Discussion

Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment

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This Paper

- Model of crises featuring
  1. **Frictional intermediation**
  2. **Sentiment** (time-varying beliefs)
     - Bayesian learning (rational)
     - Diagnostic learning (over-weights recent observations)
- Quantitative emphasis
- Results
  1. Financial frictions + (rational) sentiment fit data well
  2. Both are needed
  3. Diagnostic learning similar to Bayesian (both match data well)
  4. Similar impulse responses to policy experiments

This Paper

- Important effort connecting both literatures
- Very successful in many dimensions
  - Transparent connection to empirical work
- Scope to push this agenda further

- Roadmap
  1. Environment $\Rightarrow$ Comments
  2. Main results $\Rightarrow$ Comments

Environment (1)

- Households and bankers (log utility)
  - Linear capital technologies $\Rightarrow$ Homogeneity
  - Households more productive $\Rightarrow$ Intermediation
  - Adjustment costs to invest $\Rightarrow$ Investment sensitive to prices
- Financial friction: only short term (instantaneous) debt
  - w (bankers' wealth share) as state variable
  - Low w makes the economy fragile

Environment (2)

- Two shocks
  1. **Brownian** shock to capital accumulation (real shock)
  2. **Poisson** "illiquidity" shock (financial shock)
     - Transfer from bankers to households (run/fire-sale)
     - $\lambda_t \in \{\lambda_L, \lambda_H\}$ is the rate at which Poisson shock hits
     - Two-state Markov process ($\lambda_{L \to H}$, $\lambda_{H \to L}$)
     - Agents (only) learn about λ_t from the realization of crises
- Learning (λ as state variable)
  - **Bayesian/rational**
    - No crisis: beliefs drift down towards λ_L
    - Crisis: beliefs spike up towards λ_H
  - **Diagnostic/non-rational**
    - Agents overweight recent events (θ)
    - Faster belief dynamics (over- and under-shooting)
- Comment: very appropriate learning environment
  - Challenging to model beliefs (infinite dimensional)
  - Latent state λ_t never settles

Comments on the Environment

1. Agents know $\{\lambda_H, \lambda_L\}$, as well as $\{\lambda_{L\to H}, \lambda_{H\to L}\}$
   - Latter less compelling
   - Agents could potentially learn about those too
2. There is no default
   - Credit spreads are "shadow" (payoffs disciplined by data)
   - Not wlog
3. Parameter θ gauges diagnostic learning
   - How should we interpret θ? ($\theta = 0$ is rational)
   - Can θ be disciplined from beliefs directly?
   - What does the calibration imply for θ? I think $\theta = 1.38$
   - Suggestion: instead of choosing a θ to fit spreads show sensitivity to θ
4. No heterogeneity in beliefs (everybody is optimistic/pessimistic)
   - It'd be nice to distinguish between bankers' and households' beliefs
   - Maybe there is a way to do it preserving tractability?

Results

- Challenging solution with two state variables
- Careful calibration (16 parameters, calibration+matching)
- Main results
  1. Financial frictions + sentiment $\Rightarrow$ Fit data well
     - Stylized model
     - Low spreads and high credit predict crises
  2. Both are needed
     - Financial frictions yield amplification, match post-crises facts
     - Sentiment needed to match pre-crises facts (exuberance/frothiness $\Longleftrightarrow$ compressed credit spreads)
  3. Rational Bayesian learning is enough to fit the data
     - Diagnostic learning somewhat more powerful
     - Data doesn't distinguish between rational/behavioral learning
  4. Impulse responses with Bayesian and Diagnostic learning are similar, given state variables
     - Policy should be invariant to learning process
- First two results are unquestionable
- The last two results are more open to discussion

Broader Comments

1. The diagnostic version of the model still uses the policy functions of the rational model
   - Diagnostic learning only matters through law of motion for λ
     - Policy functions are independent of θ
   - This pushes the results towards making rational vs. non-rational versions similar
   - Common issue in these models: do non-rational learners have "rational expectations" over their non-rational beliefs?
   - Comparing both approaches would be helpful
2. Is there a more flexible way to model non-Bayesian learning?
   - At least within a class
   - Maybe in terms of drift and the dN_t-coefficient for $d\lambda_t$?
   - Constant vs. decreasing gain in adaptive learning
   - More "targets" may be needed
     - The rational learning model already fits well!
     - Data on beliefs?

Broader Comments

3. Policy experiments in the paper based on unanticipated policies
    - Lucas critique?
    - Rational vs. non-rational response to anticipated/systematic policies could be different
    - If both models fit similarly, impulse responses should be similar (back to points 1 and 2)
4. Normative analysis: next step?

    "our model is not suited for welfare analysis"

    - Challenging in this class of models (even without beliefs)
        - Reduced form assumptions?
        - Beliefs?
    - Sentiment/beliefs should not preclude welfare analysis
        - Advertisement: Davila/Walther, Prudential Policy with Distorted Beliefs (tomorrow)

Conclusion

- Very interesting paper
- Clear quantitative framework combining financial frictions and sentiment
- Lots more to explore