Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment

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The Financial (Banking) Crisis Cycle: Mean Path

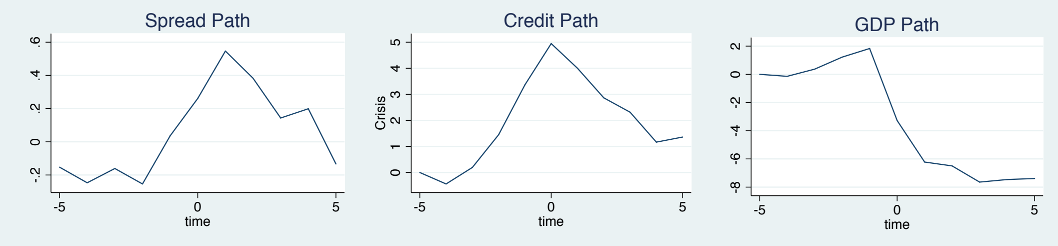


Figure: Mean paths of credit spread, bank credit, and GDP of 41 financial crises, 1870-2014.

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 (2017); Banking Crises dated by Jorda, Schularick, and Taylor (2011).

Cross-section Crisis Cycle Facts: Severity

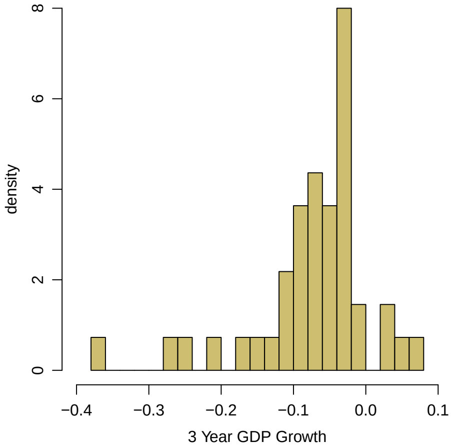


Figure: 3-Year GDP Growth after a Crisis

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 2017)

Mechanisms?

1. Financial intermediation (Brunnermeier and Sannikov 2014)
   - Losses reduce equity capital and cause disintermedation
   - 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)

This Paper

- Financial intermediation mechanism matches crises severity and post-crisis dynamics, but fails to match crisis predictability and low pre-crisis risk premium.

- Financial intermediation + time-varying beliefs (Bayesian/Diagnostic) match all crises cycle facts.
  - Introducing diagnostic belief improves quantitative fit.
  - Caking (time-varying belief) v.s. Icing (behavioral)

- A lean-against-the-wind policy has similar impact in both Bayesian and diagnostic belief models, conditional on same observables.

Model

Model Evaluation

Summary

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:

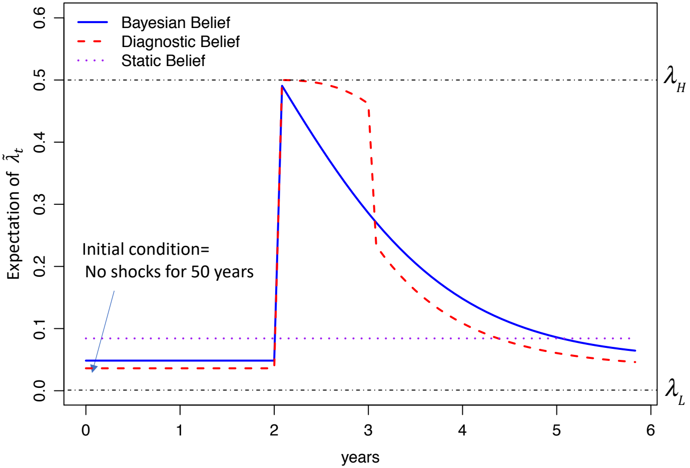
$$\frac{dk_t}{k_t} = \underbrace{\mu_t^K dt}_{\text{growth, Q-theory}} - \underbrace{\delta dt}_{\text{depreciation}} + \underbrace{\sigma^K dB_t}_{\text{capital shocks}}$$

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

- Illiquidity (purely financial) shock dN_t with hidden intensity $\tilde{\lambda}_t$.
  - Exogenous shock triggers rolling over problems of bank debt, asset sales, and a loss spiral. (microfoundations in Li (2019))
  - High fragility + illiquidity shock may lead to a banking crisis.

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 $E_t^{belief}[\tilde{\lambda}_t]$.

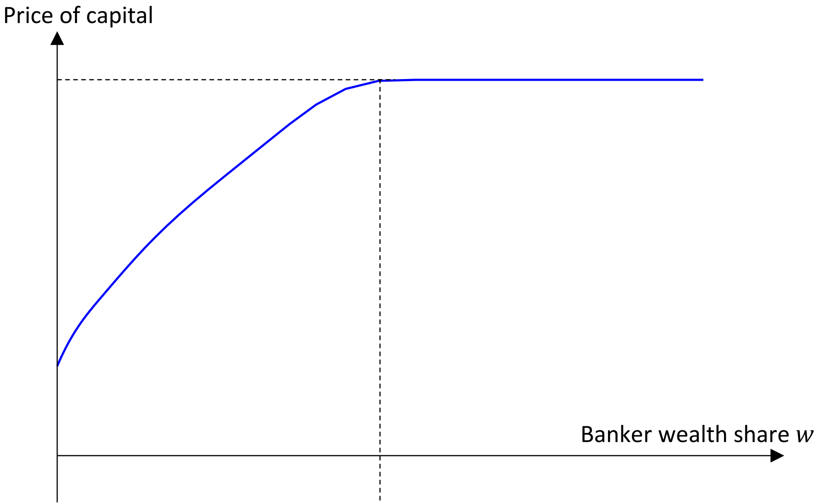


State Variables and Endogenous Outcomes

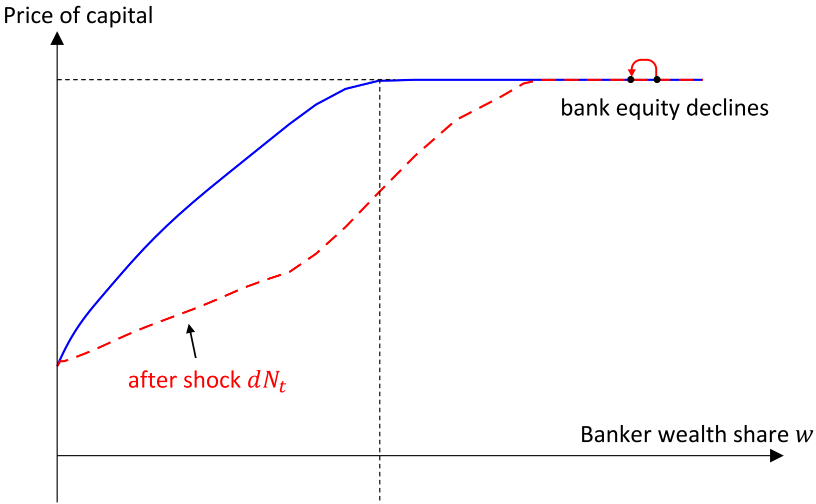
- State variables:
  - w_t: banker wealth share
  - λ_t (Bayesian) or λ_t^θ (Diagnostic): expected intensity of illiquidity shock
  - K_t: scale of the economy (this state variable can be "eliminated")
- Endogenous outcomes:
  - Output: "AK" technology
  - Value of capital $= p(w_t, \lambda_t)$
  - Bank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

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

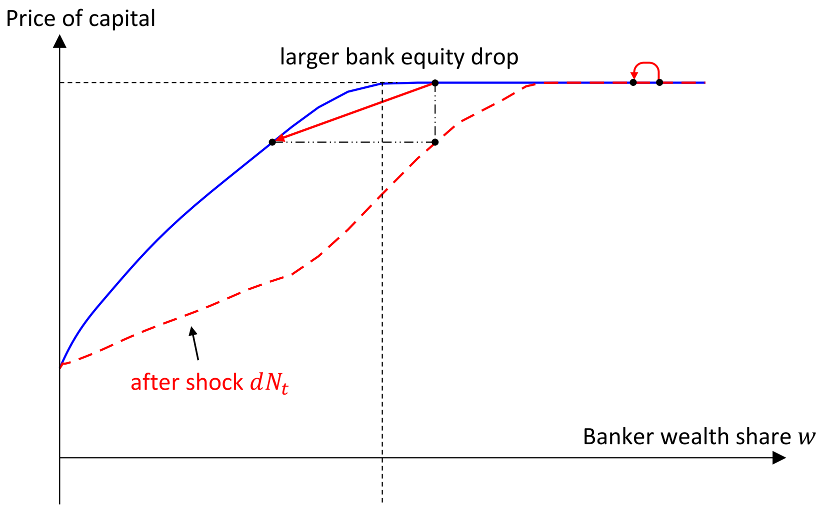
Financial Amplification Mechanism



Financial Amplification Mechanism (With Illiquidity Shock)



Financial Amplification Mechanism (Conditional Response)

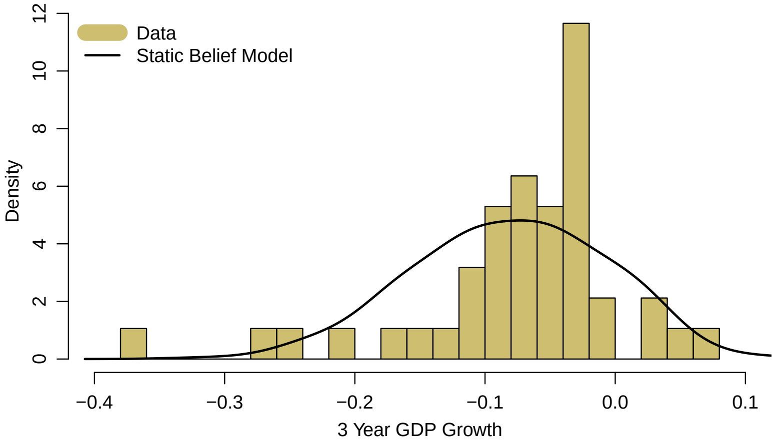


Model Calibration Strategy

- 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, $\cdots$
  - Cross-section results are not targeted and used as evaluations.

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$$*$crisis$_t$	-5.35		-3.18		-3.45		-7.46	
							(0.16)	
$(\frac{\text{bank credit}}{\text{GDP}})_t$$*$crisis$_t$		-1.04		-2.40		-3.23		-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.

Pre-Crisis Low Credit Spread X ✓ ✓

- Krishnamurthy and Muir (2017): 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	0.28	-0.18	-0.26	$-$**0.34**
				(0.15)
Observations				634

Note: regression is: $s_t = \alpha + \beta \cdot 1\{t$ is within 5-year window before a crisis$\} +$ *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 fragility
- $\Leftrightarrow$ higher risk premium

Pre-Crisis Mechanism X ✓ ✓

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

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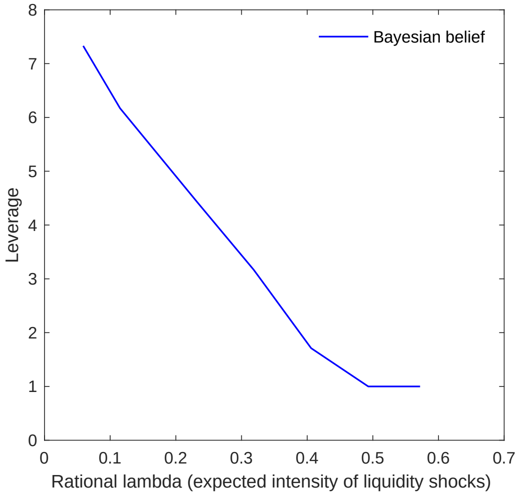
Why the Bayesian model works?



Pre-Crisis Mechanism X ✓ ✓

Why the static-belief model fails?

– one state variable w

$*$ crises more likely

$\Leftrightarrow$ low bank equity w

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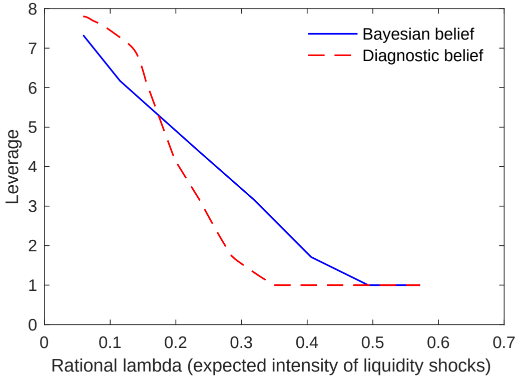
$\Leftrightarrow$ higher risk premium

Why the Bayesian model works?

Key: slope of the risk taking – belief relationship.



Predicting Crises with High Bank Credit

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

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

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Summary

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- Financial intermediation mechanism matches crises severity and post-crisis dynamics, but fail to match crisis predictability and low pre-crisis risk premium.
- Financial intermediation + time-varying beliefs (Bayesian/Diagnostic) explain all crises cycle facts.
- A lean-against-the-wind policy has similar impact in both Bayesian and diagnostic belief models, conditional on same observables.

Appendix

Predicting Crises

Leaning Against the Wind: Bayesian vs Diagnostic

Bank Credit Predicts Crises X ✓ ✓

- The static-belief model fails again.
- Both Bayesian and diagnostic model qualitatively match data.

	Dependent variable: crisis$_{t+1 \text{ to } t+5}$			
	Static Belief	Bayesian	Diagnostic	Data
	(1)	(2)	(3)	(4)
HighCredit$_t$	-0.51	0.21	0.51	**0.55**
				(0.46)
Observations				549

Note: HighFroth measures if spreads have been abnormally low in the last 5 years. HighCredit measures if credit growth has been abnormally high in the last 5 years.

Predicting crises using high leverage

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

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

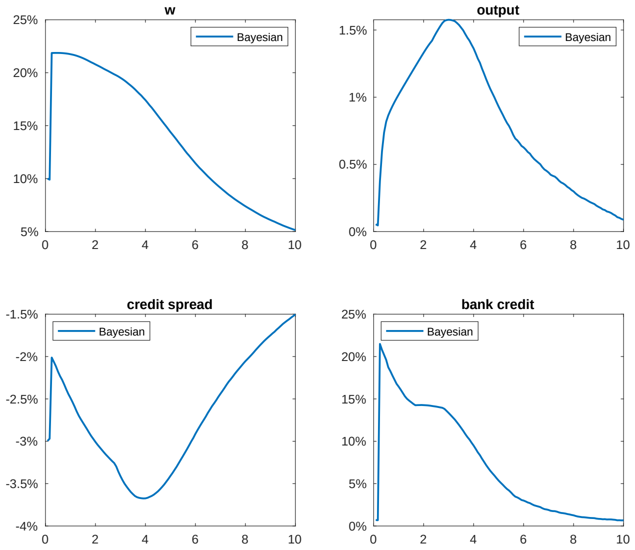
$$\underbrace{\text{Leverage}}_{\uparrow} \times \underbrace{\tilde{\lambda}_t}_{\downarrow}$$

- Leverage rises faster (as a function of $E_t[\tilde{\lambda}_t]$) in diagnostic model
- But the effects play out similarly in both Bayesian and Diagnostic belief models

Predicting Crises

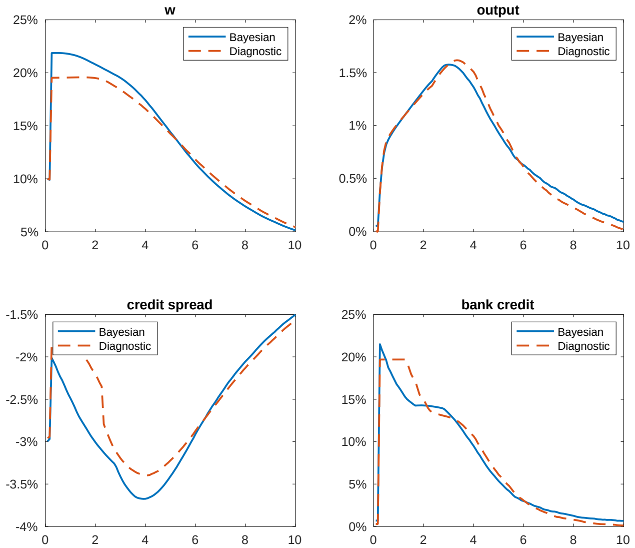
Leaning Against the Wind: Bayesian vs Diagnostic

Average Impact of a 10% Recapitalization Policy



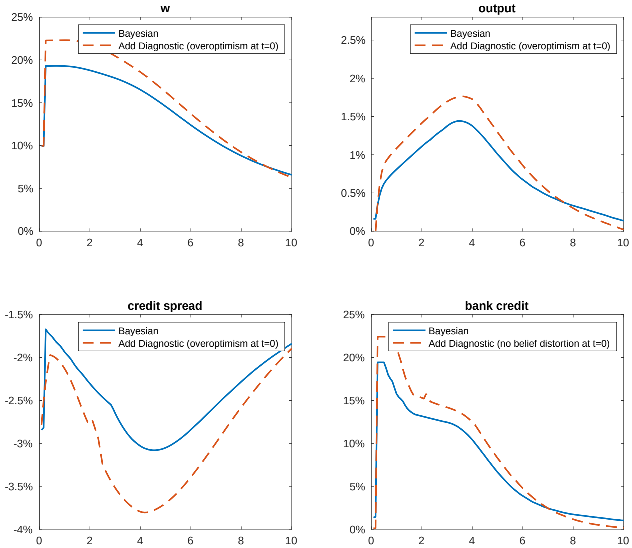
- Policy: recapitalization to "*lean against the wind*"
- Initial state: boom (high lev,low spread)
- Simulation: $dN_t = 1$ after the policy, but $dN_t = 0$ otherwise. dB_t randomly generated.
- Impact = log(with policy) − log(without policy).

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**.

Average Impulse Response Difference to a 10% Recapitalization Policy



- Diagnostic model uses Bayesian belief model parameters
- And adds a new parameter.
- “Comparative static”