Over/Under-reaction and Judgment Noise in Expectations Formation

Junyi Liao

Discussion by Savitar Sundaresan

Imperial College

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Overview

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  - One possible extension.

Canonical Measurement Error

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Meaning OLS-estimator is:

$$\hat{\beta} = \frac{cov(\tilde{x}_t, y_t)}{var(\tilde{x}_t)} = \frac{cov(x_t + u_t, \beta x_t + \epsilon_t)}{var(x_t + u_t)}$$

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But likewise $sgn(\hat{\beta}) = sgn(\beta)$.

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But also possibly $sgn(\hat{\beta}) \neq sgn(\beta)$!

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- Individual idiosyncratic and fixed shocks wash out.
- Reconciles some issues, but doesn't seem like the end of the story.

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- Information disclosure increases investor overreaction (Ho et al)

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$$E_{i,t} w_{t+1} = w_t + \underbrace{\eta_{i,t}(e_t)}_{\text{idiosyncratic learning noise}} + \underbrace{\phi_i(e_t)}_{\text{systematic tendencies}}$$

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- What is the sign/shape of $\mathbb{E}[\phi_i(e_t)]$?

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- Still a lot of pieces of evidence to go...