

Discussion of

Tail Risk, Robust Portfolio Choice, and Asset Prices

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European Finance Association — August 2017

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 - ▶ A fat-tailed distribution...
 - ▶ **This paper:** A set of possible fat-tailed distributions! (ambiguity aversion)

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 - ▶ (4) Fat tails $\uparrow \implies \partial$ Disaster exposure $/\partial$ Ambiguity \uparrow (Effect 1 is stronger)

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$$\max_{\pi} E[u(W)]$$

$$W = 1 + \pi X$$

$$X = \mu + \sigma \epsilon$$

$$\epsilon \sim \mathcal{N}(0, 1)$$

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 - ★ Trade-off: Pessimism vs. degree of faith in the original “reference” model $\hat{P} = (\hat{p}, \hat{F}) \in \mathcal{P}$

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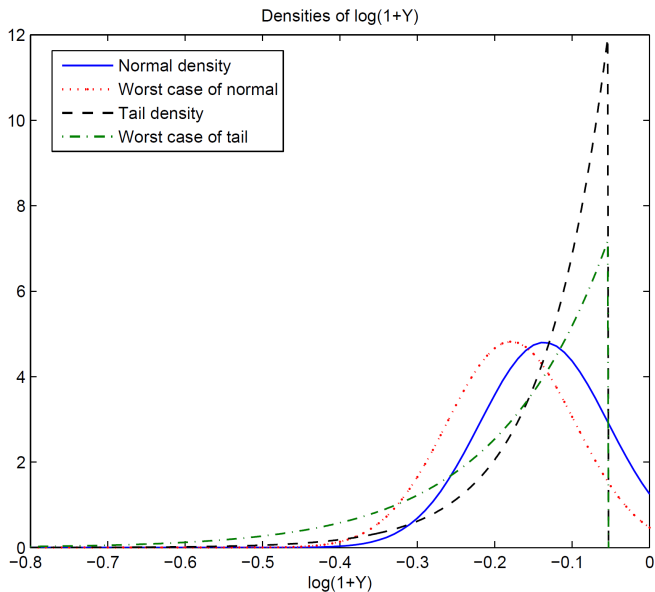
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- Full model: multiple assets + continuous time with terminal date T

Key Finding: Need Both Fat Tails and Ambiguity Aversion



Observationally Equivalent Reformulation

From Hansen and Sargent (2008)

$$\begin{aligned} \max_k \min_{P \in \mathcal{P}} \left\{ E_P[u(c)] + \theta \text{Entropy}(P, \hat{P}) \right\} \\ \Leftrightarrow \max_k \left\{ -\theta \log E_{\hat{P}} \left[e^{-\frac{1}{\theta} u(c)} \right] \right\} \end{aligned}$$

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- Do agents not know the true jump model or are they just particularly averse to jumps?
- Not a bad thing, just a helpful way to think about this if you're not familiar with robust control

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 - ▶ How does ambiguity about jump tail risks affect optimal risk-sharing, connecting this work to Ibragimov et al (2011)?

Conclusion

- Interesting paper; I learned a lot.
- Full set of model features seems necessary to get quantitative results
- Since crisis motivates the paper, I encourage authors to apply model to other asset classes, particularly those held by financial intermediaries.