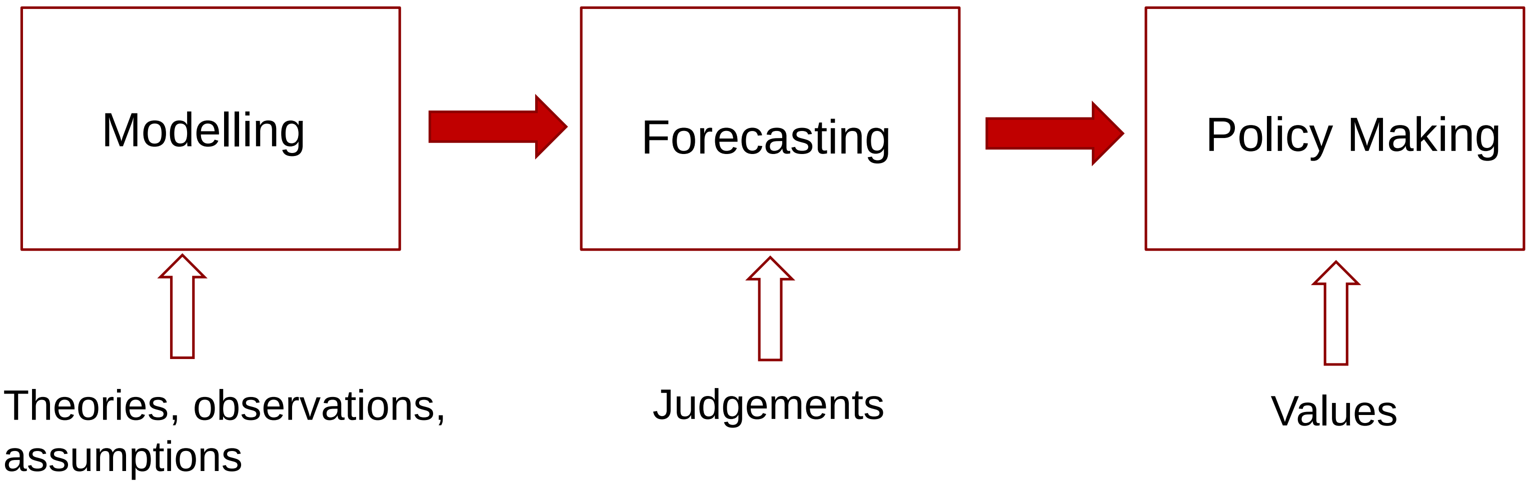
Model Uncertainty and Policy Making

Evidence-Based Policy
Stockholm, October 2016

Outline

1. Economics and Policy Making
2. Uncertainty
3. Model Averaging
4. Robustness
5. Confidence

From Models to Policy



"It is also important to emphasise that the model is a computational tool and considerable human judgement must be applied to produce a coherent forecast. Two forecasters using exactly the same model could end up with very different forecasts because the judgements underpinning them differ." – *The Macroeconomic model*, OBR briefing paper 5, 2013

Models and Policy

- The core of an economic (policy) model is a specification of the causal and functional relationships between target variables (*T*) and policy (*P*) and other variables (V_i). Formally:

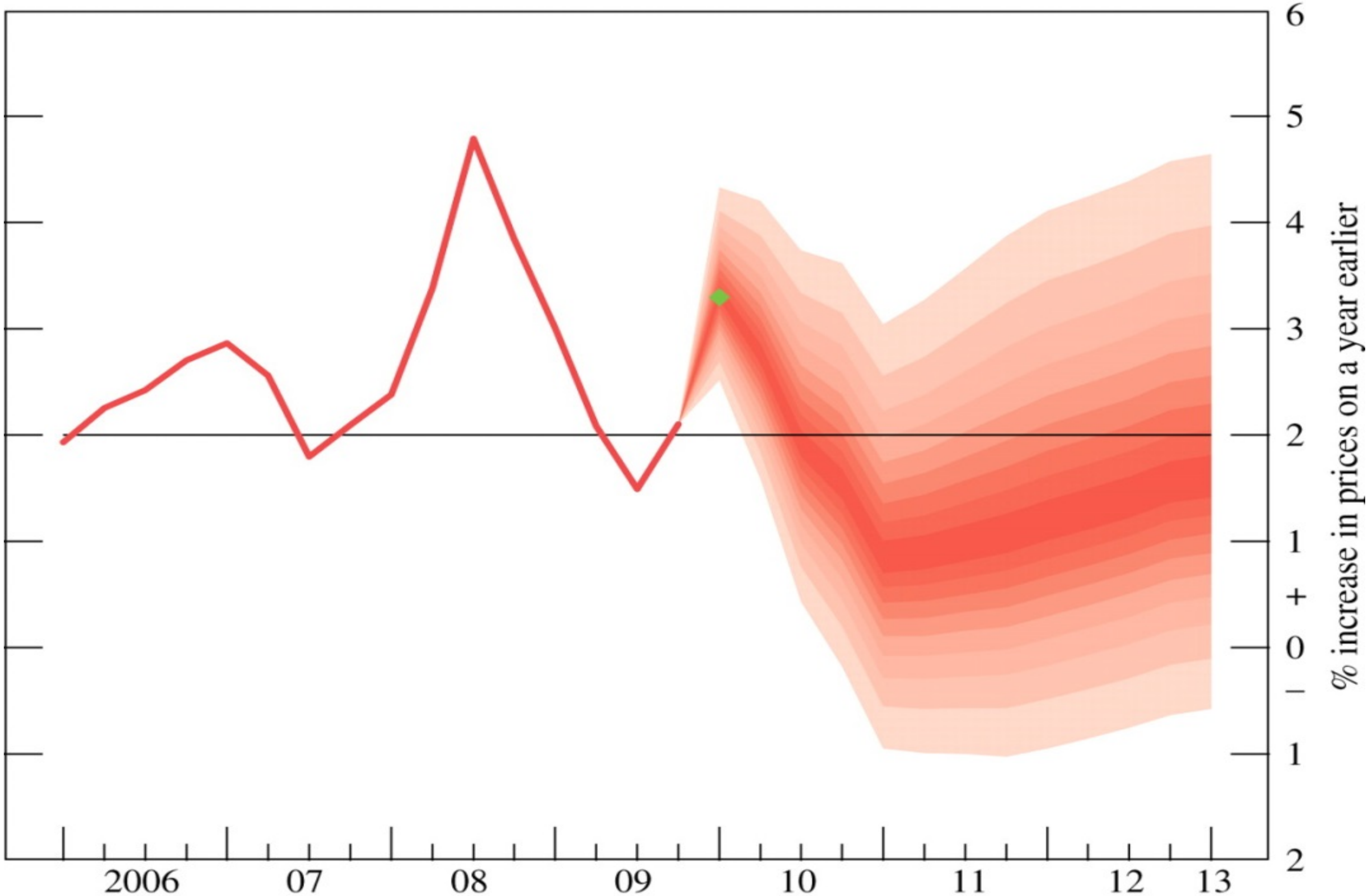
$$T = M(P, V_i)$$

- Models provide knowledge both about the evolution of key economic variables – the 'facts' – but also about the effect of policy interventions on target variables – the 'counterfacts'.
- Correct identification of causal structure is essential to predictions about the effects of interventions. But hard to achieve (counterfacts are not observable!).
- "Credible policy analysis must recognise and express the uncertainties we face" – Manski (Brit Academy lecture)

Uncertainty

- Uncertainty has different sources:
    1. Objective
    2. Measurement of initial conditions
    3. External shocks
    4. Uncertainty about the underlying causal or structural relationships between variables
- Some of this uncertainty can be managed by:
    - ➢ Associating model with predictions that are intervals or probability distributions over values (ensemble forecasts).
    - ➢ Making policy decisions by maximizing expected utility relative to the probabilistic forecast.

Representing Uncertainty



Model Uncertainty

- Model uncertainty arises because empirical evidence typically doesn't suffice to fix the causal-functional relationships or corresponding parameter values.
- This is especially true if model only induces a probability distribution over target variables.
- Even if there is a best fitting model, its reasonable for modellers:

1. To have doubts about the predictions it yields e.g. because they know that it idealises in various ways
2. To consider a range of models that perform tolerably well but which are based on different assumptions

- Let's consider three ways such model uncertainty can be managed

Model Averaging

- General idea:

1. Give each model a score to reflect how good it is in terms of fit with the data (also simplicity and explanatory power).
2. Weight each model's predictions by its score to produce an average probability for the target variables.
3. Maximise expected utility in policy making relative to average probabilities.

- Bayesian model averaging:
  - Include models in the algebra of events.
  - Treat model uncertainty as factual uncertainty.

Bayesian Model Averaging

- Assume that uncertainty regarding initial conditions, shocks, etc., is encoded in a probability distribution (or family of them) :

$$Pr_M(T|P, Evidence)$$

Then residual uncertainty only concerns the models M.

- Assign a probability to each M. Then, assuming that the M are independent of the P, we have:

$$Pr_M(T|P, Ev) = \sum_i m_i \cdot \Pr(T|P, M, Ev)$$

where:

$$m_i = \Pr(M_i|Ev)$$

Problems for Model Averaging

- May not be possible to assign weights in non-arbitrary way because of lack of information (model ambiguity).
- Probabilistic consistency requires that you average over a partition of models. But the models we have are not always mutually exclusive or exhaustive.
- ‘All models are false’. Hence what matters is verisimilitude not probability of truth.
- Models encode assumptions that forecasters may have doubts about. Assumptions can’t be averaged.
- Different models are good for different things. So the weight we give a model should depend on the proposition we are interested in.
- Conclusion: Bayesian averaging misrepresent the role that models play in supporting forecasting.

Robust Intervals

- General idea:

1. Take intervals (of values or probabilities) as decision inputs.
2. Employ a decision rule that is robust with respect to the corresponding range of expected utilities.

- Robust Control (Hansen and Sargent):

1. Start with a reference model (a probability distribution)
2. Generate a family of models that are a certain Kullback-Leibler distance away from the reference model. (Size of family measures the degree of model uncertainty.)
3. Maximize minimum expected utility relative to this family.

Robust Intervals

- Maximin EU can lead to cautious decision making: how cautious depends on the width of the set of models.
- Main question: How do we choose the set of models (the size of the 'entropy ball')?
  - Is it a scientific question, determined by a measure of model uncertainty?
  - Is it something to be settled by policy maker on basis of their caution?
- Suggestion: Work with a set of models that is sufficient to give us confidence in policy relevant predictions.

IPCC Language of Uncertainty

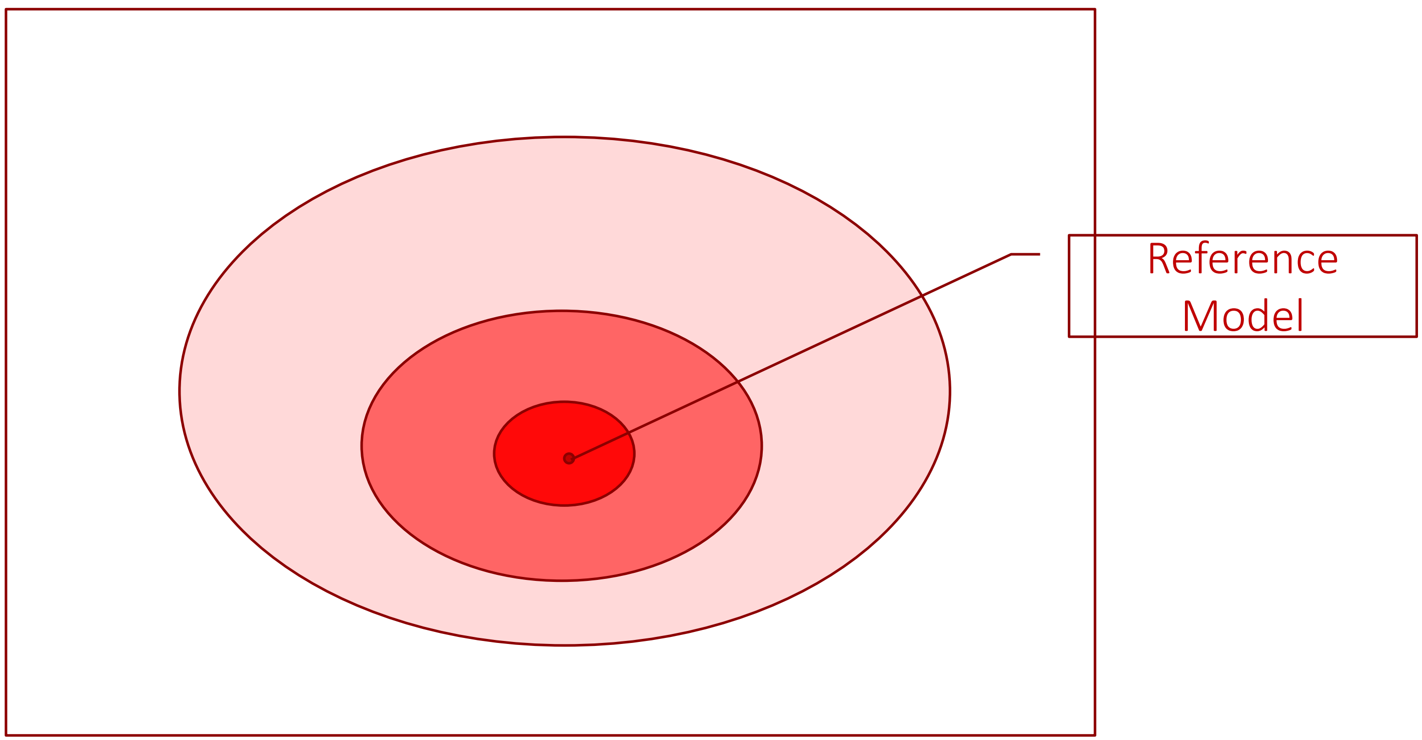
IPCC uses two metrics for communicating uncertainty in key findings:

1. Probabilistic measures of uncertainty in a finding (based on statistical analysis or expert judgment).
2. Confidence in the validity of a finding, based on the type, amount, quality, and consistency of evidence. Confidence is expressed qualitatively.

e.g. "For average annual NH temperatures, the period 1983–2012 was very likely the warmest 30-year period of the last 800 years (high confidence) and likely the warmest 30-year period of the last 1400 years (medium confidence)."

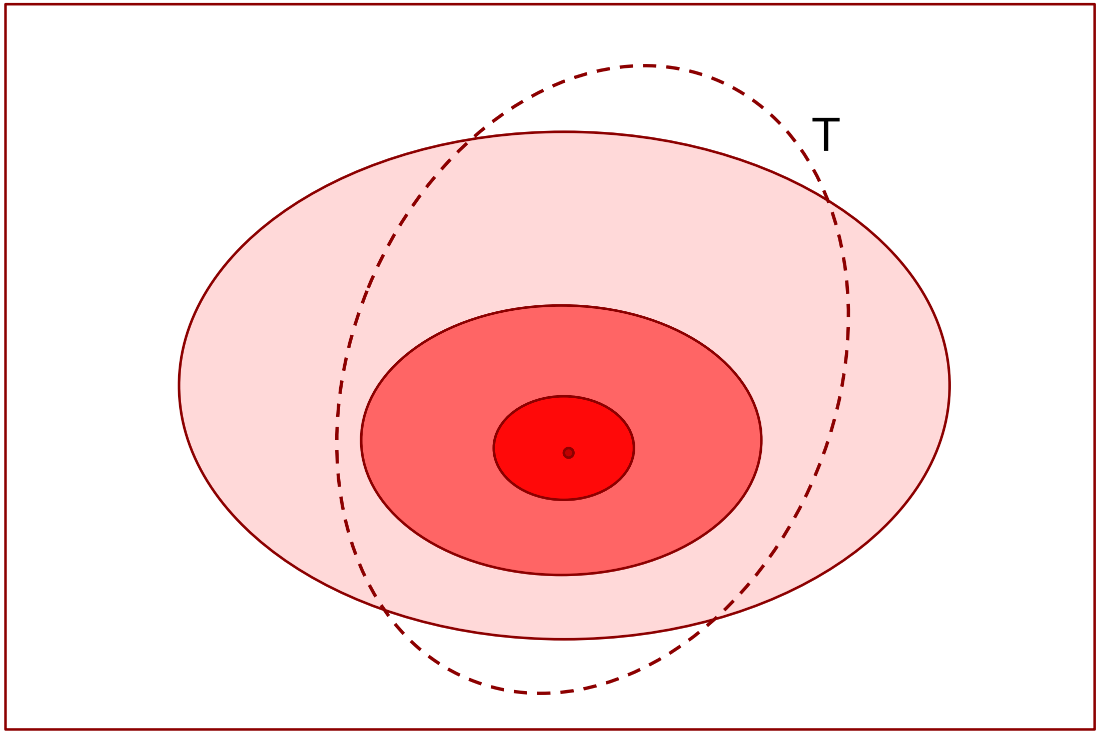
Confidence

- Represent model uncertainty by a nested family of probability distributions, centred on the reference model (if there is one).



Confidence

- Nested family encodes confidence judgements in the predictions / findings supported by the models.

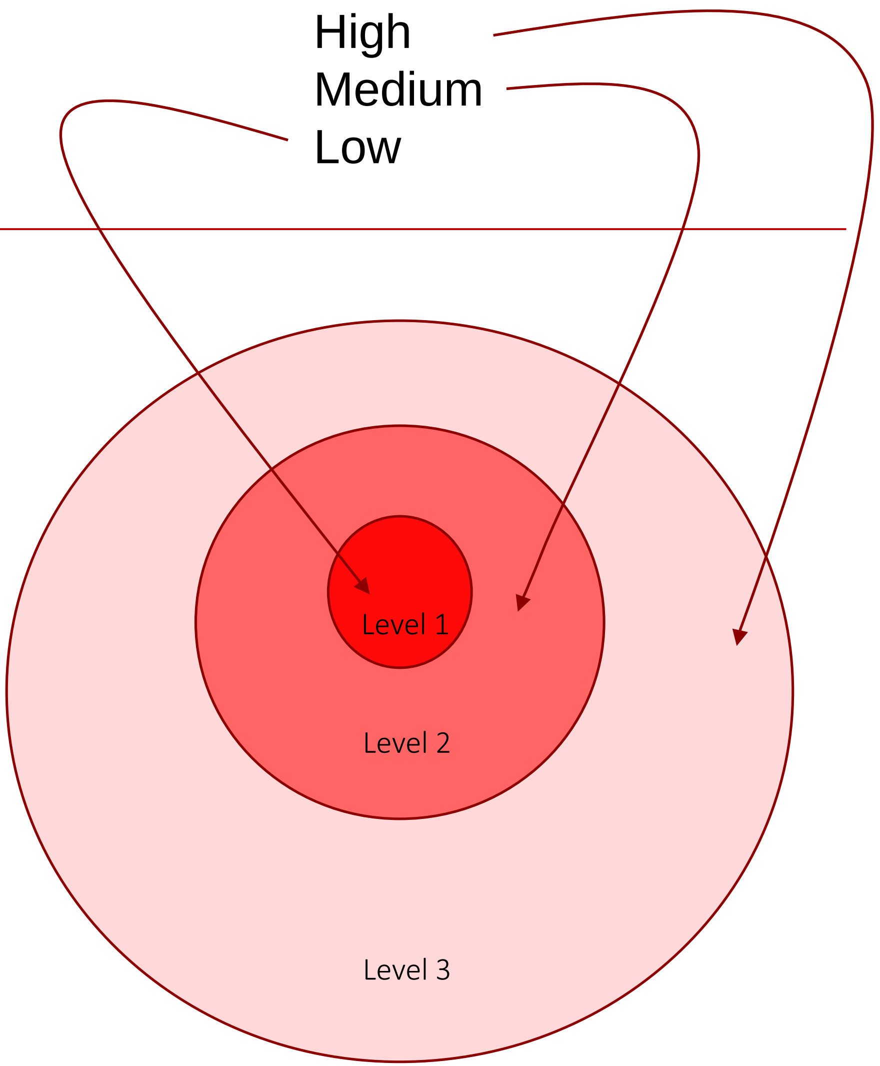


Choosing with Sufficient Confidence

- Observation: How much confidence in a prediction that is required for a decision depends on what is at stake.
- Confidence-based decisions (Hill, 2013)
  - Determine a stake-sensitive confidence threshold for the decision you are making.
  - Base your decision on the smallest set of probabilities that achieves the confidence threshold
  - If the smallest set is a singleton, maximise EU relative to it. If not apply a rule for decision making under ambiguity relative to the expected utilities associated with the set.

If stakes are:

Then base decision on this confidence level



Summary

	Representation of Model Uncertainty	Policy Rule
Model Averaging	Probability on models and target variables	Expected Utility maximisation
Robust Control	Sets of probabilities on target variables	Maximin Expected Utility
Confidence	Nested family of probabilities	Confidence sensitive Maximin EU