Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment

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Overview

- **Question:** What mechanisms are needed to explain salient features of financial crises (pre-crisis "froth," rare large crashes, slow recoveries)?
- **Approach:** Quantitative model in spirit of He and Krishnamurthy (2019) with time-varying, potentially non-Bayesian beliefs, estimated to match key data moments.
- **Main Results:**
  - Time varying beliefs needed alongside financial friction/shock to match data (necessary).
  - Model with time varying beliefs + financial friction/shock fits well (largely sufficient).
  - Bayesian, diagnostic expectations cannot be easily distinguished by the data.
- **My Evaluation:**
  - Great paper making compelling point.
  - Quantitative impact of model more in mechanisms being sufficient than necessary.
  - Bayesian model works well, but could be far from rational.

Time-Varying Beliefs are Necessary

- Model with only financial intermediation can generate crash but not low pre-crisis spreads.
- Recall model mechanism:
  - Crises are caused by illiquidity shocks that induce extra financing fee on all outstanding debt.
  - Shock itself is exogenous, but consequences vary endogenously with state of the economy.
  - Much more severe when bank leverage is high (“crisis”).
- Intuition behind authors’ finding:
  - Under constant arrival risk beliefs, investors understand that high leverage implies larger crises if shock hits, would demand **larger** credit spreads.
- My take: this is a great point, but probably don’t need a serious model to show this.
  - Although providing tractable implementation is obviously a big contribution.

Financial Intermediation + Time-Varying Beliefs are Sufficient

- Instead, main quantitative result of model (in my opinion) is that financial intermediation + time-varying beliefs are **sufficient** to explain many features of the data.
  - Skewed output growth, slow recoveries, time-varying risk premia, pre-crisis "froth," etc.
- Parsimonious model that doesn't require many of the shocks common in macro models.
  - Feature or bug?
- Bug view: if we believe that other channels are important, then explaining most/all variation in model means we are probably overstating the strength of these mechanisms.
- Feature view: interesting new evidence that single "main business cycle shock" drives much of the economy, is unrelated to inflation (Angeletos, Collard, and Dellas 2020).
  - Basu, Candian, Chahrour, Valchev (2021) shows this shock is closely linked to risk premia.
  - Would be exciting to see how this shock aligns with financial intermediation indicators.

Bayesian Beliefs

- Authors find that Bayesian and diagnostic expectations can both fit the data well.
  - Diagnostic expectations have advantage on matching pre-crisis credit spreads, speed of spread recovery, but also have an extra free parameter.
- Note: Bayesian does not necessarily mean rational. Many irrational beliefs can be supported by Bayesian learning if the underlying model is misspecified.
  - Entering state where rare events no longer occur ("this time is different") easy to rationalize.
  - Instead, need data to discipline model independent from belief-induced behavior or prices.
- "Rational" beliefs (in my opinion) are combination of Bayesian learning, and a **reasonable underlying model**.

Case Study: Housing

- House prices played a major role in driving 2008 financial crisis. What role did beliefs play?
- Below: Lehman Brothers scenario analysis for MBS (from Foote, Gerardi, Willen (2012))
  - Expected losses by 3-year average house price growth scenarios (afterwards project 5% growth).
- Loss forecasts are reasonable conditional on scenario.
  - Actual loss on this subprime MBS was 22% given total house price decline of $\sim$ 30%.
- Instead, probabilities were distorted, pretty clearly overoptimistic.
  - But likely consistent with Bayesian beliefs under model with perpetual high growth state.

Scenario	Aggressive (1)	Aggressive (2)	Baseline	Pessimistic	Meltdown
House Price Growth (3yrs)	11%	8%	5%	0%	-5%
Expected Loss	1.4%	3.2%	5.6%	11.1%	17.1%
Probability	15%	15%	50%	15%	5%

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Bayesian Beliefs

- In housing case, can make statistical and economic arguments against perpetually (or very persistently) high growth.
- For rare disaster events like illiquidity shock, can try to measure probability directly from other economic indicators (Marfe and Penasse, 2021).
  - Bayesian model implies pre-crisis states are especially **unlikely** to observe illiquidity shock.
- For two state case, could also potentially exploit feature that events are bunched.
  - More likely to see clusters of events during high probability state.
  - Then long gaps during low probability state.
  - Stands in contrast to uniform arrival rate or model where crises more likely as people "forget."
- These tests would provide additional info about rationality beyond "Bayesianity."

Bayesian vs. "Rational" Beliefs

- However, Bayesian beliefs do put some economic discipline on the process.
  - Impose link between persistence and frequency of changes.
  - Diagnostic beliefs allow agents to become certain faster holding unconditional arrival rate fixed.
- My suggestion for future work: shift information friction discussion to arrival of financial distress shock itself.
  - Even if statistical process for arrivals is perfectly rational, the arrival itself may be generated by large shifts in possibly irrational/non-Bayesian beliefs (e.g., 2008 housing crash).
  - Could be important for policy, especially if underlying beliefs use endogenous variables as signals and are diagnostic/extrapolative.
  - Model has potentially interesting interpretation as "good" banker who understands other lenders are irrational but can't model/forecast exactly how.

Conclusion

- Great paper making important point about financial intermediation models.
  - Informational frictions, time-varying beliefs matter!
  - Provides tractable and successful modeling mechanisms to fill this gap.
- Qualitative contribution that time-varying beliefs + intermediation frictions are necessary, quantitative contribution that they are largely sufficient.
- Bayesian beliefs can be very irrational if underlying model not disciplined.
  - Could directly test two-state model more directly.
  - Lots of interesting research opportunities linking beliefs to arrival rate of financial distress.