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Evaluating Climate Policies Under Severe Uncertainty: an Application of the Smooth Ambiguity Model

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Abstract

I identify the limitations of the Expected Utility Model under severe uncertainty when applied to climate change mitigation policy, including its inability to incorporate multiple probability distributions, subjective probabilities and uncertainty aversion. I argue that Klibanoff et al.'s Smooth Ambiguity Model provides a superior means to compare climate policies by accounting for the limitations in the Expected Utility Model. I justify applying subjective probabilities across objective probabilities to account for important information available to the decision-maker.

Keywords: Klibanoff; Smooth Ambiguity Model; Expected Utility Theory

1. Introduction

Climate change is the "biggest threat that modern humans have ever faced" (UN Security Council, 2021), and public decision-makers face the task of deciding which policies best mitigate the adverse effects. However, despite significant progress in recent decades, we are not able to assign precise probabilities to the impact of increased carbon dioxide concentrations on the climate (Hausfather, 2018). Consequently, decision-makers must choose between policies with wildly varying probability distributions of effectiveness – they must choose under 'severe uncertainty'. In this essay, I outline the limitations of the Expected Utility Model in the presence of severe uncertainty and consider the Smooth Ambiguity Model proposed by Klibanoff, Marinacci and Mukerji (2005) as an alternative. I evaluate the benefits of the model, which include a superior treatment of varying probability distributions and an account of uncertainty aversion and subjective probabilities.

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2. Climate policy choice under the Expected Utility Model

Perhaps the best known and most widely accepted normative theory of decision-making is the Expected Utility Model (EUM, hereafter), developed by Leonard Savage (1954). The basic idea of the EUM is that one first determines the probability P of each state of the world (SOTW) ω_i, then averages the utilities of the outcomes of each action by the probabilities of the state of the world in which they occur. So, the expected utility of action a over n possible states of the world is given by:

$$U(a) = E[u(a)] = \sum_{i=1}^{n} u\big(a(\omega_i)\big) \cdot P(\omega_i)$$

The decision-maker then chooses the action with the highest expected utility. For example, consider a decision-maker who is choosing between two climate policies in a highly stylised environment.

Policy a_1: *do nothing.*

Policy a_2: *limit carbon dioxide concentrations in the atmosphere.*

Suppose there are two states of the world:

SOTW ω_1: the *climate has a **low** sensitivity to increased carbon dioxide concentrations.*

SOTW ω_2: the *climate has a **high** sensitivity to increased carbon dioxide concentrations.*

For which the probability distribution is:

$$P(\omega_1) = 0.1$$

$$P(\omega_2) = 0.9$$

The utility derived from doing nothing if the state of the world turns out to be that the climate has low sensitivity to increased CO_2 concentrations is 0 – there is no utility derived from the action, but there is no harm either. If, however, action is taken to reduce CO_2 concentrations and it turns out sensitivity is low, resources have been used unnecessarily, so the utility derived from this policy is -5. If the state of the world turns out to be that the climate is highly sensitive to increased CO_2 concentrations, then doing nothing results in a utility of -10 as climate-related events wreak destruction. If action is taken to limit CO_2 concentrations, the resources are still spent, but no further harm is caused by climate-related events, hence the utility derived from this action is -5. This information is represented in Table 1.

Table 1: Simple Case of the EUM

	ω_1 (P=0.1)	ω_2 (P=0.9)
$u(a_1)$	0	-10
$u(a_2)$	-5	-5

Hence, the expected utility of taking action a_1 is $(0.1 \times 0) + (0.9 \times -10) = -9$ and the expected utility of taking action a_2 is $(0.1 \times -5) + (0.9 \times -5) = -5$. Hence, the decision-maker would choose action a_2 since the expected utility is higher. This example demonstrates the attractiveness of the simplicity of the EUM in known probability situations.
But now suppose that the decision-maker is presented with not one, but many probability distributions. One expert tells her that $P(\omega_1) = 0.001$, whilst another tells her that $P(\omega_1) = 0.5$, and myriad others give predictions in between. Let those probability distributions which are consistent with present information about climate sensitivity form the set Δ, which we shall call the set of 'objective' probability distributions, following the notational convention established by Klibanoff, Marinacci and Mukerji (KMM, hereafter). They are objective in the sense that they are data-driven predictions made by experts.

The decision-maker then faces 'severe uncertainty' – she cannot assign precise probabilities to climate sensitivity. But it is not the case that severe uncertainty implies ignorance (Heal & Millner, 2014). To the contrary, we know a great deal about the challenge we face. We know that a response of significant size is required, it is simply a question of *how significant*. Therefore, it is not permissible to justify inaction based on uncertainty, as many decision-makers have. However, if our decision-maker is to use the EUM as we have stated it, she must essentially guess which probability distribution is correct. She may have some good reason to guess between distributions, for example by considering the past predictive success of each expert, but by choosing any single probability distribution to rely on she is immediately discarding the information contained in all the others.

This issue essentially divides decision models into two groups: those which consider all probability distributions which are consistent with present information, which tend to be more complex, and those which discard them and either focus on the extremes or on a single 'median' distribution, which tend to be simpler. In my view, given the existence of, albeit many and varying, probability distributions regarding climate sensitivity, discarding them risks omitting important information which could help to inform policy decisions. Considering this, I shall focus on the former category, and specifically the Smooth Ambiguity Model proposed by Klibanoff, Marinacci and Mukerji (2005).

3. The Smooth Ambiguity Model

The Smooth Ambiguity[1] Model (SAM, hereafter) provides a method that uses the information contained in all the distributions which are consistent with present information. It does so by

[1] I use the term 'severe uncertainty' in the paper to conform with course terminology, but 'ambiguity,' as it is used by KMM, is synonymous.

combining all objective probability distributions on the outcomes of an action and generating an overall objective expected utility for an action, considering all of the distributions:

$$U_{objective}(a) = E_{\pi}[u(a)]$$

Where $E_{\pi}[u(a)]$ is the expected utility aggregated[2] across all probability distributions $\pi \in \Delta$. One should note that the SAM makes use of the same principles in calculating the expected utility under each distribution, and hence it could be seen to be *building* on the EUM. Returning to our decision-maker, this means that each of the distributions she is presented with is used to calculate an expected utility for action a_1, and these are aggregated to give a single *objective expected utility* for the action, and likewise for a_2. If desired, we could stop here, and simply choose the action with the highest objective expected utility. But so far, we have only dealt with what we have called 'objective' probabilities – those which are driven by data. We have, however, failed to account for a phenomenon known as uncertainty aversion.

It is important to take pause here and offer a more thorough treatment of the concept of uncertainty aversion. A decision-maker is uncertainty averse if she prefers known risks over unknown risks. Indeed, the more uncertainty averse she is, the more weight she will apply to the probability distributions which infer low expected utilities. In our case then, the uncertainty averse decision-maker is more inclined to insure against the probability distributions which predict higher climate sensitivity, and therefore greater damage. There is evidence of this attitude in practice. Indeed, the literature is unified on the existence of uncertainty aversion as a motivation for climate change mitigation (Dietz, 2014)[3]. Furthermore, one analysis suggests that as much as half the willingness to spend on climate mitigation could stem from uncertainty aversion (Millner et al., 2013). It is important to note that uncertainty aversion is a different concept from risk aversion, which, if present, is accounted for by the utility function in the EUM and the SAM. The SAM accounts for uncertainty aversion, in contrast to standard EU models.

The SAM admits uncertainty aversion and takes account of 'subjective' probabilities, that is, the attitudes that the decision-maker holds over the probability distributions with which she is presented. As previously mentioned, this may be due to considerations such as the reputation of the researchers who produced the distributions. Such subjective probabilities can form an important part of the information to which the decision-maker has access. Uncertainty aversion is held towards the distributions themselves. For example, she may assign more importance to those distributions which predict higher climate sensitivity, insuring against the worst-case scenarios, which not only satisfies an egalitarian concern for the worst-off under such conditions but also will be more satisfactory to an uncertainty averse public. One might object on the grounds that over-insuring might occur, but the advantage of this model is that subjective probabilities are tempered by the objective probabilities contained in the objective expectation function above. Such subjective beliefs can be represented as a subjective probability distribution over the objective probability distributions, and hence we can use a double expectation function to calculate the overall expected utility of an action $V(a)$, which includes both all the objective distributions and the subjective probability distribution across it:

[2] $E_{\pi}[u(a)] \doteq \int_S u(a) d\pi$ where S is the set of all states of the world. In our simplified example, S consists of a high climate sensitivity world and a low climate sensitivity state of the world.

[3] Whether uncertainty aversion is permissible is a subject of debate, but to discuss this debate falls beyond the scope of this paper. For the purposes of this paper, I assume permissibility (for justification, see, e.g., Gilboa et al., 2009).

$$V(a) = E_{\mu}[\phi(E_{\pi}[u(a)])]$$

Where $E_{\mu}[\cdot]$ captures[4] the subjective probabilities μ across the set of objective probabilities, and ϕ captures the uncertainty aversion of the decision-maker. Specifically, the more concave is ϕ, the more uncertainty averse the decision-maker (just as concavity in the utility function in the EUM infers risk aversion) and likewise a linear ϕ implies uncertainty neutrality. This follows from the definition of uncertainty aversion since each marginal increase in uncertainty yields a smaller expected utility than the last. Hence, we account for both considerations in the model.

Oliver (2013) would likely claim that such over-reliance on modelling would be counterproductive. However, I believe that the use of this model allows us to capture information that would otherwise be missed, and in a matter as sensitive to not only new information but also public opinion, using information other than simply the 'best guess' probabilities is necessary. The advantages of such an approach are that (a) we include all the information provided by the probability distributions available to us, weighted to account for the preferences of the decision-maker, and (b) we generate smooth rather than kinked indifference curves. The appeal of (a) is clear: we do not miss important information, but we also allow for the preferences of the decision-maker to temper the impact of distributions she considers less 'important on the final calculation. This could mean that if she is more concerned about the impact in states of the world where climate sensitivity is high, she can express a preference for distributions that assign a high probability to such states through μ, and she can express greater trust in more reputable research through ϕ. The appeal of (b) is more subtle but is the reason why I believe this model is preferable over other models which use a range of objective probability distributions. Smooth indifference curves allow for greater tractability than kinked curves since they are more responsive to new information.

4. Conclusion

This paper has identified three limitations of the Expected Utility Model when applied to climate policy decision-making under severe uncertainty. Firstly, it does not allow for the incorporation of multiple probability distributions and may discard otherwise useful information. Secondly, it does not permit subjective probabilities and hence fails to capture information other than that contained in the objective probability distributions, which the decision-maker holds, and which may be beneficial to the analysis. Thirdly, it does not permit uncertainty aversion, which can lead to genuine concerns of the decision-maker being omitted from a comparison of policies. I have evaluated an alternative decision model, the Smooth Ambiguity Model, which addresses each of these limitations in turn and provides a means by which to allow for the discretions of the decision-maker whilst including all the relevant information, and I have defended the use of subjective probabilities as a complement to the objective probabilities provided by experts and driven by data.

[4] $E_{\mu}[\phi(E_{\pi}[u(a)])] \doteq \int_{\Delta} \phi\left(\int_{S} u(a)d\pi\right)d\mu$, such that μ is the decision-maker's beliefs over Δ, the set of all objective probability distributions.

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