends do not deviate much from current trends.[31] In SSP2, resource and energy use intensity decreases, whereas global population growth is moderate and plateaus in the latter half of the century. Globally, there are medium challenges to climate change mitigation and adaptation. Thus, we illustrate how this method can provide insights into specific R&D investments, including identifying areas of agreement and disagreement.

We note that this method can be used to integrate multiple technologically detailed IAMs, which would address structural uncertainty more deeply, accounting for different input data and assumptions and modeling approaches on aspects such as technological competition.[30,32] The challenge, however, is in running large-scale harmonized scenario analysis across these complex and computationally expensive models. Thus, this is left for future work.

RESULTS

In this section, we use the proof of concept to illustrate the kinds of insights that can arise from this methodology.

Disagreement is more important under less stringent policies

We identify a set of non-dominated portfolios for each of the three global climate policies. The size of the set of non-dominated portfolios decreases as the stringency of the climate policy increases. Figure 1 shows the non-dominated portfolios under the most stringent policy. The first five columns show the portfolios, displaying the level of investment in each technology. In the following column, the R&D expenditures for each portfolio are presented (the portfolios are presented in ascending order of R&D). The last three columns display the objective value under each of the three cost-benefit IAMs, averaged across the three expert elicitations with equal weighting. The objective value is the expected value of the opportunity cost of R&D plus

Portfolio	Technologies					Annual R&D (million USD)	Average of ENPV (trillion of $2020)		
	Solar	Nuclear	Biofuels	Bio-elec	CCS		DICE	FUND	PAGE
1	High	Low	Low	High	Low	63	110	365	455
2	High	Low	Mid	High	Low	65	110	367	457
3	High	Low	Low	High	Mid	75	110	369	457
4	High	Mid	Low	High	Low	76	107	360	451
5	High	Mid	Mid	High	Low	78	108	363	455
6	High	Low	High	High	Low	82	110	370	460
7	High	Mid	Low	High	Mid	88	107	359	450
8	High	Mid	Mid	High	Mid	90	107	363	455
9	High	Mid	High	High	Low	95	107	364	456
10	High	Mid	High	High	Mid	107	107	366	457
11	High	High	Low	High	Low	235	107	364	457
12	High	Mid	Low	High	High	239	107	368	458
13	High	High	Low	High	Mid	247	106	362	454
14	High	High	Mid	High	Mid	249	107	367	459
15	High	High	High	High	Low	254	107	368	461
16	High	High	Low	High	High	398	107	371	463

Figure 1. Non-dominated portfolios for the $125/tCO_2$ tax policy

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. The last three columns show the expected NPV (net present value) of the total cost of abatement plus damages plus the cost of investment in each portfolio under each of the three cost-benefit IAMs, averaged across the three expert elicitations.

the cost of abatement plus the cost of climate damages, using the expert elicitation probabilities over technological outcomes (see Table S2 for the non-averaged data). Under a $125/tCO_2$ tax policy, out of the 243 possible portfolios, just 16 portfolios are non-dominated across the expert elicitations and the models.

Less stringent policies result in larger numbers of non-dominated portfolios across all elicitation teams and models (see Tables S3 and S4). There are 37 and 56 non-dominated portfolios, respectively, under the $50/tCO_2$ tax policy and under the BAU case. More stringent climate policy increases the cost competitiveness of clean energy technology, resulting in rapid deployment in GCAM. Rapid decarbonization decreases climatic damages but raises abatement costs. As a result, the damage estimates play a smaller role in the objective when the policy is stringent. Decreased disagreements among the models contribute to the smaller number of non-dominated sets as the policy becomes more stringent. This pattern implies that the set of non-dominated portfolios would be even smaller under a net-zero target because this would leave even less room for disagreement among the damage models.

On the other hand, less stringent climate policy leads to higher emissions. With higher emissions, the disagreement about the estimated climate damages is more significant. Therefore, as the policy becomes less stringent, the damage models and expert beliefs on technology cost are both important in the objective, leading to a larger non-dominated set (see Figure S1 for the proportion of each technology in the non-dominated portfolios across different policies for all the models).

Nevertheless, we note that four portfolios (those labeled 5, 7, 13, and 15 in Figure 1) were present in each of the three non-dominated sets resulting from the three

Portfolios	Robustness Concepts			
	Minmax Regret	*SEU*	α-*Maxmin*	KMM (equal weights)
1				
2		PAGE-FEEM		
3				
4		FUND-Harvard, PAGE-Harvard		
5				
6		FUND-FEEM		
7		FUND-UMass, PAGE-UMass, Equal Weight	α = 0....0.6	Above 76
8			α = 0.7....0.9	
9				
10		DICE-FEEM	α = 1 (Maxmin)	0.05 - 1
11				
12				
13	Minmax Regret	DICE-Harvard		1.2 - 75
14				
15		DICE-UMass		
16				

Figure 2. Non-dominated portfolios and solutions to robustness concepts for the $125/tCO$_2$ tax policy non-dominated portfolio
Shaded rows are not solutions to any of the robustness concepts considered. The values in the last column are ambiguity tolerance measured in trillions of dollars.

policies. These four portfolios include high investments in solar and bioelectricity, mid-high investments in nuclear energy, and low or mid investments in biofuels and CCS. This is a significant advantage of the approach implemented here, suggesting that, independent of policy stringency, we can identify some agreement on investment levels in individual technologies, despite disagreement among models, policies, and expert beliefs.

This method encompasses other robustness concepts and uncovers new portfolios of interest

Baker et al.[21] showed that the non-dominated set under belief dominance encompasses the solutions from a number of other robustness concepts, including α-maxmin expected utility,[33] where the decision maker considers the weighted average of the worst expected payoff and the best-expected payoff, minmax regret with multiple priors,[34] Klibanoff smooth ambiguity (KMM),[35] and subjective expected utility using averaged (SEUa) probabilities.[36] At least one optimal solution under each of these concepts is in the belief-non-dominated set. Any optimal solution to a robustness concept that is not in the belief-non-dominated set is (1) no better than those optimal solutions that are in the belief-non-dominated set under the robustness concept and (2) strictly worse than the solutions in the belief-non-dominated set under at least one plausible probability distribution. In Figure 2, we illustrate how these decision rules relate to the non-dominated set. In each case, we treat each combination of elicitation and model as a single belief. For example, the solution to the

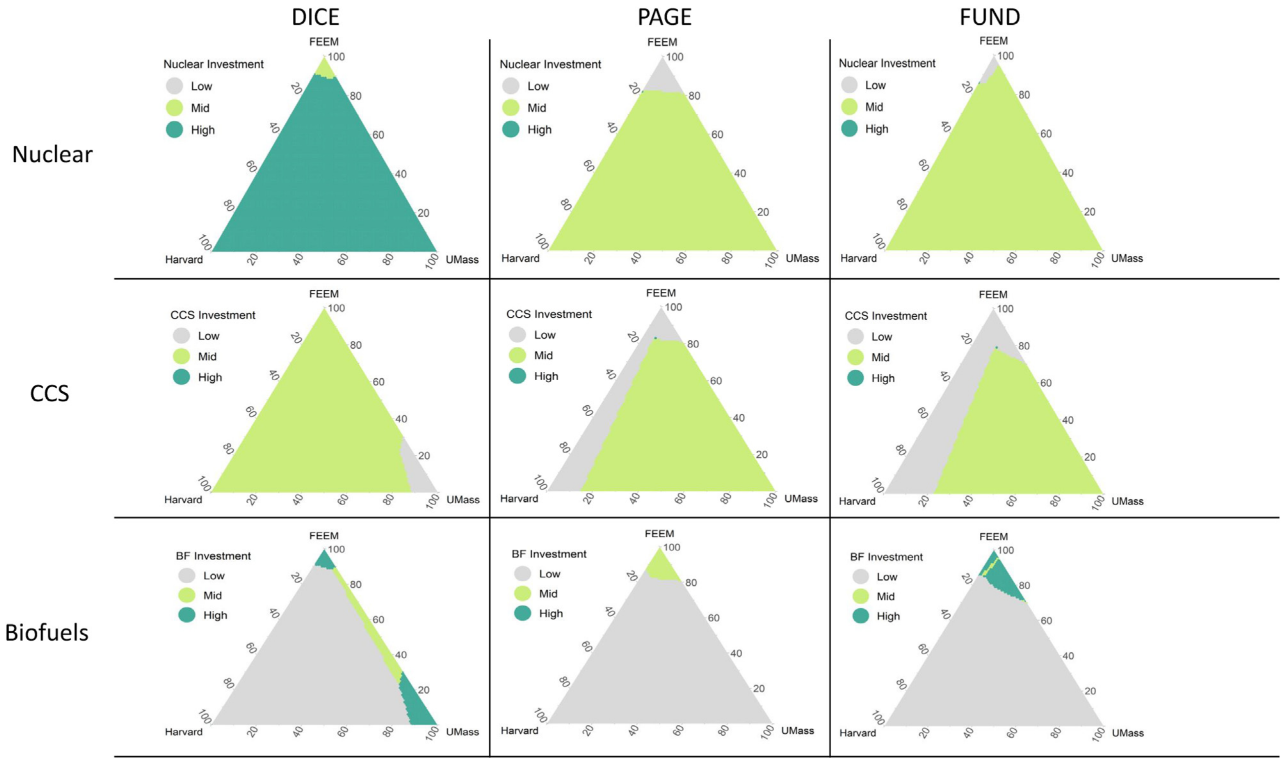

Figure 3. Each ternary diagram shows the optimal investment in the technology in that row, for each combination of the three elicitation teams (Harvard, UMass, and FEEM), given the model (DICE, PAGE, and FUND) in the column. Each point on the ternary diagram represents a weighting of the three elicitation teams.

minmax regret decision rule is portfolio 13, where the minmax regret is taken over all nine combinations of expert beliefs and models. For SEUa, if equal weight is given to FEEM, Harvard, and UMass and to DICE, PAGE, and FUND, the optimal portfolio is 7; if all weight is put on the combination of PAGE with FEEM, the optimal portfolio is 2. For α-maxmin, the optimal portfolio moves from 7 to 8 to 10 as α is increased from 0 to 1 (implying increasing ambiguity aversion). The KMM results move from 7 to 10 to 13 as ambiguity aversion increases (shown in Figure 2 is ambiguity tolerance, measured in trillions of dollars). Note that even considering a wide range of robustness concepts and variations within those, the non-dominated set contains several portfolios (i.e., 1, 3, 5, 9, 11, 12, 15, and 15), which were not uncovered by these other methods.

Finding common ground and key disagreements

We further investigate the portfolios in Figure 3, which arise under a $125/t$CO_2$ carbon tax. We find common ground; high R&D investment in solar and Bioelectricity is robust across experts and damage models. On the other hand, the other three technologies show different investment levels among the non-dominated portfolios, suggesting that disagreement is more relevant for these technologies under this policy. These disagreements are driven by (1) expert disagreement on the effectiveness of R&D in the individual technologies, (2) differences in marginal damages across the models, and (3) assumptions in GCAM about technology competition.

To explore this disagreement further, Figure 3 shows how the different combinations of models (columns) under the different elicitation teams impact the different levels of investments in individual technologies (rows) for nuclear, CCS, and biofuel technologies. The ternary diagrams provide a visualization of which of the three investment levels is present in the optimal portfolio for each combination of 5,150 feasible weightings (in steps of 0.01) of the three expert beliefs. Each point on the diagram represents a weighting of the three teams: the center point is an equal weighting, and the corners put all weight on one team. The most striking difference between the models is observed for investment in nuclear energy. Almost all combinations of elicitation teams lead to a high investment in nuclear under DICE, whereas almost all combinations of elicitation teams point to a mid-investment under PAGE and FUND.

Despite their similarities, these models differ significantly in terms of their input assumptions and structure, particularly with regard to the degree of regional and sectoral disaggregation, formulation of climate damages, and treatment of adaptation. These factors impact the estimated level of damages for each model for a given temperature and emissions trajectory. Of importance, in this case, is that the \$125/tCO_2 tax policy implemented here limits temperature change to less than 2.5°C under all the portfolios. FUND has global net benefits (negative damages) under 2.5°C from increased agricultural productivity due to CO_2 fertilization[37] and reduced heating demand (that is, avoided energy costs). The inclusion of adaptation in PAGE means that economic consequences can be largely averted until at least the 3°C threshold. The damages in PAGE below 3°C are dominated by non-economic impacts (see Table S1). By contrast, DICE has a simple quadratic damage function. This means that below 2.5°C warming, DICE has the highest marginal damages among the three models. Additionally, nuclear R&D is expensive, as seen in Table 1.

Finally, this version of GCAM[26] allows for significant nuclear expansion, under the implicit assumption that all safety and waste disposal issues are adequately addressed and improved to the point where social acceptability does not constrain large-scale expansion of nuclear power.[38] Thus, when R&D is successful at lowering the cost of nuclear, it has a significant impact on abatement. Adding all this up, the more expensive but effective R&D portfolios that include nuclear are significantly more attractive under the higher marginal damages in DICE than under the less severe marginal damages in PAGE and FUND.

In the case of biofuels and CCS, there is a great deal more agreement between the models regarding R&D expenditure on these technologies. The disagreement around these technologies is driven more by the elicitations rather than the models, which can be seen in Baker et al.[4] Although 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, most possible combinations of beliefs and models result in a mid-level investment in CCS.

DISCUSSION

Key results and contributions

Over the last decade, expert elicitation and IAMs have become integral to analysts and decision makers as they formulate policy responses to climate change. For example, the Intergovernmental Panel on Climate Change Sixth Assessment Reports (IPCC AR6)[39] applied expert judgment to characterize uncertainty to provide insights into specific risks around strategies and policies to address climate change impact, adaptation, and vulnerability. The US government calculates the social cost of carbon (SCC), a monetary estimate of the societal costs of the climate damage caused by an extra unit of CO_2 emitted into the earth's atmosphere, by averaging the three highly aggregated cost-benefit models we used here.[40] These models have long histories and have produced most of the SCC estimates in recent scientific literature. Averaging captures central tendencies, yet, according to the flaw of averages by Savage,[41] "decisions based on the assumption that average conditions will occur are wrong on average." Thus, our key contribution is methodological—we present a method that uses analysis to rigorously define a set of plausible portfolios under model uncertainty, as well as parametric uncertainty. This method does not present a single best answer but rather provides analysis that can inform negotiations among a range of complex interacting stakeholders and decision makers.[15,42,43] One key strength of this method is finding common ground by identifying robust individual investments.[2,9,43]

Our proof of concept illustrates that this method can highlight both common ground and key places of disagreement. Under a \$125/tCO_2 tax on emissions, we find common ground despite disagreement among the expert beliefs and the models, indicating that high investment in bioelectricity and solar is 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 find that the disagreement about investment in biofuels and CCS is largely parametric (relating to costs and efficiencies), whereas nuclear is largely structural (relating to the diversity of the damage 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. 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 because 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.

The contribution of this work is that we go beyond the qualitative comparisons that have been used in the past, where there was disagreement among models. In particular, it has been very challenging to find ways to combine models, as averaging them does not make sense. Thus, results presented here related to the robustness, or lack thereof, across the models are new. A particular technology that is robust across elicitations in one model is not guaranteed to be robust across multiple models. The key example here is nuclear, which shows a high level of agreement when using one model but shows significant disagreement when using more than one model. The most important thing learned here is that the structure of damages is important for determining the investment in nuclear R&D.

Limitations and future work

A limitation of this study is that the proof of concept only includes the five technologies for which elicitations that are dependent on R&D investments exist. It is possible that, with the addition of other technologies, some of the robust portfolios would change. Olaleye[44] illustrated how optimal portfolios of energy R&D change if individual technologies are eliminated and found intuitive results. If technologies act as complements within the energy system, then excluding one of the technologies would result in a sub-optimally low investment. If they act as substitutes, it would result in a sub-optimally high investment. The impact in this framework is that adding another technology may change which portfolios are in the non-dominated set. One important technology that is excluded here is wind, especially offshore wind, which is a competitive, carbon-free intermittent electricity generation technology. Thus, it is possible that high investment in solar would not be as robust if wind energy were included. On the other hand, there are a number of technologies that are likely competitive with both wind and solar, such as electrolyzers/hydrogen and transmission. Including these would make a high investment in solar more robust, but it would also push up wind. Future work is needed to disentangle these effects.

Expert elicitations provide an important but imperfect way to forecast technological change.[45] The studies used in this paper were conditioned on R&D investments. This provides probability information that cannot be easily obtained by backward-looking methods, such as experience curves. However, recent work has shown expert elicitations to have systematically underestimated technological change,[12,46] and portions of the elicitations used in this study include forecasts that have already been bettered. Meng et al.[12] showed that recent expert elicitations systematically underestimated technological change in solar and overestimated technical change in nuclear. The implications for this on R&D portfolios are ambiguous. On the one hand, if we assume that solar will continue to overperform, this would underline our results that high investment in solar is robust. Similarly, if we assume that nuclear will continue to underperform, this would indicate the lack of robustness and imply fewer high investments in nuclear in the non-dominated set. However, recent rapid reductions in solar could imply slower improvements in the future, thus implying that high investments are not robust. Overall, future work should include more types of forecasts, including experience curves and updated elicitations using new methods.

Even if the overall magnitude of the elicitations is off, the relative proportions of R&D investment would depend on the relative future improvements of the technologies. The justification for the method employed here is finding portfolios that are robust to multiple studies rather than putting all weight on a single study. An important direction for future work is to expand this analysis to include more dimensions of policy and uncertainty. Some directions of particular interest include exploring using data- and model-based forecasts on cost that are conditioned on the modeling approach and not necessarily conditioned on R&D, integrating multiple technologically detailed IAMs, perhaps in conjunction with a model comparison study, and analyzing the implications of net zero carbon goals on R&D portfolios.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Franklyn Kanyako (fkanyako@umass.edu).

Materials 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.

Data and code availability

The code for the IAM 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 GCAM are publicly available at https://zenodo.org/record/5093192 and http://jgcri.github.io/gcam-doc/, respectively. Model output and expert elicitation

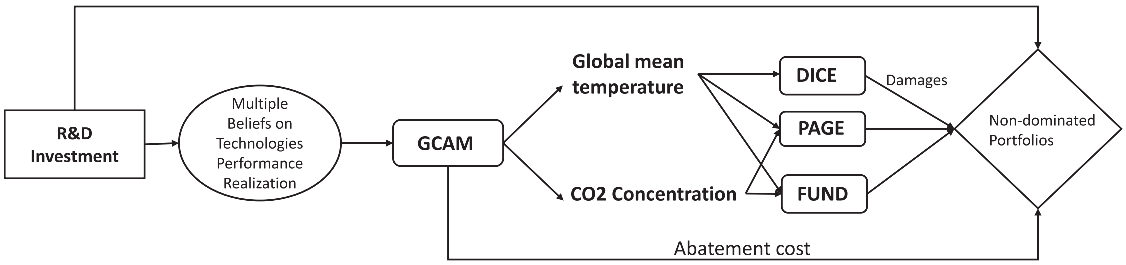

Figure 4. A schematic diagram representing the decision framework

The objective (represented by the diamond node) used to identify the non-dominated portfolios is to minimize the cost of R&D plus the cost of abatement, plus the damages from climate change. This means that the non-dominated portfolios depend on the marginal damages from climate change. Thus, the different damage models in the IAMs will lead to different portfolios and technologies.

of R&D investment data are publicly available at https://doi.org/10.5281/zenodo.5748125.

Methods

We employ a multi-model framework that comprises four IAMs and the RPDA[21] framework to uncover non-dominated R&D portfolios across cost-benefit IAMs and elicitation studies. 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. Each set of performance metrics will result in different emissions paths and thus different paths for CO_2 concentrations and global mean temperatures. These differ in terms of the overall level of emissions and in terms of the timing of emissions. More success in technology will typically lead to lower marginal costs and overall lower emissions. Due to various constraints and initial conditions in GCAM, success in different technologies will lead to different time paths. The cost-benefit IAMs (DICE, PAGE, and FUND) take the GCAM climate variables as input and estimate the climate damages (see Table S1 for damage description).

The main objective is to minimize the sum of the cost of abatement, the cost of climate damages, and the cost of R&D investment. We implement the RPDA framework previously employed by Baker et al.[21] to identify the non-dominated portfolios for each of three policies: reference and the two-carbon tax policy cases (\$125/tCO_2 and \$50/tCO_2) each increasing at 3% annually beginning 2025. There is no constraint on emissions in the reference scenario. In each scenario, we used the SSP2, which follows a trajectory in which social, economic, and technological trends do not deviate much from trends.[31] In SSP2, resource and energy use intensity decreases, whereas global population growth is moderate and plateaus in the latter half of the century. Globally, there are moderate challenges to climate change mitigation and adaptation due to uneven development and income growth, slow progress in achieving sustainable development goals, and challenges to reducing vulnerability to societal and environmental changes. These factors pose obstacles and complexities to climate change mitigation and adaptation efforts.

Below we discuss how expert elicitations are implemented into GCAM and provide more detail on the objective and decision framework.

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 supplemental information section "overview of the global integrated assessment models (IAMs) used in this study" GCAM description and technology competition). The performance metrics used as inputs are sampled from the harmonized probability distribution from Baker et al.[4] 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 1,000 samples from each of the eight probability distributions using the Latin hypercube sampling method, making a total of 8,000 parameters to be evaluated. Each of the 1,000 samples reflects a potential future state of the world of the cost and efficiency of the clean energy technologies listed above. We implement each of the 1,000 states of the world, one at a time, in GCAM, repeated for all three policy cases: the business-as-usual case, with no climate policy in place, and the two carbon tax policy cases. The elicitation dataset contains static values representing the states of the world of technology cost and efficiency 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 5 years between 2015 and 2030 and subsequent years after 2030 using a slight modification of Moore's law, shown in Equations 1 and 2. See Kanyako and Baker[8] for more details.

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

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

Let c_{ij} be Moore's constant associated with sample i and metric j. The constant is calculated based on the elicitation data for the year 2030. $z_{ij}(t)$ is metric j (cost or efficiency) for sample i, at time tt. 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.[26] Note, Equations 1 and 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.

Other methods for characterizing uncertainty

We note that choosing an R&D portfolio inherently requires probability distributions that are conditioned on R&D investment, independent of the specific analysis method. We are not aware of any methods other than expert elicitation that can provide conditional probability distributions that differentiate between technologies. One method ripe for future research is using experience curve analysis to inform and bound expert elicitations.

The RPDA method introduced in this paper, however, can be used for a range of decision problems, some of which do not require conditional probability distributions.

In such a case, empirical methods can be used to provide forecasts, with multiple methods representing multiple beliefs (see Meng et al.[12] for examples of multiple methods). Such non-conditional probabilistic forecasts could inform robust near-term investments in infrastructure such as transmission, for example.

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 f funding level. We define portfolio x as a vector of binary variables such that $x_{hf} = 1$ if technology h is invested in at the f^{th} funding level and 0 otherwise. Each technology in portfolio x can be invested in at one of the three levels of investment (f = 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. We use a value of $k = 4$ for the opportunity cost multiplier (see Nordhaus[47] and Popp[48] for details on the opportunity cost multiplier). Previous research (Baker et al.,[21] Baker et al.,[9] and Baker and Solak[10]) have applied this approach without strong sensitivity to this assumption. Table 1 shows the R&D cost assumptions for different levels of investment. These assumptions came from the harmonization of the expert elicitation studies.

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

$$H(x; m; \tau) \equiv \left[\sum_{i=1}^{1,000} f_\tau(z_i|x)\{TAC(z_i, s) + D_m(z_i, s)\} \right] + kB(x) \qquad \text{(Equation 3)}$$

$$s.t. \sum_f x_{hf} = 1 \, \forall \, h$$

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,[49] we find the non-dominated sets. A portfolio x belief dominates x' if $H(x; m; \tau) \leq H(x'; m; \tau) \, \forall \, md, \tau$ with strict inequality for at least one of the beliefs. A portfolio xx is non-dominated if it is not dominated by any other feasible portfolio.

TAC

The cost of reducing CO_2 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.[50] By applying a real discount rate of 3% per year to future values, the discounted sum of the annual abatement costs from 2020 to 2100 equals the total present value of the TACs $TAC(z_i, s)$ under policy s and scenario z_i

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

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 1,000 states of the world implemented in GCAM leads to different emissions and temperature paths. These emissions and temperature paths are used as input to estimate climate damages using the cost benefit models for each of the world (DICE, PAGE, and FUND). GCAM is a complex IAMs that uses linked modules representing the global economy, energy, land, and climate systems to model energy technologies, energy use choices, land-use changes, and societal trends that cause or prevent greenhouse gas emissions. In contrast to GCAM, cost benefit models are simple IAMs used to estimate the SCC. A monetary estimate of the quantifiable costs and benefits associated with emitting one additional ton of CO_2 (see supplemental information section "overview of the global integrated assessment models (IAM) used in this study").

We use GCAM's detailed energy module to estimate the impact of different levels of R&D investment in clean energy technologies through technology cost and efficiency improvement on the CO_2 emission abatement cost and climate variables (CO_2 emissions and temperature change). The CO_2 emissions and temperature change output from GCAM are used as input into the cost benefit IAMs to estimate the impact of R&D investment on climate damages. For example, the global mean temperature output from GCAM is used in DICE and PAGE from 2010 to 2100 for each scenario. FUND is slightly more complicated. For each of the 14 impact sectors in FUND, the temperature change, CO_2 concentration, or CO_2 emission output from GCAM are used as input depending on main drivers of climate impact of that sector. For each climate policy, \$125/tCO_2 and \$50/tCO_2 (each increasing at 3% annually beginning 2025) and a reference case and damages are estimated for all 1,000 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.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.joule.2023.08.014.

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AUTHOR CONTRIBUTIONS

F.K. and E.B. designed the research. F.K. and D.A. developed the modeling 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.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

We support inclusive, diverse, and equitable conduct of research.

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Joule, Volume *7*

Supplemental information

Identifying low-carbon energy R&D portfolios that are robust when models and experts disagree

Franklyn Kanyako, Erin Baker, and David Anthoff

Supplemental Introduction

S1. Overview of the global Integrated Assessment Models (IAM) used in this study.

Integrated assessment (IA) modeling has emerged as a key technique in climate policy research[1]. IA modeling is a structured process of combining interdisciplinary strands of knowledge and insights from the economic, social, environmental, and institutional dimensions into one framework. The goal is to provide integrated insights to decision-makers by representing tradeoffs and interactions between different parts of society. Various modeling platforms could give other answers to the same question and input parameters.

Below we provide a brief overview of the four IAMs used in this dissertation. We first introduce the technologically detailed cost-effectiveness model (GCAM), followed by the three high-level cost-benefit IAMs - DICE, PAGE, and FUND. Each of these models has different assumptions about the climate variables, a market economy, human relationships, and technological change, all aimed at providing insights to decision-makers through trade-offs and interactions between these climate variables and the impact sectors. Detailed characteristics of the three cost-benefit models, including input assumptions and structures, degrees of regional and sectoral aggregation, and formulation of the damage functions, are found in Table S1.

GCAM – Description

The global change assessment model (GCAM) is a global change integrated multi-sector model that explores both human and earth system dynamics. GCAM is an open-source model developed and maintained by the Joint Global Change Research Institute (JCRI); the model's complete documentation is accessible at this website (http://jgcri.github.io/gcam-doc/overview.html)[2]. GCAM depicts the behavior and interaction of five systems at the global and regional scales: energy, water, land, climate, and the economy, all of which are integrated into a unified computing framework. The climate model is used to investigate climate change mitigation measures such as carbon taxes, carbon trading, regulations, and rapid energy technology deployments[3]. The global energy-economic system is divided into 32 regions that are inextricably linked by international commerce in energy commodities, agricultural and forest products, and other items such as emission permits. The magnitude of economic activity is determined by population size, age, and gender, as well as labor productivity in each region.

GCAM is a dynamic recursive partial equilibrium model that solves each five-year timestep between 1990 and 2100, modifying prices until supply and demand equilibrium is achieved in all energy and agricultural sectors. It is based on the market equilibrium concept, in which representative agents in GCAM make resource allocation decisions based on knowledge about prices, costs, and other relevant aspects. These agents transmit information about supply and demand for products and services to marketplaces. Markets exist for physical commodities such as energy or agricultural commodities, but they may also exist for non-physical products and services such as tradable emissions permits. GCAM finds a set of market pricing that balances supply and demand across all markets in the model. GCAM solves problems by iterating on market prices until an equilibrium is found within a user-specified tolerance threshold[4]. Following each period, the model will use as a starting point the resulting state of the world, including the impact of decisions taken in that period (for example, resource depletion, withdrawals from the capital stock and installations, changes in the landscape, and emissions) for the next period.

Energy Technology Competition in GCAM

GCAM's main energy module encompasses all primary, intermediate, and end-use energy markets, as well as greenhouse gas (GHG)markets, if a cap-and-trade mechanism is implemented. Primary energy reserves and energy resources are expected to be substantial, which, along with projected technical advancement, leads to decreased extraction costs due to resource depletion. Coal, gas, oil, and biomass are traded worldwide in the model, but wind, solar, geothermal, and hydropower are considered renewable energy sources that are not sold across regions in the model. The logit choice formulation is used to determine the market competitiveness and market share of each technology[5]. Options/choices are ordered according to preferences, with cost or profit as the key determinant.

In the case of energy, the model considers input costs, output prices, and technological features to determine the market share of each technology. However, it should be noted that the best choice does not capture the entire market, as numerous factors such as individual preferences, local variation in cost/profit, and simple happenstance may cause some of the market to gravitate toward alternatives that are theoretically inferior choices based on their cost or profit alone[4]. Relative cost differences drive substitution across energy types in the supply sector, and the logit formulation ensures that a winner-take-all result is avoided. The precise share allocated to each technological choice is determined by the share weight of the logit exponent[4]:

$$s_i = \frac{\alpha_i c_i^{\gamma}}{\sum_{j=1}^{N} \alpha_j c_j^{\gamma}} \tag{1}$$

Where s_i, c_i, α_i are the market share, cost, and share weight of each technology, and γ is the logit exponent, which is determined exogenously and controls the extent to which cost affects the market share of each technology. The share weight calculated in the historical period is used in GCAM to ensure that the model can replicate historical data. The share weights are also used to phase in new technologies into the market gradually. To do this, GCAM initially sets the share weights for new technologies at low levels and progressively increases them as the technology becomes more generally accessible.

DICE Model

DICE-2013 (Dynamic Integrated Model of Climate and the Economy) is an inter-temporal optimization model of economic growth for the world as a single region, developed in 1990 by Nordhaus[6]. The model balances the cost of mitigation against the costs of climate change-related damages. Damages are assessed using a quadratic relationship between temperature change and damage. The highly aggregated model accounts for many features, such as the economic value of losses from biodiversity, ocean acidification, extreme events such as changes in ocean circulation, the effect of adaptation, and uncertainty implicitly through a simple damage function[6].

FUND Model

FUND (The Climate Frameworks for Uncertainty, Negotiation, and Distribution) model of climate economics is a simplified representation of development, energy use, carbon cycle, and climate developed by Richard Tol and David Anthoff[7]. The model has been used to investigate the costs and benefits of cost-effective, efficient, viable, and equitable climate policy. It is distinct from comparable integrated assessment models by its more thorough depiction of the economic consequences of climate change at the sectoral and regional levels, encompassing 14 different impact sectors and 16 main geographical regions. The costs of emission reduction are weighted against the avoided damage of climate change. The climate damages from each of the 14 impact sectors are analyzed and estimated separately for each of the 16 regions. The parameters that define these regional sectorial damages are estimated from parametric uncertainty analysis with thousands of Monte Carlo simulations. The damages in each sector are scaled with dynamic vulnerability. Exposure or vulnerability to climate impacts changes dynamically over time, depending on the socioeconomic parameters such as population, GDP growth, and technological change[8].

PAGE Model

The PAGE09 (Policy Analysis of the Greenhouse Effect) model developed by Hope[9] assesses climate change implications and the costs of mitigation and adaptation policies. PAGE09 models eight world regions, taking income, population, and emissions policy as inputs. It estimates the impact of emissions on four impact sectors: "sea-level rise, economic damages, non-economic damages, and discontinuities"[9]. The four impact sectors are modeled independently and reflect damages as a proportion of GDP.

PAGE09 performs parametric uncertainty analysis with thousands of Monte Carlo simulations from each sector to estimate the total damages from climate change. Before adaptation, the economic and non-economic impacts reflect the vulnerabilities of different regions and use a polynomial function to estimate temperature impacts over time. Sea level rise is a lagged linear function of global mean temperature. Discontinuity, or the risk of climate change triggering large-scale damages, reflects a variety of different possible types of disasters. The model also includes two kinds of exogenously defined adaptation costs in each region. The increase in the modest sea-level rise or warming without suffering any damages represented by the 'plateau' and the reduction in 'impacts' from the remaining damage is characterized by the fixed percentage reduction.

Table S1. Key characteristics of the three-cost benefit IAMs

Model details	DICE2013	FUND	PAGE09
Regions	One region: world	Sixteen regions	Eight regions
Damage function	$D = \delta_1 \Delta T + \delta_q T^2$ δ_1 and δ_q are the coefficients of the linear and quadratic damage function and ΔT is temperature change	Sector-specific damages are formulated differently, with the damage function f scaled by a dynamic vulnerability term, for example: $D = f(\Delta T^x)\left(\frac{YPC_t}{YPC_0}\right)^{-\varepsilon}$ x is the exponent of the climatic variable, YPC denotes per capita income, t and 0 represent the current and reference periods, and ε denotes income elasticity.	Estimates residual damages as a percentage loss of regional GDP following adaptation: $D = \delta\Delta(T_r - T_{adapt})^x + C_{adapt}$ The exponent x is uncertain, ranging between 1 to 3.
Climate variable	Global mean temperature change, global mean seal level rise (SLR)	Global mean and regional temperature change, CO2 concentrations, global mean sea-level rise (SLR), ocean temperature	Regional mean temperature change, global seal level rise (SLR)
Socioeconomic drivers	Global income	Population, income, technological change, production cost, the land value	Productivity, regional capacity for adaptation and cost, Scaling factor at the regional level, moderate equity weights
Uncertainty	No	No	Exponent and uncertain threshold damages
Upper bound	Rational	By sector	No

S2: Supplemental Result

Figure S1 shows, for each policy, the proportion of investment level into each technology that is low, mid, or high among the portfolios in the non-dominated sets. We see a general trend toward increased investment, there is a higher proportion of portfolios with high investments in technologies as we increase the stringency of the climate policy. The DICE damage module tends to lead to higher levels of investment in each of the technologies except CCS. CCS does increase with the stringency of the climate policy. There are several areas of convergence across models, such as a lack of "high" investment in CCS and uniform high investment in solar and bioelectricity under the $125/tCO2 tax policy. While the stringency of policy objectives is crucial for investment in individual technologies, areas of convergence on investment levels in individual technologies can still be found regardless of expert beliefs, policies, or models.

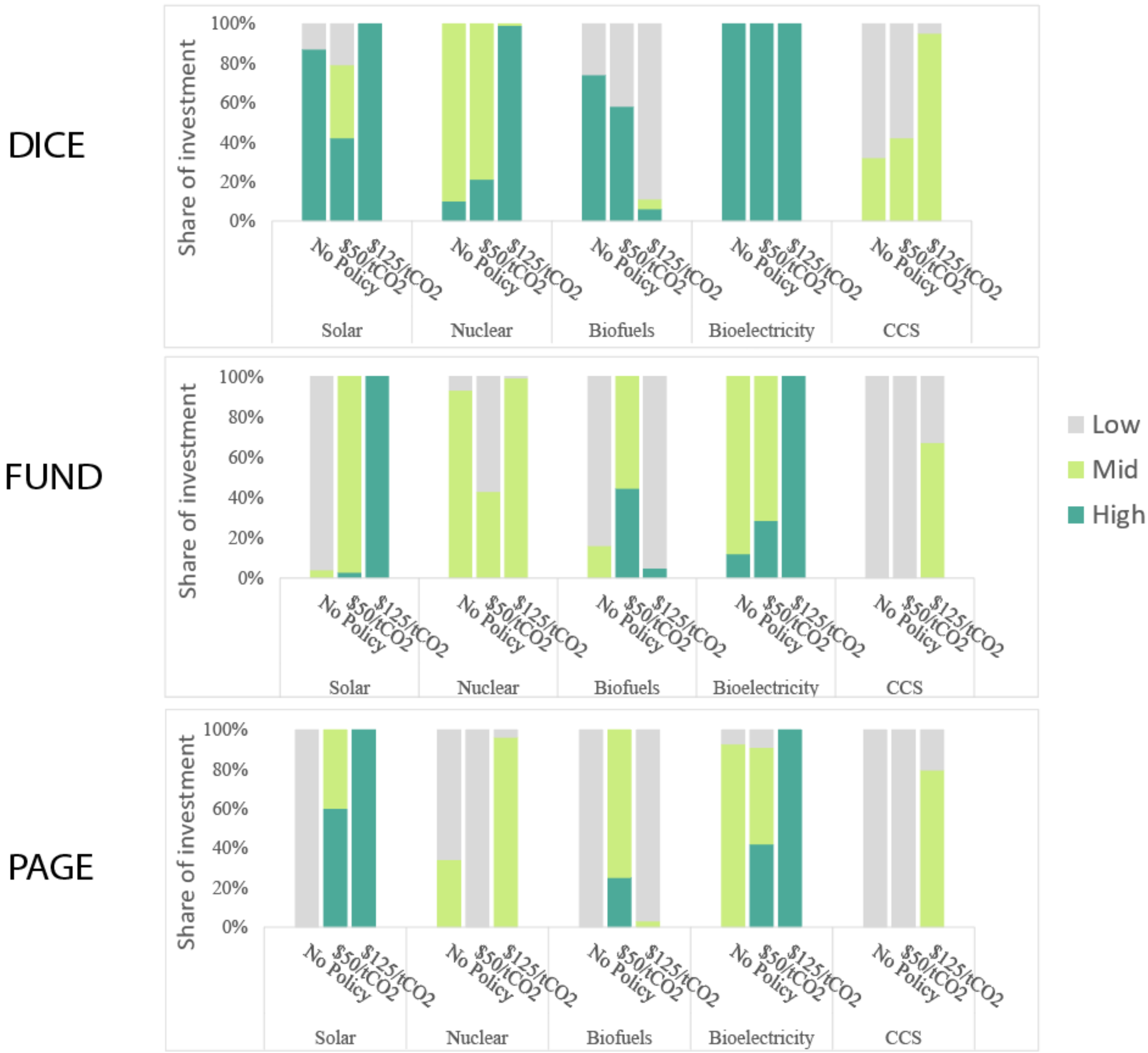

Figure S1: Proportion of each technology in the non-dominated portfolios across different policies for all the models.

Table S2: Non-dominated portfolios for the \$125/tCO2 tax policy. 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. The last 9 columns show the Expected NPV of the total cost of abatement plus damages plus the cost of investment in each portfolio under each of the three cost-benefit IAMs, across the three expert elicitations.

Portfolio	Technologies					Annual R&D (In million USD)	DICE ENPV (In trillion of \$2020)			FUND ENPV (In trillion of \$2020)			PAGE ENPV (In trillion of \$2020)		
	Solar	Nuclear	Biofuels	Bio-elec	CCS		Harvard	FEEM	UMASS	Harvard	FEEM	UMASS	Harvard	FEEM	UMASS
1	High	Low	Low	High	Low	63	92590	94711	92687	30852	31736	30440	38612	39213	37972
2	High	Low	Mid	High	Low	65	93173	94449	92480	31518	31605	30318	39270	39116	37890
3	High	Low	Low	High	Mid	75	92376	94491	92996	31136	31885	30868	38835	39323	38328
4	High	Mid	Low	High	Low	76	91149	94532	87531	30299	31807	29472	38169	39312	37400
5	High	Mid	Mid	High	Low	78	92379	94316	87252	31278	31682	29466	39096	39217	37462
6	High	Low	High	High	Low	82	93164	94284	91775	31632	31580	30893	39399	39128	38615
7	High	Mid	Low	High	Mid	88	90683	94107	86941	30410	31845	29094	38237	39326	37010
8	High	Mid	Mid	High	Mid	90	91967	93883	87374	31315	31725	29505	39102	39237	37462
9	High	Mid	High	High	Low	95	92418	94140	86950	31415	31646	29554	39245	39219	37610
10	High	Mid	High	High	Mid	107	92054	93867	87431	31474	31795	29863	39272	39337	37853
11	High	High	Low	High	Low	235	91007	94665	86889	30629	32443	29713	38555	40004	37723
12	High	Mid	Low	High	High	239	92320	94564	86697	31843	32571	29198	39581	40023	37109
13	High	High	Low	High	Mid	247	90379	94032	86330	30633	32334	29271	38527	39884	37263
14	High	High	Mid	High	Mid	249	91902	94005	86214	31652	32290	29431	39492	39855	37511
15	High	High	High	High	Low	254	92523	94375	86050	31874	32282	29495	39748	39895	37635
16	High	High	Low	High	High	398	92186	94406	86219	32150	32991	29347	39948	40518	37323

S3-S4: Supplemental Tables

Less stringent policies result in a larger number of non-dominated portfolios across all elicitation teams and models. For instance, under the \$50/tCO2 tax policy, 37 portfolios are non-dominated, and 56 are non-dominated under the reference base. 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.

Table S3: Non-dominated portfolios for the \$50/tCO2 tax policy. 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. The last 9 columns show the Expected NPV of the total cost of abatement plus damages plus the cost of investment in each portfolio under each of the three cost-benefit IAMs, across the three expert elicitations.

Portfolio	Technologies					Annual R&D (In million USD)	DICE ENPV (In trillion of $2020)			FUND ENPV (In trillion of $2020)			PAGE ENPV (In trillion of $2020)		
	Solar	Nuclear	Biofuels	Bio-elec	CCS		Harvard	FEEM	UMASS	Harvard	FEEM	UMASS	Harvard	FEEM	UMASS
1	Low	Low	Low	Mid	Low	18	81564	83478	80379	2096	2459	1983	11173	11240	11060
2	Low	Low	Mid	Mid	Low	20	81852	83121	81762	2082	2247	1999	11122	11070	11023
3	Mid	Low	Mid	Low	Low	21	82505	83016	82556	2348	2226	2032	11259	11004	10999
4	Mid	Low	Mid	Mid	Low	22	81556	82821	82127	2047	2171	2105	11081	10979	11076
5	Low	Mid	Low	Mid	Low	31	80843	83343	76995	2121	2528	1918	11239	11319	11182
6	Low	Mid	Mid	Mid	Low	33	81350	82984	77328	2109	2311	1966	11185	11144	11215
7	Mid	Mid	Low	Mid	Low	33	80864	83043	78325	2115	2456	1977	11206	11237	11120
8	Mid	Mid	Mid	Mid	Low	35	80966	82698	77919	2049	2239	1911	11131	11058	11111
9	Mid	Low	Mid	High	Low	36	81420	82448	81205	2073	2146	2217	11127	11001	11223
10	Low	Low	High	Mid	Low	37	81811	82901	81303	2142	2139	2111	11190	10999	11171
11	Mid	Low	High	Low	Low	37	82468	82688	80949	2418	2140	1970	11334	10965	11035
12	Mid	Low	High	Mid	Low	39	81478	82602	80817	2101	2058	2200	11147	10906	11250
13	Low	Mid	Low	High	Low	45	80374	82896	77007	2084	2478	1985	11258	11322	11248
14	Mid	Mid	Low	High	Low	47	80395	82625	77782	2088	2403	1996	11230	11239	11161
15	High	Low	Low	Mid	Low	49	81398	83084	81213	2112	2439	2101	11149	11185	11018
16	Mid	Mid	Mid	High	Low	49	80783	82332	77396	2071	2208	1990	11176	11075	11228
17	Low	Mid	High	Mid	Low	50	81286	82757	76873	2167	2204	2000	11253	11075	11303
18	Mid	Mid	High	Low	Low	50	81927	82409	79481	2504	2178	2153	11448	11028	11282
19	High	Low	Mid	Mid	Low	51	81254	82678	81621	2043	2213	2136	11090	10997	11033
20	Mid	Mid	High	Mid	Low	52	80888	82469	76942	2102	2128	1872	11195	10987	11160
21	Mid	Mid	High	Mid	Low	52	80888	82469	76942	2102	2128	1872	11195	10987	11160
22	Mid	Low	High	High	Low	53	81327	82201	80672	2122	2037	2285	11188	10935	11356
23	Low	Mid	Low	High	Mid	56	80022	82963	77033	2405	2900	2110	11533	11666	11334
24	Mid	Mid	Low	High	Mid	59	80159	82642	77451	2424	2815	2141	11512	11575	11266
25	High	Mid	Low	Mid	Low	62	80614	82975	77531	2071	2508	2003	11175	11264	11111
26	High	Mid	Mid	Mid	Low	64	80745	82567	77637	2052	2280	2012	11143	11076	11156
27	High	Low	Mid	High	Low	65	81120	82338	81376	2062	2183	2083	11127	11013	10964
28	Mid	Mid	High	High	Low	66	80703	82079	76909	2121	2094	2027	11237	11005	11328
29	High	Low	High	Low	Low	66	82223	82574	80576	2400	2228	1935	11317	11030	10938
30	High	Low	High	Mid	Low	68	81219	82466	80683	2103	2118	2153	11160	10939	11134
31	High	Mid	Low	High	Low	76	80238	82595	77380	2048	2467	2039	11190	11270	11164
32	High	Mid	Mid	High	Low	78	80585	82235	77133	2072	2248	2036	11181	11089	11231
33	High	Mid	High	Mid	Low	81	80726	82339	77322	2113	2186	2014	11213	11020	11231
34	High	Low	High	High	Low	82	81068	82086	80239	2118	2095	2077	11193	10964	11094
35	High	Mid	Low	High	Mid	88	80091	82462	77224	2478	2791	2172	11554	11545	11270
36	High	High	Low	High	Mid	247	80225	82675	77108	3148	3499	2850	12273	12291	12002
37	High	High	High	High	Low	254	80946	82411	76618	2861	2930	2778	12006	11831	12100

Table S4: Non-dominated portfolios under the reference case (Business as usual). 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. The last 9 columns show the Expected NPV of the total cost of abatement plus damages plus the cost of investment in each portfolio under each of the three cost-benefit IAMs, across the three expert elicitations.

Portfolio	Technologies					Annual R&D (In million USD)	DICE ENPV (In trillion of $2020)			FUND ENPV (In trillion of $2020)			PAGE ENPV (In trillion of $2020)		
	Solar	Nuclear	Biofuels	Bio-elec	CCS		Harvard	FEEM	UMASS	Harvard	FEEM	UMASS	Harvard	FEEM	UMASS
1	Low	Low	Low	Low	Low	16	77184	76975	77249	-2235	-2199	-2257	1552	1537	1558
2	Low	Low	Low	Mid	Low	18	75564	77136	74904	-2540	-2214	-2499	1513	1556	1487
3	Low	Low	Mid	Low	Low	18	76744	77039	76935	-2303	-2216	-2296	1543	1548	1553
4	Mid	Low	Low	Low	Low	18	76929	76830	77064	-2242	-2196	-2245	1550	1540	1559
5	Low	Low	Mid	Mid	Low	20	75855	76939	76074	-2471	-2245	-2373	1526	1555	1535
6	Mid	Low	Low	Mid	Low	20	75754	76856	76174	-2465	-2220	-2339	1525	1553	1537
7	Mid	Low	Mid	Low	Low	21	76355	76830	76592	-2329	-2215	-2303	1537	1548	1548
8	Mid	Low	Mid	Mid	Low	22	75587	76665	76342	-2475	-2249	-2326	1524	1553	1551
9	Low	Mid	Low	Low	Low	29	76021	76869	75037	-2309	-2161	-2445	1560	1583	1530
10	Low	Mid	Low	Mid	Low	31	74939	77001	72016	-2553	-2181	-2763	1541	1601	1437
11	Low	Mid	Mid	Low	Low	31	76222	76837	75191	-2309	-2190	-2433	1574	1590	1541
12	Mid	Mid	Low	Low	Low	31	76124	76749	74387	-2280	-2156	-2481	1571	1586	1514
13	Low	Low	Low	High	Low	32	75299	76854	74949	-2542	-2212	-2446	1570	1612	1552
14	Low	Mid	Mid	Mid	Low	33	75404	76804	72236	-2473	-2212	-2738	1560	1600	1450
15	Mid	Mid	Low	Mid	Low	33	74950	76732	73114	-2514	-2186	-2609	1548	1598	1479
16	Mid	Mid	Mid	Low	Low	34	75835	76650	73967	-2334	-2187	-2534	1568	1591	1506
17	Low	Low	Mid	High	Low	34	75755	76681	75072	-2434	-2235	-2439	1587	1612	1563
18	Mid	Low	Mid	Mid	Mid	34	75587	76615	76111	-2436	-2211	-2306	1569	1598	1590
19	Low	Low	High	Low	Low	35	76718	76807	75105	-2254	-2202	-2443	1596	1594	1539
20	Mid	Mid	Mid	Mid	Low	35	75063	76543	72734	-2489	-2215	-2663	1556	1598	1474
21	Mid	Low	Mid	High	Low	36	75485	76399	75465	-2437	-2240	-2378	1585	1609	1584
22	Mid	Low	High	Low	Low	37	76297	76597	75042	-2283	-2202	-2432	1588	1594	1545
23	Mid	Low	High	Mid	Low	39	75495	76561	75059	-2436	-2220	-2430	1574	1603	1562
24	Low	Mid	Low	Mid	Mid	42	74736	77066	72042	-2527	-2130	-2718	1579	1649	1483
25	Low	Mid	Low	High	Low	45	74571	76708	72026	-2563	-2179	-2709	1594	1656	1501
26	Low	Mid	Mid	Mid	Mid	45	75264	76739	72173	-2452	-2176	-2703	1601	1644	1494
27	Mid	Mid	Low	Mid	Mid	45	74831	76732	72974	-2484	-2141	-2584	1589	1644	1520
28	Low	Mid	Mid	High	Low	47	75275	76546	72026	-2439	-2202	-2718	1620	1657	1508
29	Mid	Mid	Low	High	Low	47	74586	76471	72677	-2520	-2181	-2607	1601	1655	1529
30	Mid	Mid	Mid	Mid	Mid	47	75032	76464	72609	-2453	-2181	-2640	1601	1642	1516
31	Mid	Low	Mid	High	Mid	48	75466	76371	75334	-2400	-2200	-2350	1630	1653	1625
32	Low	Mid	High	Low	Low	48	76159	76521	73647	-2263	-2184	-2546	1626	1633	1539
33	Mid	Mid	Mid	High	Low	49	74924	76285	72242	-2456	-2206	-2676	1616	1654	1523
34	Low	Mid	High	Mid	Low	50	75324	76684	71759	-2431	-2185	-2756	1611	1650	1488
35	Mid	Mid	High	Low	Low	50	75771	76335	73551	-2289	-2183	-2540	1619	1634	1544
36	Low	Low	High	High	Low	50	75690	76530	74664	-2389	-2212	-2455	1638	1660	1603
37	Mid	Mid	High	Mid	Low	52	74974	76425	71861	-2450	-2188	-2730	1607	1648	1500
38	Mid	Low	High	High	Low	53	75382	76246	74918	-2399	-2219	-2411	1635	1658	1620
39	Low	Mid	Low	High	Mid	56	74256	76765	72081	-2548	-2124	-2661	1628	1703	1549
40	Mid	Mid	Low	High	Mid	59	74365	76474	72474	-2500	-2132	-2587	1639	1700	1568
41	Mid	Mid	Mid	High	Mid	61	74885	76189	72298	-2421	-2174	-2633	1661	1697	1570
42	High	Mid	Low	Mid	Low	62	74775	76634	72439	-2416	-2072	-2534	1652	1705	1566
43	Low	Mid	High	High	Low	63	75195	76394	71663	-2396	-2180	-2729	1671	1705	1551
44	Mid	Mid	High	Mid	Mid	64	74985	76380	71988	-2408	-2149	-2678	1653	1696	1550
45	Mid	Mid	High	High	Low	66	74834	76126	71764	-2416	-2186	-2699	1667	1703	1562
46	High	Mid	Low	High	Low	76	74489	76410	72341	-2406	-2056	-2499	1708	1763	1627
47	Mid	Mid	High	High	Mid	78	74849	76094	72006	-2373	-2144	-2632	1713	1749	1616
48	High	Mid	Mid	High	Low	78	74779	76166	72012	-2357	-2090	-2557	1722	1760	1624
49	High	Mid	Low	High	Mid	88	74317	76281	72281	-2381	-2028	-2469	1748	1803	1671
50	High	Mid	Mid	High	Mid	90	74720	76056	72274	-2322	-2064	-2494	1765	1802	1679
51	High	Mid	High	Low	Mid	91	75364	76014	73438	-2164	-2053	-2367	1761	1781	1696
52	High	Mid	High	High	Low	95	74743	75990	71626	-2312	-2072	-2572	1774	1808	1668
53	High	Mid	High	High	Mid	107	74721	75955	72075	-2272	-2035	-2487	1819	1854	1728
54	High	High	Low	High	Low	235	74677	76655	72223	-1826	-1459	-1938	2329	2385	2237
55	High	High	Low	High	Mid	247	74426	76449	72221	-1808	-1440	-1903	2366	2423	2283
56	High	High	High	High	Low	254	75056	76323	71475	-1714	-1467	-2020	2400	2434	2278

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