Discussion of "Robust Inattentive Discrete Choice" by Lars Peter Hansen, Jianjun Miao & Hao Xing

Monika Piazzesi
Stanford, CEPR & NBER

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"Robust Inattention" seems very appealing

- Many situations in which "right model" is unknown
  - newspapers report more shark sightings,
    overfishing has sharks looking for prey closer to the coast,
    warming NorCal waters attracts sharks from south,
    marine protections lead to bigger population of sharks etc.
- Preference for robustness may lead to extremely cautious actions
  - no more paddle boarding in NorCal waters!
- Good data on shark tracking is cheap to get
  - discard some models, keep paddling!

More formally

- Agent has prior distribution $\mu(x)$ over state x in finite state space X
  - Shannon entropy measures prior uncertainty

$$H(\mu) = -\sum_x \mu(x) \ln \mu(x)$$

- Agent observes signal s with distribution $d(s|x)$ in finite set S
  - posterior distribution of x given signal s

$$\mu(x|s) = \frac{d(s|x)\,\mu(x)}{\sum_x d(s|x)\,\mu(x)}$$

  - marginal distribution of signal s

$$v(s) = \sum_x d(s|x)\,\mu(x)$$

  - posterior uncertainty

$$H(\mu(\cdot|s)) = -\sum_s v(s) \ln \mu(\cdot|s)$$

Rational Inattention and Robustness

- Agent obtains information from the signal

$$I_{d\otimes\mu}(x;s) = H(\mu) - H(\mu(\cdot|s))$$

- Choose action $a = \sigma(s)$ and signal precision

$$V(\mu) = \max_{(d,\sigma)} E_{d\otimes\mu}[u(x,\sigma(s))] - \lambda I_{d\otimes\mu}(x;s)$$

where $\lambda =$ cost of information/signal precision

- Several prior distributions $\widehat{\mu}$ are plausible with relative entropy

$$R(\mu|\widehat{\mu}) = \sum_x \mu(x) \ln \frac{\mu(x)}{\widehat{\mu}(x)}$$

- Robust rational inattention problem

$$\min_{\mu} \max_{(d,\sigma)} E_{d\otimes\mu}[u(x,\sigma(s))] - \lambda I_{d\otimes\mu}(x;s) + \theta R(\mu|\widehat{\mu})$$

where $1/\theta =$ preference for robustness

On the relationship between RI and robust control

- Both originated in engineering literature
- RI
  - interpretation of errors: due to limited information
  - minimize sum of squared errors subject to lower bound (depends on information cost)
- Robust control
  - interpretation of errors: due to model mispecification
  - zero-sum game between agent who plays against evil agent who maximizes errors subject to an upper bound (depends on model uncertainty)
- Kasa (2006) has observational equivalence result
  - in continuous time Kalman filter setting
  - higher Kalman gain if lower information cost or higher preference for robustness
- Combination of the two is very interesting!