Smooth Diagnostic Expectations

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ASSA Meetings

Introduction

- Growing interest in psychological foundations for belief formation in Economics.
- Diagnostic Expectations (DE): Overreaction driven by the representativeness heuristic.
- Smooth DE: A new paradigm linking representativeness and uncertainty in dynamic models.

Novel Contributions

- High-uncertainty environments amplify overreaction.
- Smooth DE bridges Diagnostic Expectations and Uncertainty literatures.
- Comprehensive explanation of survey data patterns.

Key Concepts

- Representativeness heuristic: Selective memory recalls events that are representative of current news.
- Smooth DE:
  - Overreaction depends on uncertainty.
  - Joint foundation for survey evidence and business cycle properties.

Empirical Evidence

- Survey forecasts show:
  - Overreaction to news.
  - Stronger overreaction at longer horizons.
  - Overconfidence in subjective uncertainty.
- Novel finding: Overreaction amplifies under high uncertainty.

Theoretical Framework

- Smooth DE connects belief distortions with time-series dynamics.
- Business cycle implications:
  - Asymmetric cycles: Recessions sharper than expansions.
  - Countercyclical volatility at micro and macro levels.
- Policy insights: Reducing idiosyncratic uncertainty stabilizes macroeconomy.

Comparison: Smooth DE vs. Standard DE

- Standard DE
  (Bordalo, Gennaioli, and Shleifer, 2018; Bianchi, Ilut, and Saijo, 2024; L'Huillier, Singh, and Yoo, 2024):
  - Captures overreaction but lacks flexibility.
  - Ignores interaction with uncertainty.
- Smooth DE:
  - Explains overconfidence.
  - Adapts dynamically to uncertainty levels.

Key Equations and Corollary

Key Equations:

$$R_{t+h|t,t-J} = \frac{\sigma^2_{t+h|t}}{\sigma^2_{t+h|t-J}} \tag{11}$$

$$E_t^\theta(x_{t+h}) = \mu_{t+h|t} + \underbrace{\theta \frac{R_{t+h|t,t-J}}{1+\theta(1-R_{t+h|t,t-J})}}_{\equiv \tilde{\theta}_t} (\mu_{t+h|t} - \mu_{t+h|t-J}) \tag{12}$$

$$V_t^\theta(x_{t+h}) = \frac{\sigma^2_{t+h|t}}{1+\theta(1-R_{t+h|t,t-J})} \tag{13}$$

Corollary 1 (Condensed):

- Overreaction increases with relative uncertainty: $\frac{\partial \tilde{\theta}_t}{\partial R_{t+h|t,t-J}} > 0$.
- Overconfidence when $R_{t+h|t,t-J} < 1$.
- Underconfidence when $R_{t+h|t,t-J} > 1$.

AR(1) PROCESS: KEY INSIGHTS

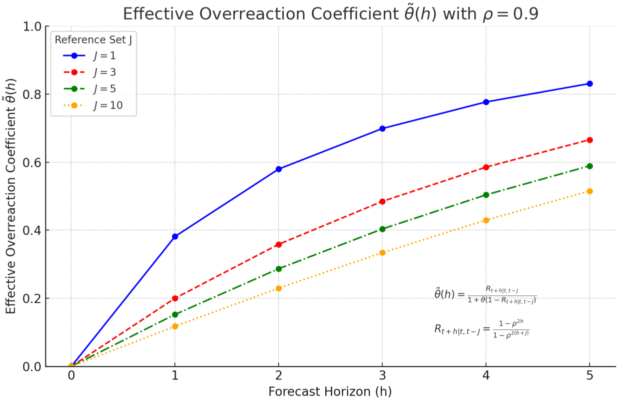
- Smooth DE applied to an AR(1) process: $x_{t+1} = \rho x_t + \epsilon_{t+1}$.
- Effective overreaction ($\tilde{\theta}_t$) depends on the ratio of conditional variances:

$$R_{t+h|t,t-J} = \frac{1-\rho^{2h}}{1-\rho^{2(h+J)}}.$$

- Predictions:
    - Overreaction increases with forecast horizon h.
    - Subjective overconfidence ($V_t^{\theta} < V_t$) typical in stationary settings.
    - Explains survey findings: stronger overreaction for long-term forecasts.

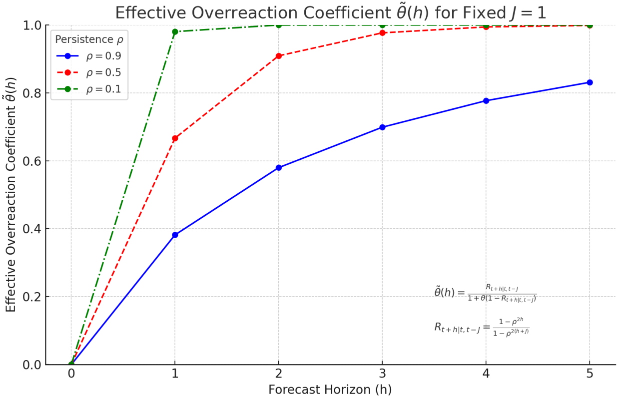
$R_{t+h|t,t-J}$ AS A FUNCTION OF J AND h

- Vary J (e.g., $J = 1, 3, 5, 10$).
- Fix $\rho = 0.9$ and compute $\tilde{\theta}_t^{h,J}$.



$R_{t+h|t,t-J}$ AS A FUNCTION OF ρ AND h

- Fixed $J = 1$.
- Vary ρ across $[0.1, 0.9]$ and compute $\tilde{\theta}_t^{h,J}$.



Sign of $\frac{\partial R}{\partial \rho}$ for $h = 1$

- For $J = 1$:
  - $\frac{\partial R}{\partial \rho} < 0$: R decreases with ρ.
  - Sensitivity decreases at higher ρ values.
- For $J = 2$:
  - $\frac{\partial R}{\partial \rho} < 0$: R continues to decrease with ρ.
  - Negative derivative becomes more pronounced for small ρ.
- For $J = 3$ and $J = 4$:
  - $\frac{\partial R}{\partial \rho} < 0$: Similar trends observed.
  - Higher J values amplify the rate of decrease.
- Implication: For small horizons h, R is consistently decreasing in ρ across all J.

effective overreaction is decreasing in ρ

Conclusion

- Smooth DE provides a unified framework for overreaction and overconfidence.
- Empirical evidence supports uncertainty-dependent overreaction.
- Implications for macroeconomic modeling and policy design.

Overall:

- Very rich paper with lot of applications
- Quibble: I want more on each of the applications.

Derivation of conditional variance

- Starting from the AR(1) process: $x_{t+1} = \rho x_t + \epsilon_{t+1}$.
- Conditional variance of x_{t+h} at t:

$$\sigma^2_{t+h|t} = \sigma^2_\epsilon \sum_{i=0}^{h-1} \rho^{2i} = \sigma^2_\epsilon \frac{1-\rho^{2h}}{1-\rho^2}.$$

- Conditional variance at reference set horizon J:

$$\sigma^2_{t+h|t-J} = \sigma^2_\epsilon \frac{1-\rho^{2(h+J)}}{1-\rho^2}.$$

- Ratio of conditional variances:

$$R_{t+h|t,t-J} = \frac{\sigma^2_{t+h|t}}{\sigma^2_{t+h|t-J}} = \frac{1-\rho^{2h}}{1-\rho^{2(h+J)}}.$$

Conditional Variance Dynamics

- Why conditional variance changes with horizon:
  - Persistence of shocks: Influence decays with $|\rho| < 1$.
  - Cumulative uncertainty: Accumulates over longer horizons.
  - Stationarity: Variance stabilizes as $h \to \infty$.
- $R_{t+h|t,t-J}$ encapsulates how uncertainty varies with horizon and reference set.