Discussion of Fabio Milani, “Learning and Time-Varying Macroeconomic Volatility.”

James Bullard

President and CEO
Federal Reserve Bank of St. Louis

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International Research Forum on Monetary Policy
ECB, FRB, CGES, CFS

Views expressed are those of the author and do not necessarily reflect official positions of the FOMC or the Federal Reserve System.
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- Widespread agreement on the nature of the great moderation in the U.S.
  - The volatility of HP-filtered real output fell by about 1/2 after 1984.
  - Volatility of many other macroeconomic variables also fell significantly.

- Explanations.

- This paper focuses on the third possibility.
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- Replace rational expectations with learning.
- Learning takes place via recursive algorithms.
  - With expectational stability, equilibrium will still be REE.
- Suppose agents suspect structural change.
  - Large shocks may indicate structural change is occurring.
  - Agents discount past data more.
  - Decisions are based on recent, volatile data.
  - This increases volatility still further.
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- **Standard learning via recursive algorithms.**
- **Critical: Time-varying gain.**
  - Inspired by Marcet and Nicolini (2003).
- **Estimate using Bayesian methods.**
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- Model can generate time-varying volatility.
- Right order of magnitude to contribute to explaining the great moderation.
- Standard naive econometric exercise would wrongly conclude shock volatility has declined.
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Main Ideas

- What the Author Does

Environment

- Simulation and estimation

More findings

Summary

Relatively standard NK model.

- Three shocks, including a monetary policy shock.
- Monetary policy is a Taylor-type rule with inertia.
- Preference and sticky price parameters are constant.
- Inertia parameter and policy parameters are time-varying.

- Policy rule is operational in the sense of McCallum.
- Shock innovations have constant variance.
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Learning

- Replace the RE assumption with learning.
- Agents have a perceived law of motion that corresponds to the REE.
- They update coefficients in the PLM using standard recursive algorithms.
- Importantly, the gain is time-varying:
  \[
g_{t,y} = \begin{cases} 
  t^{-1} & \text{if } \sum_{j=0}^{J} \frac{|y_{t-j} - E_{t-j-1} y_{t-j}|}{y_{t-j}} < v_t^y \\
  \bar{g}_y & \text{if } \sum_{j=0}^{J} \frac{|y_{t-j} - E_{t-j-1} y_{t-j}|}{y_{t-j}} \geq v_t^y 
  \end{cases}
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  for \( y = \pi_t, x_t, i_t \).
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- Calibrated case, with large gain threshold.
- Clear evidence of volatility clustering, even though the innovation variances are constant.
- If there were no switching in the gain, there would be no volatility clustering.
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  “Times of great uncertainty and large shocks are also times when past data is discounted most heavily.”
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Estimation

- Bayesian methods allow joint estimation of structural and learning parameters.
- $J = 4$, window of one year, results not too sensitive to this.
- Gain parameters are relatively high in volatile periods.
- Taylor principle is satisfied.
- Simulation with estimated parameters: 10,000 samples of 185.
- Time-varying volatility.
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- Inflation s.d. ratio 0.39 versus 0.35 in the data.
- Output gap s.d. ratio 0.42 versus 0.50 in the data.
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- More standard econometrics tends to argue for the “less frequent and smaller shocks” explanation.
- This paper has some endogenous interaction between shocks and decisions of agents.
- Large shocks cause agents to react more aggressively to incoming data.
- It is a good idea.
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- Many feel that recursive learning should be Bayesian.
- Bullard and Suda (2008).
- Standard recursive learning exercise, but replace classical econometricians with Bayesian econometricians.
- Main results still hold:
  - Stability still an issue.
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Final thoughts

- Very nice paper in a very nice conference.
- This paper has a compelling endogenous explanation for clustered macroeconomic volatility.
- I think further research and exploration of this idea is warranted.
- Important implications for how we perceive the role of stabilization policy.
- Stabilization policy keeping agents within thresholds produces an extra measure of volatility reduction.
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- I think further research and exploration of this idea is warranted.
- Important implications for how we perceive the role of stabilization policy.
- Stabilization policy keeping agents within thresholds produces an extra measure of volatility reduction.
  - “Nonlinear volatility reduction” as in Bullard-Singh (2007).