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Decision frameworks and the investment in R&D

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HIGHLIGHTS

- We introduce a new technique for integrating probability distributions with large scale IAMs.
- We find that investment in energy technology R&D is important with or without a climate policy.
- We illustrate the importance of considering two-stage problems under uncertainty.
- Prospects for technological change and economic interactions must both be taken into consideration when crafting R&D policy.

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ABSTRACT

In this paper we provide an overview of decision frameworks aimed at crafting an energy technology Research & Development portfolio, based on the results of three large expert elicitation studies and a large scale energy-economic model. We introduce importance sampling as a technique for integrating elicitation data and large IAMs into decision making under uncertainty models. We show that it is important to include both parts of this equation – the prospects for technological advancement and the interactions of the technologies in and with the economy. We find that investment in energy technology R&D is important even in the absence of climate policy. We illustrate the value of considering dynamic two-stage sequential decision models under uncertainty for identifying alternatives with option value. Finally, we consider two frameworks that incorporate ambiguity aversion. We suggest that these results may be best used to guide future research aimed at improving the set of elicitation data.

1. Introduction

The ultimate goal of collecting information on the impacts of R&D and of running simulations on Integrated Assessment Models (IAMs) is to inform decision making. In this paper we discuss how R&D data and IAM outputs can be used in different frameworks, and the impact that the different frameworks have on the ultimate results. We do this with an objective of providing insights into the optimal government funded energy technology R&D portfolio.

The Elicitation and Modeling Project (TEaM)[1] has provided a set of probability distributions over the outcomes of energy technology R&D investment, based on three sets of expert elicitations performed over 5 years by three different research teams: Anadón et al. (2012, 2014), Baker et al. (2008c, 2008b, 2009a, 2009b, 2010, Baker and Keisler (2011), Bosetti et al. (2011, 2012), Catenacci et al. (2013). The R&D outcomes are measured in terms of the future performance of energy technologies, including their costs and

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[1] http://www.feem.it/getpage.aspx?id=4278&sez=research&padre=18&sub=70&idsub=86&pj=ongoing.

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efficiencies. Though it is informative to consider the impact of R&D investments on these technological outcomes, it is also important to consider how specific technological outcomes are likely to impact economy-wide outcomes. The implications of R&D on the cost of a specific technology might be very large, but if there are less expensive alternatives to that technology, this impact might be smaller than one would expect prior to an equilibrium analysis. In order to evaluate the impact of technology improvements on societal outcomes, the TEaM project has used IAMs to translate technological characteristics into metrics of interest, such as the cost to achieve a particular carbon emissions path, or the diffusion of different technologies into the economy. In this paper we focus on results from GCAM, but a similar analysis can be done using the results from the other IAMs.

The next step is to use the resulting distributions over economic impacts to inform decisions: it is not easy to anticipate *a priori* how data distributions translate into optimal decisions (Baker and Solak, 2011). The optimal decision under uncertainty is not necessarily some average of the optimal decisions under certainty, nor is it necessarily near the optimal decision under a central case (Baker, 2009; Dow and Werlang, 1992; Santen and Anadon, submitted for publication).

Different questions require different decision support frameworks. In a world in which a stabilization goal has been chosen through political negotiation, the best framework is one that takes this goal as given. However, in a world in which decisions about environmental goals are ongoing, and are likely to depend on the outcome of uncertainties, a framework that allows for flexible adjustment of the strategy once learning has taken place is more appropriate. Additionally, some people argue that in a world with multiple conflicting probability distributions, decision frameworks should account for ambiguity-aversion. In this paper we consider how the optimal R&D portfolio differs across elicitation teams, and when (1) the stabilization pathway is a second stage choice compared to when it is given; and (2) the impact on a one-stage model of using a simple ambiguity-averse framework.

In this paper, we find that the different expert judgment studies on the expected returns to technology R&D lead to different optimal R&D portfolios; and that moreover, the optimal portfolios under a traditional optimization and two different extreme ambiguity averse frameworks all lead to different optimal portfolios. On the other hand, we find that while knowing the expected returns to technology R&D is crucial, it is not enough: both sides of the equation are important here.

An important finding of this paper is that investing in public R&D is important, even in a world with no emissions policies; in fact, the optimal R&D investment may be higher in worlds with no emissions policies than in worlds with moderate emissions policies. A strand of the literature has found a somewhat similar result: in the presence of endogenous technical change, optimal carbon taxes may be higher than pigovian taxes (Hart, 2008; Greaker and Pade, 2009). These two results are related in that they both find that if we are restricted to one policy instrument rather than two, that policy instrument may have to be more stringent. In related work, Acemoglu et al. (2012) find that it is not optimal to have only a carbon tax and no R&D subsidy. In this paper, we examine whether it is still worthwhile to invest in technological change even in the absence of an emissions policy.

In Section 2 we discuss a number of different frameworks and the optimization models that we focus on. In Section 3 we describe our detailed numerical example, comparing decision frameworks across different elicitation teams. We present assumptions, data, and solution methods, and discuss the methods for integrating the elicitation data into IAMs. In Section 4, we present the results of our numerical example; and conclude in Section 5.

2. Frameworks for uncertainty analysis

2.1. A review of decision frameworks

In this section we discuss a set of frameworks, including sensitivity analysis, Monte Carlo type analysis, single-stage decision making under uncertainty (DMUU), sequential DMUU, and frameworks to account for ambiguity aversion.

2.1.1. Sensitivity analysis

When there is uncertainty over the values of inputs, the first level of analysis is sensitivity analysis. This is the most common approach taken by Integrated Assessment modelers. Sensitivity analysis can reveal which parameters are most important to carefully characterize, and can sometimes provide an estimate for how outputs of interest change with the uncertain input parameters (see *e.g.* Bosetti et al. (2015)). Another approach is a global scenario analysis on a small set of assumptions about uncertain model inputs: specifically focusing on technological outcomes (McJeon et al., 2011) shows that significant substitution exists between supply technologies; the relative value of advancement in a technology depends on the interaction effects within technologies in that scenario.

The benefits of sensitivity analysis are that it is relatively easy to undertake this analysis, and it shows how one output changes when an input changes. This allows modelers to get an idea of which parameters are most important to model carefully; and it can give some policy insights into how outputs change with inputs. The limitation of sensitivity analysis is that it will often not address the impact of non-linearities: the best alternative under uncertainty may not be equal to some kind of average of the best alternatives under certainty. Moreover, sensitivity analysis is generally done in the absence of probabilities, thus the analyst is unable to determine whether “interesting” effects have much, or even any, likelihood of arising.

2.1.2. Monte Carlo-type analysis

When a probability distribution over uncertain inputs is available, a Monte Carlo-type analysis can be performed: the analyst is able to estimate the distribution of the outputs by using draws from the distribution of the inputs. (We call it “Monte Carlo-type” analysis to include more sophisticated sampling techniques such as Latin Hyper Cube). This has been commonly used in the IAM literature to investigate uncertainty (see Crost and Traeger (2013) for examples). Monte Carlo-type analysis can provide a layer of insights above sensitivity analysis. It is particularly useful for descriptive models, in which we are most interested in gaining an understanding of the state of world.

Monte Carlo-type analysis is less useful for decision models, in which we are most interested in understanding near-term optimal decisions. In fact, the key limitation to Monte Carlo is that, generally, each run of the model is run under the assumption of the certainty of the sampled input values. That is, all uncertain outcomes are realized before the model is run and decisions are made. It is possible, but not often done, to restrict early decisions in a model to be identical across all samples. However, this early scenario tends to be arbitrary, rather than a response to the actual uncertainty. Monte Carlo cannot tell us what the impact of uncertainty on the optimal decisions is, just what the range of uncertainty over the outcomes is. Crost and Traeger (2013) present an excellent discussion of the limitations of Monte Carlo, as well as a numerical example using the DICE model.

2.1.3. Single stage decision under uncertainty

Like Monte Carlo, this framework explicitly incorporates uncertainty. Unlike Monte Carlo, this method includes an