Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment

Arvind Krishnamurthy[1] Wenhao Li[2]

[1]Stanford Graduate School of Business and NBER

[2]USC Marshall Business School

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The Financial (Banking) Crisis Cycle: Mean Path

Figure: Mean paths of credit spread, bank credit, and GDP of 41 financial crises, 1870-2014.

Notes: Units for spread path are 0.5 means spreads are 0.5σs above average for a given country. Units for credit path are that 5 indicates that credit/GDP is 5% above the trend for a given country. Units for GDP path are that -8 means that GDP is 8% below trend for a given country.
Source: Krishnamurthy and Muir (2020); Banking Crises dated by Jorda, Schularick, and Taylor (2011).

Cross-section Crisis Cycle Facts: Severity

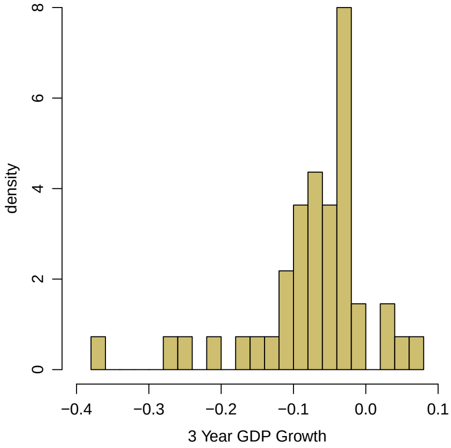


Figure: 3-Year GDP Growth after a Crisis

Conditional on a crisis, we observe:

- Left-skewed GDP growth
- Larger post-crisis output drop
  $\Leftarrow$ More pre-crisis bank credit, or larger in-crisis spike of credit spread.

Cross-section Crisis Cycle Facts: Predictability and Risk Premium

- Predicting crises:

$$Prob(Crisis_{i,t}|Credit_{i,t-1}, CreditSpread_{i,t-1})$$

  Higher credit growth predicts more crises (Schularick and Taylor 2012) and equity crashes (Baron and Xiong 2017)

- Higher credit growth predicts lower expected excess bond/equity returns (Greenwood and Hanson 2013; Baron and Xiong 2017)

- Lower credit spread before crises (Krishnamurthy and Muir 2020)

Mechanisms?

1. Financial intermediation
   - Losses reduce equity capital and cause disintermediation
   - Credit contraction ... amplification mechanism

2. Beliefs/Sentiment
   - Good news $\Rightarrow$ more optimistic $\Rightarrow$ growth of credit and decline in credit spread.
   - Bad news $\Rightarrow$ sharp revision of beliefs $\Rightarrow$ transition to crisis.
   - Bayesian updating, similar to Moreira and Savov (2017)

   or Diagnostic updating, as in Bordalo, Gennaioli, Shleifer (2018)

* Literature: Maxted (2020) combines financial intermediation and diagnostic updating on mean growth in TFP

Agents and Preferences

- Two agents: bankers and households, optimizing expected log utility.

$$\max \ E^{belief}[\int_0^\infty e^{-\rho t} \log(c_t) dt]$$

- Bankers raise only demandable debt and inside equity (banker wealth).
- Production is through 'A-K" technology. Bank productivity $\bar{A} >$ household productivity $\underline{A}$.
- Kiyotaki and Moore (1997), Brunnermeier and Sannikov (2014)

Shocks

- Capital accumulation process:

$$\frac{dk_t}{k_t} = \underbrace{\mu_t^K dt}_{\text{growth, Q-theory}} - \underbrace{\delta dt}_{\text{depreciation}} + \underbrace{\sigma^K dB_t}_{\text{capital shocks}}$$

  where dB_t is a Brownian motion representing "real" shocks.

- Illiquidity (purely financial) shock dN_t with hidden intensity $\tilde{\lambda}_t$.
  - Exogenous shock makes all debtors demand their funds back, and triggers sale of capital
  - Capital liquidation: illiquidity discount α^0 and endogenous capital price decline.
  - High leverage + illiquidity shock may lead to a banking crisis:

$$\text{Prob of crisis} \propto \text{Leverage} \times \tilde{\lambda}_t$$

- *Beliefs over second moment (prob of dN_t) in our model; in Maxted (2020) beliefs are over the first moment (drift of dB_t)*

Banker's Optimization Problem

- Due to log-utility, the equivalent banker optimization problem is

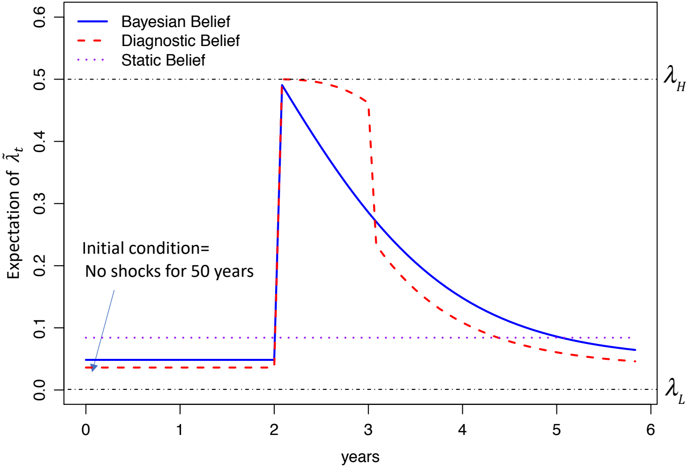
$$\max_{c_t^b, x_t^b, x_t^f} \left\{ \log(c_t^b) + \frac{1}{\rho} \left(E_t^{belief}[\frac{dw_t^b}{w_t^b}]/dt - \frac{1}{2} \left(\frac{dw_t^b}{w_t^b} \right)^2 /dt \right) \right\}$$

s.t.

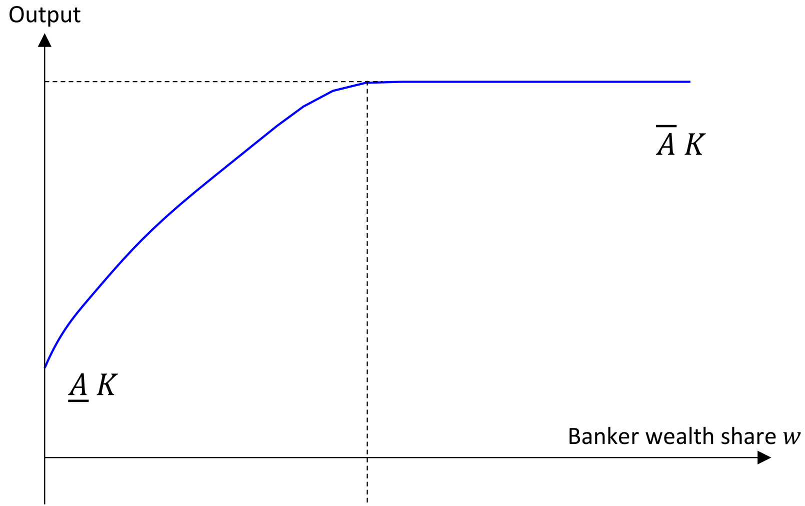
$$\begin{aligned} \frac{dw_t^b}{w_{t-}^b} =& (\underbrace{r_t^f}_{\text{interbank rate}} + x_t^K \cdot \underbrace{(\mu_t^R + \frac{\bar{A}}{p_t} - r_t^f)}_{\text{capital excess return}} + x_t^d \cdot \underbrace{(r_t^f - r_t^d)}_{\text{debt funding benefit}})dt - \frac{c_t^b}{w_t^b} dt \\ & + x_t^K (\sigma^K + \sigma_t^p) dB_t - \underbrace{(\frac{\alpha^0}{1-\alpha^0} x_{t-}^d + x_{t-}^K \kappa_{t-}^p)}_{\text{losses in a distress}} dN_t \\ x_t^d =& x_t^K + x_t^f - 1 \end{aligned}$$

Beliefs

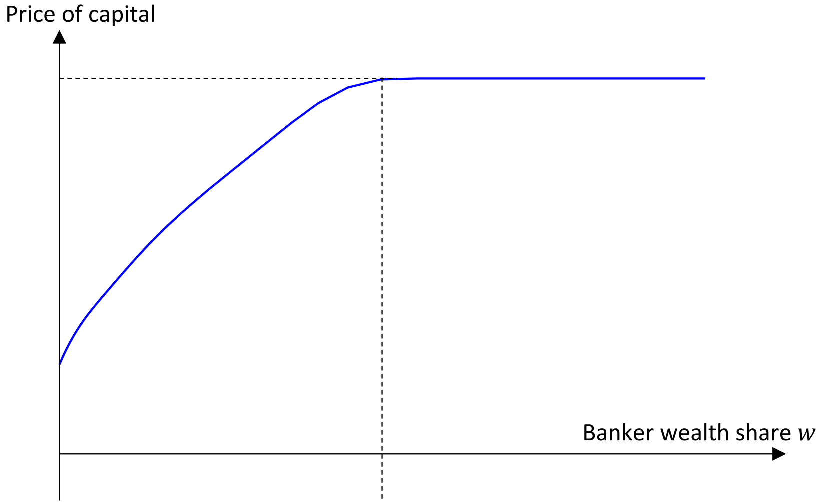
- Hidden intensity $\tilde{\lambda}_t \in \{\lambda_H, \lambda_L = 0\}$ is a continuous-time Markov process with switching rate $\lambda_{H \to L}$ and $\lambda_{L \to H}$. Expected intensity is $E_t^{belief}[\tilde{\lambda}_t]$.



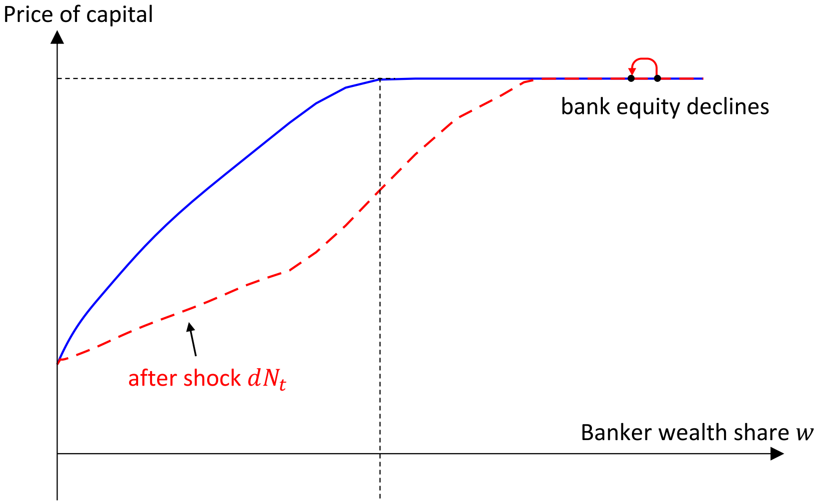
Financial Amplification Mechanism (Output)



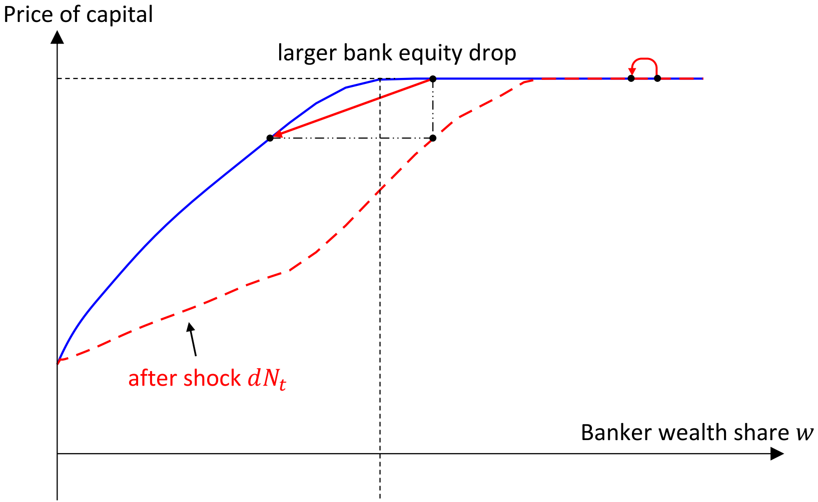
Financial Amplification Mechanism (Asset Price)



Financial Amplification Mechanism (With Illiquidity Shock)



Financial Amplification Mechanism (Conditional Response)



State Variables and Endogenous Outcomes

- State variables:
  - w_t: banker wealth share
  - λ_t (Bayesian) or λ_t^θ (Diagnostic): expected intensity of illiquidity shock
  - K_t: scale of the economy (this state variable can be "eliminated")
- Endogenous outcomes:
  - Output: "AK" technology
  - Value of capital $= p(w_t, \lambda_t)$
  - Bank credit: amount of capital held by the banks.
  - Credit spread: defaultable bond yield - safe bond yield.
  - Crisis: a period when bank credit/GDP is below 4% quantile. **Not the same as dN_t!**

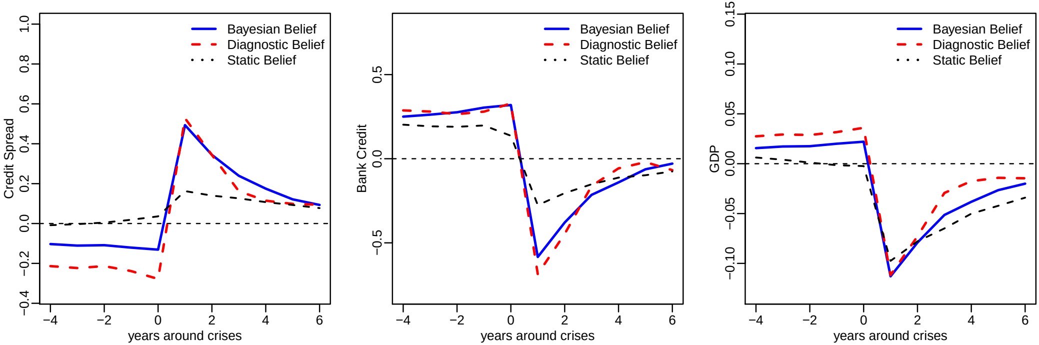
$$\text{Prob of crisis} \propto \text{Leverage} \times \tilde{\lambda}_t$$

Model Calibration Strategy

- We evaluate three versions of the model.
  - Static belief model: no belief variation.
  - Rational model: Bayesian belief.
  - Diagnostic model: diagnostic belief.

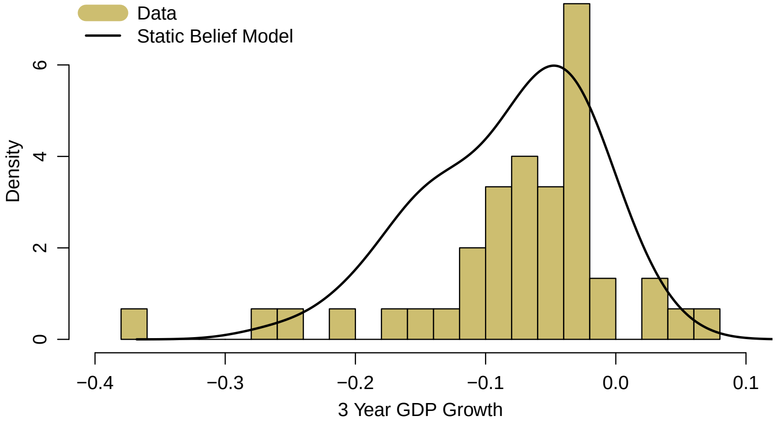
- We separately solve parameters for each model to match the same targets.
  - Targets: average output declines in a crisis, frequency of liquidity shocks $\cdots$
  - Cross-section results are not targeted and used as evaluations.

Mean paths



Bayesian Belief
Diagnostic Belief
Static Belief
Credit Spread
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−4
−2
0
2
4
6
years around crises
Bank Credit
0.5
0.0
−0.5
GDP
0.15
0.10
0.05
0.00
−0.05
−0.10

Criss-section: Left-Skewed Distribution of 3-Year Post-Crisis GDP Growth ✓✓✓



Severity of Crises, Bank Credit, and Credit Spread ✓✓✓

- Intermediation mechanism is enough.

	Dependent variable: GDP Growth from t to t + 3							
	Static Belief		Bayesian		Diagnostic		Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δcredit spread$_t$ $*$crisis$_t$	-6.19		-4.07		-3.88		-7.46 (0.16)	
$(\frac{\text{bank credit}}{\text{GDP}})_t * \text{crisis}_t$		-1.40		-2.61		-3.48		$\mathbf{-0.95}$ (0.30)
Observations							641	641

Note: Model and data regressions are normalized so that the coefficients reflect the impact of one sigma change in spreads, and bank credit/GDP.

Severity of Crises, Bank Credit, and Credit Spread ✓✓✓

- Intermediation mechanism is enough.

	Dependent variable: GDP Growth from t to $t+3$							
	Static Belief		Bayesian		Diagnostic		Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δcredit spread$_t$$*$crisis$_t$	-6.19		-4.07		-3.94		$\mathbf{-7.46}$	
							(0.16)	
$(\frac{\text{bank credit}}{\text{GDP}})_t$$*$crisis$_t$		-1.40		-2.61		-3.72		-0.95
								(0.30)
Observations							641	641

Note: Model and data regressions are normalized so that the coefficients reflect the impact of one sigma change in spreads, and bank credit/GDP.

Bank Credit and Risk Premium ✓✓✓

- Matched well across models. Reason: all driven by **credit supply** variations.

	Dependent variable: Excess return $_{t+1}$			
	Static Belief	Bayesian	Diagnostic	Data
$\left(\frac{\text{bank credit}}{\text{GDP}}\right)_t$	-0.02	-0.01	-0.01	$\mathbf{-0.02}$ (0.01)
Observations				867

Note: Model excess return is defined as the return to capital minus the risk-free rate. Data excess return is from Online Appendix Table 3 of Baron and Xiong (2017). To ensure comparability, the model return to capital has been normalized to equal the standard deviation of returns reported by Baron and Xiong (2017).

Pre-Crisis Low Credit Spread X ✓ ✓

- Krishnamurthy and Muir (2020): credit spread is unusually low in the pre-crisis period
- Static belief model fails to match pre-crisis spreads. Sign is wrong!

	Dependent variable: credit spread$_t$			
	Static Belief	Bayesian	Diagnostic	Data
	(1)	(2)	(3)	(4)
pre-crisis indicator	0.22	−0.14	−0.29	**−0.34**
				(0.15)
Observations				634

Note: regression is: $s_t = \alpha + \beta \cdot 1\{t \text{ is within 5-year window before a crisis}\} + \textit{controls}$. For both model and data, controls include an indicator of within 5 years after the last crisis. Data regression has more controls such as country fixed effect.

Pre-Crisis Mechanism X ✓ ✓

Why the static-belief model fails?
– one state variable w

- * crises more likely
- $\Leftrightarrow$ low bank equity w
- $\Leftrightarrow$ higher bank leverage and fragility
- $\Leftrightarrow$ higher risk premium

Pre-Crisis Mechanism X ✓ ✓

Why the static-belief model fails?
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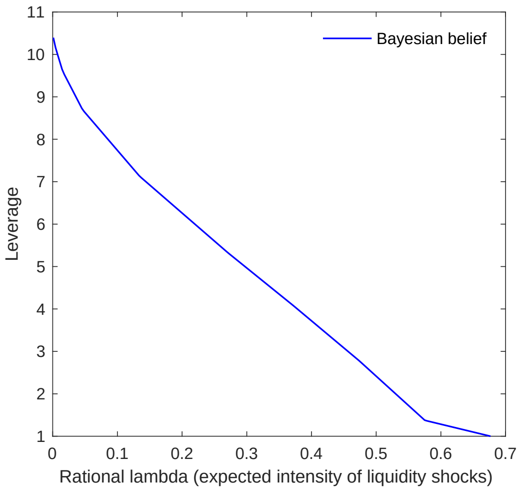
Why the Bayesian model works?



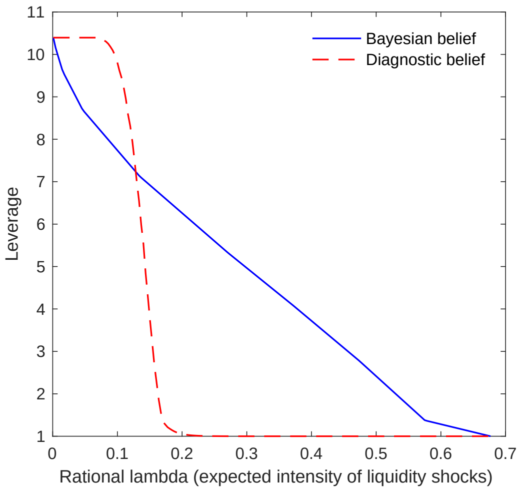
Pre-Crisis Mechanism X ✓ ✓

Why the static-belief model fails?
– one state variable w

* crises more likely
- ⟺ low bank equity w
- ⟺ higher bank leverage and fragility
- ⟺ higher risk premium

Why the Bayesian model works?

Key: slope of the risk taking – belief relationship.



Predicting crises using high leverage

$$\text{Prob of crisis} \propto \text{Leverage} \times \tilde{\lambda}_t$$

Predicting crisis is a race between two effects: As $\tilde{\lambda}_t$ falls:

$$\underbrace{\text{Leverage}}_{\uparrow} \times \underbrace{\tilde{\lambda}_t}_{\downarrow}$$

- In both Bayesian and Diagnostic belief models, leverage is inversely related to $\tilde{\lambda}$.
- Slope is higher in diagnostic model...
- But the effects play out qualitatively similarly

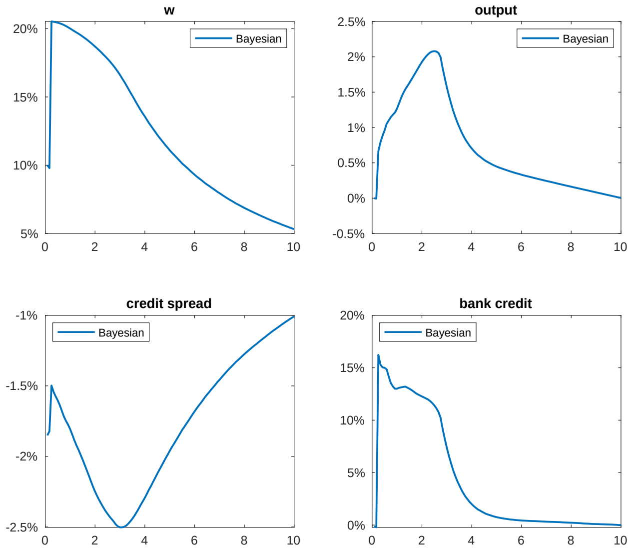
Model

Model Evaluation

Leaning Against the Wind: Bayesian vs Diagnostic

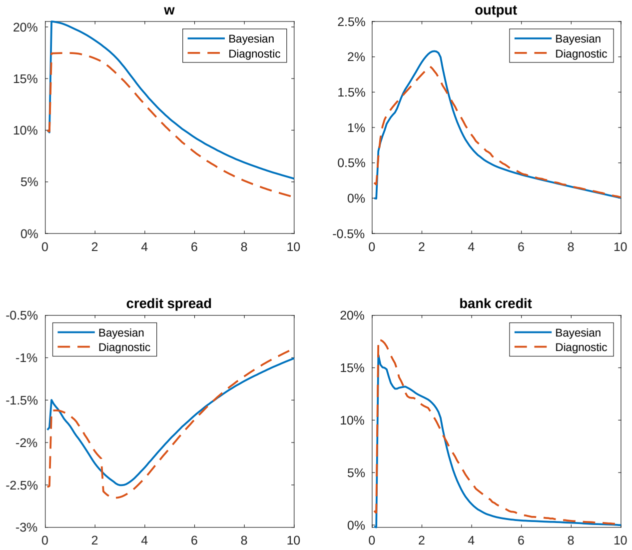
Contribution

Average Impact of a 10% Recapitalization Policy



- Policy: recapitalization to "*lean against the wind*"
- Initial state: boom (high lev,low spread)
- Simulation: $dN_t = 1$ after the policy, but $dN_t = 0$ otherwise. dB_t randomly generated.
- Impact = log(with policy) − log(without policy).

Average Impact of a 10% Recapitalization Policy



- Impact is similar.
- Initial state solved via **observables** – the same credit spread and bank leverage.
- Both models are calibrated to the **same moment targets**.

Model

Model Evaluation

Leaning Against the Wind: Bayesian vs Diagnostic

Contribution

Contribution 1: Quantitative modeling of crises

- Non-linear macro-finance models: Mendoza (2010), He-Krishnamurthy (2013), Brunnermeier-Sannikov (2014), Gertler-Kiyotaki-Prestipino (2019)
- Empirical crisis literature: Bordo et. al. (2002), Reinhart-Rogoff (2009), Jorda, Schularick, Taylor (2011), Schularick-Taylor (2012), Baron-Xiong (2017), Baron-Verner-Xiong (2021), Krishnamurthy-Muir (2020)
- Literature bridging the models and the empirical patterns: He-Krishnamurthy (2019), Gertler-Kiyotaki-Prestipino (2019), Maxted (2020) match 2008 crisis

This paper: Nonlinear macro-finance model confronts facts from empirical crisis literature

- Financial intermediation + time-varying beliefs (Bayesian/Diagnostic) matches all crises cycle facts
- In Maxted (2020) high TFP growth pre-crisis (agents over-extrapolate), but that seems at odds with data. In our model, its quiet before the storm.

Contribution 2: Beliefs

Belief variation is key, Diagnostic vs. Bayesian less so

- Models of opacity can drive sudden shifts in beliefs (Gorton-Ordonez, 2013; Dang, Gorton, Holmstrom, 2020)
- Or, models of extrapolative expectations (Bordalo, Gennaioli, Shleifer, 2020)

"Icing" vs "cake"

- "Icing": Negative expected returns in extreme credit growth episodes in Baron and Xiong (2017). Biased Survey expectations from Bordalo, et. al.
- ...but there are also the securitization/opacity/debt observations of Gorton, et. al.
- "Cake": All of the other crisis cycle facts