

# Aggregation of Multiple Prior Opinions

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May 27, 2010

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- Different utilities (Impossibility by Mongin, 1995)
- Manipulability (Impossibility by Gibbard-Satterthwaite, 1973)

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- Can be derived from a unanimity condition a la Harsanyi (1955)
- Can be interpreted as a Bayesian belief if one expert knows the true probability, and  $\lambda$  is the DM's belief about which expert it is.

## Knightian Uncertainty/Ambiguity

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- “Ambiguity” in Ellsberg’s (1961) terms, showing violations of Savage’s P2
- A rich history: Shafer (1986) argues that Bernoulli (1713) had non-additive probabilities in mind for court cases
- **Main point: it is not about bounded rationality. It is not necessarily more rational to pretend that one has probabilities than to admit that one doesn’t.**



## How Do We Model Uncertainty?

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- Maxmin EU: there exists a set of probabilities  $C$  such that

$$V(f) = \min_{P \in C} \int_S u(f(s)) dP(s)$$

We do not discuss here...

- Nau (2006), Klibanoff-Marinacci-Mukerji (2005): “smooth preferences”

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- We assume the simple maxmin model.

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- If  $\Lambda$  is a singleton, the decision maker is Bayesian
- If  $\Lambda = \Delta(\{1, \dots, n\})$  the DM is maxmin over the experts

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- Implied by a unanimity condition of sorts

## Unanimity

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- Doesn't suffice for our purposes



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- The axiom requires this to hold for several  $f_i$ 's and any convex weight vector

## Why “Uncertainty Aversion”?

- Suppose that

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- ... not if she is uncertainty averse:  $f$  offers state-by-state insurance, which is valuable when the DM doesn't know which expert is right.

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- **Mixture operation:** for every  $P, Q \in L$  and every  $\alpha \in [0, 1]$ ,  $\alpha P + (1 - \alpha)Q \in L$  is given by

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- $F_c$  – all constant acts.
- Each of  $\succsim_i$  is maxmin EU: there exist a non-constant utility  $u_j : X \rightarrow \mathbb{R}$  and a convex and closed set of measures on  $S$ ,  $C_i$ , such that

$$f \succsim_i g \quad \text{iff} \quad J_i(f) \geq J_i(g)$$

where

$$J_i(f) = J_{u_i, C_i}(f) \equiv \min_{p \in C_i} \int u(f) dp. \quad (3)$$

Moreover,  $(u_j, C_j)$  are the unique pair that represents  $\succsim_j$  as in (3) (up to an increasing affine transformation of  $u_j$ ).

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- Meaning: a bit of richness. Note that full dimensionality is not required.

## The Main Axiom: Expert Uncertainty Aversion (EUA)

- For every acts  $f \in F$ ,  $f_k \in F$ ,  $k = 1, \dots, K$ , and every numbers  $\alpha_k \geq 0$  such that  $\sum \alpha_k = 1$

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- Stated in terms of the valuations  $J_i$  – can be translated to certainty equivalents

## Theorem

- *The following three conditions are equivalent:*

- (i)  $(\lambda_i)_{i=0}^n$  satisfy **EUA**
- (ii) *There is a convex and closed set  $\Lambda \subseteq \Delta(\{1, \dots, n\})$  such that*

$$J_0(f) = \min_{\lambda \in \Lambda} \sum_{i=1}^n \lambda_i J_i(f).$$

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- The sets  $\Lambda$  are generally non-unique (say, if all experts agree on everything)
- However, any  $\Lambda$  that satisfies (ii) satisfies (iii) and vice versa