Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment

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Financial (Banking) Crisis Cycles: Mean Path and Severity

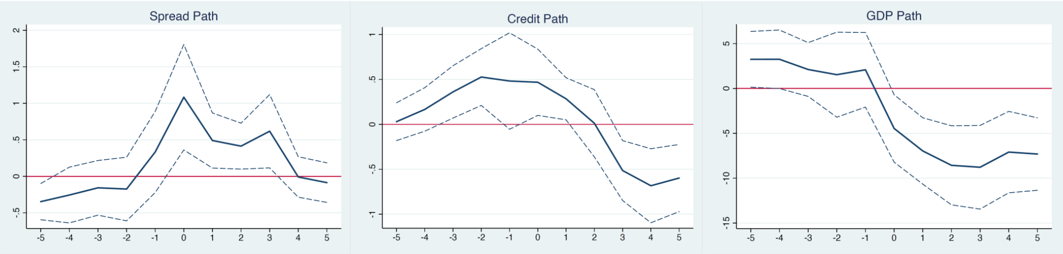


Figure: Mean paths of credit spread, bank credit, and GDP of 41 financial crises, 1870-2014.

- Conditional on crises, we observe
  - Left-skewed GDP growth
  - More pre-crisis bank credit or larger in-crisis credit spread spike ⇒ larger output drop

Source: Krishnamurthy and Muir (2020); Banking Crises dated by Jorda, Schularick, and Taylor (2011).

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)

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

Matching the crisis cycle

1. Financial intermediation
   - Losses reduce bank equity capital, cause disintermediation
   - Credit contraction, output falls, asset prices fall ... amplification mechanism

   $\Rightarrow$ Matches crisis+ aftermath patterns, given a shock that pushes economy into a crisis

2. Beliefs/Sentiment
   - Crises are sharp and need a trigger: news triggers a revaluation of assets.
   - The pre-crisis build-up period is characterized by optimism (or overoptimism?)
   - Bayesian model of beliefs and diagnostic model as in Bordalo, Gennaioli, Shleifer (2018)

   $\Rightarrow$ Need belief fluctuation to match pre-crisis build-up

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 $\underline{A}$.
- Bankers become households at flow rate ηdt.

Capital and shocks

- Illiquidity shock dN_t with intensity $\tilde{\lambda}_t$. Brownian shock dB_t. Capital price process:

$$\frac{dp_t}{p_{t-}} = \mu_t^p dt + \sigma_t^p dB_t - \kappa_{t-}^p dN_t,$$

- Investment rate:

$$p_t = \phi'(\mu_t^K) \quad \Rightarrow \quad \mu_t^K = \delta + \frac{p_t - 1}{\chi}.$$

- Capital accumulation

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

  - Illiquidity shock is a pure financial shock; has no direct impact on output or productivity
  - dB_t is a Brownian motion representing real/TFP shocks.

Shocks: Interpretation

- Illiquidity shock dN_t with **hidden** intensity $\tilde{\lambda}_t$.
- Exogenous shock makes all debtors demand their funds back, and triggers sale of capital (microfoundation in Li (2023))
- Capital liquidation: illiquidity discount α^0 and endogenous capital price decline.
- High credit + illiquidity shock may lead to a banking crisis:

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

Beliefs

- Hidden intensity (unobservable) $\tilde{\lambda}_t \in \{\lambda_H, \lambda_L = 0\}$ is a continuous-time Markov process with switching rate $\lambda_{H\to L}$ and $\lambda_{L\to H}$.
- Observing dN_t for inference. Model differences arise in the expected intensity $E_t^{belief}[\tilde{\lambda}_t]$.

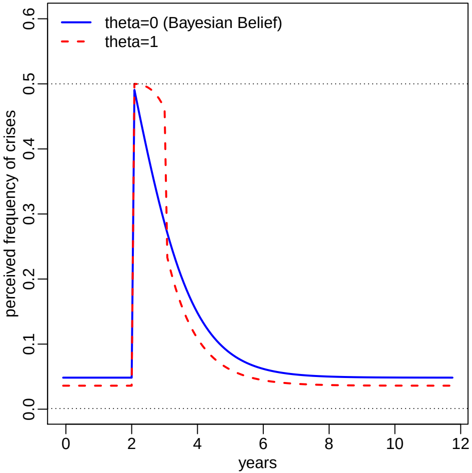
Bayesian filtering problem:

$$d\lambda_t = \begin{pmatrix} (\lambda_L - \lambda_{t-})\lambda_{H\to L} + (\lambda_H - \lambda_{t-})\lambda_{L\to H} \\ -(\lambda_{t-} - \lambda_L)(\lambda_H - \lambda_{t-}) \end{pmatrix} dt + \frac{(\lambda_{t-} - \lambda_L)(\lambda_H - \lambda_{t-})}{\lambda_{t-}} dN_t$$

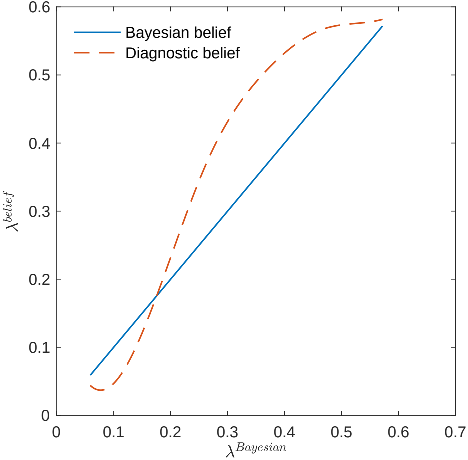
Diagnostic:

$$\lambda_t^\theta = \lambda_L + (\lambda_t - \lambda_L)\frac{(\lambda_H - \lambda_t) + (\lambda_t - \lambda_L)}{\left(\frac{\lambda_t^T - \lambda_L}{\lambda_H - \lambda_t^T} / \frac{\lambda_t - \lambda_L}{\lambda_H - \lambda_t}\right)^\theta (\lambda_H - \lambda_t) + (\lambda_t - \lambda_L)}$$

Beliefs



(a) Simulation of Beliefs



(b) Diagnostic Belief v.s. True λ_t

Aggregate Variables

Share of capital owned by bankers:

$$\psi_t = \frac{x_t^K W_t^b}{x_t^K W_t^b + y_t^K W_t^h}.$$

Aggregate production:

$$Y_t = (\psi_t \bar{A} + (1 - \psi_t)\underline{A})K_t.$$

Aggregate wealth dynamics:

$$\frac{dW_t^b}{W_{t-}^b} = \frac{dw_t^b}{w_{t-}^b} - \eta dt$$

$$\frac{dW_t^h}{W_{t-}^h} = \frac{dw_t^h}{w_{t-}^h} + \eta \frac{W_{t-}^b}{W_{t-}^h} dt,$$

$$w_t = \frac{W_t^b}{W_t^b + W_t^h}$$

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
  - Bank debt (credit): amount of borrowing 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!**

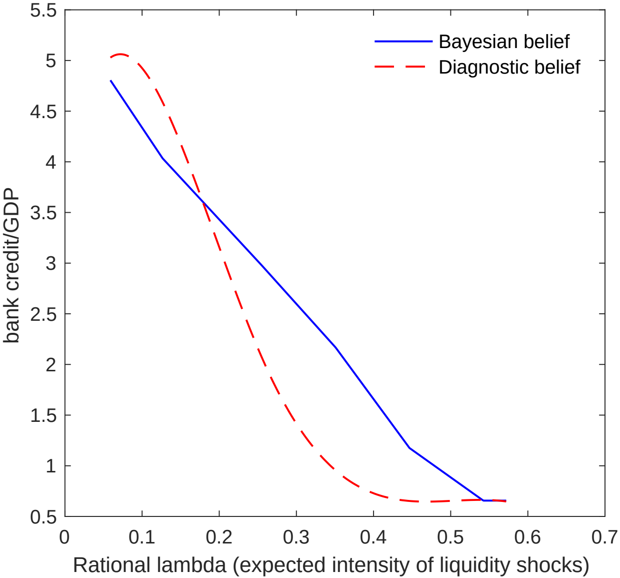
$$\text{Prob of crisis} \propto \text{Credit/GDP} \times \tilde{\lambda}_t$$

Equilibrium Definition

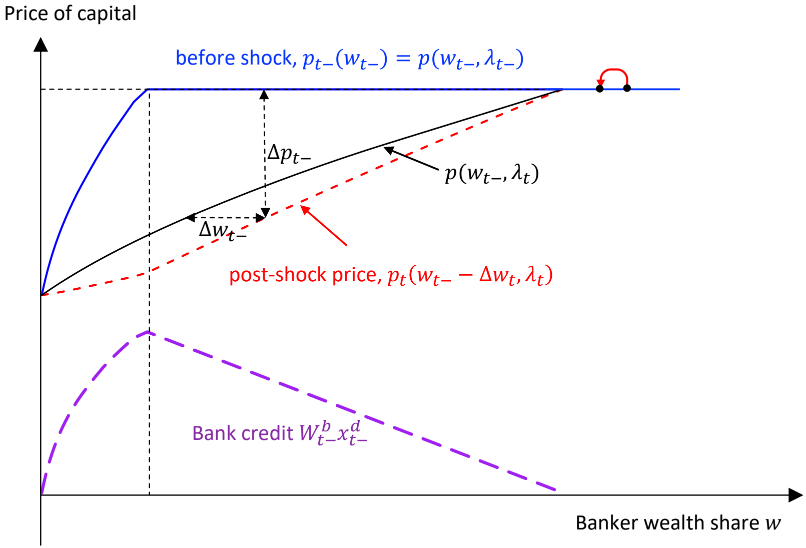
An equilibrium is a set of functions, including the price of capital $p(w_t, \lambda_t)$, household consumption wealth ratio $\hat{c}^h(w_t, \lambda_t)$ and capital holdings $y^K(w_t, \lambda_t)$, banker consumption wealth ratio $\hat{c}^b(w_t, \lambda_t)$ and capital holdings $x^K(w_t, \lambda_t)$, such that

- Consumption, investment and portfolio choices are optimal.
- Capital good market clears
$$W_t^b x_t^K + W_t^h y_t^K = p_t K_t.$$
- The aggregate wealth equals to total value of capital
$$W_t^b + W_t^h = p_t K_t.$$
- Consumption goods market clears
$$\hat{c}_t^b W_t^b + \hat{c}_t^h W_t^h = (\psi_t \bar{A} + (1 - \psi_t)\underline{A})K_t - i_t K_t.$$

Belief Mechanism



Financial Amplification Mechanism



Model Calibration Strategy

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

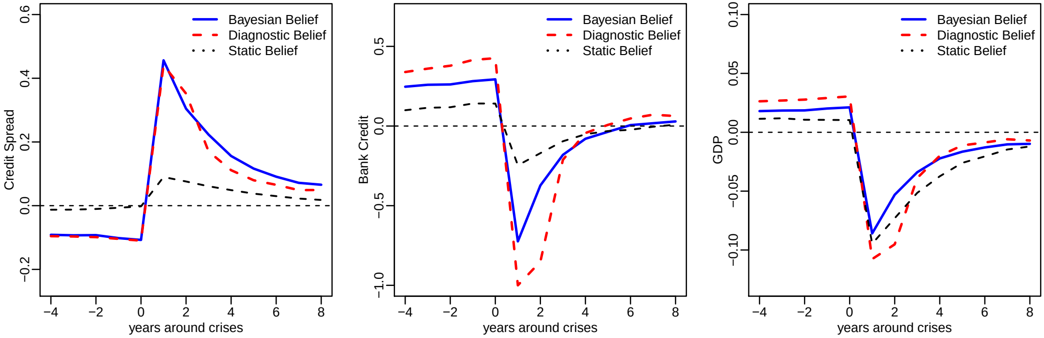
- We separately solve parameters for each model to match the same targets.
  - Targets: average output declines in a crisis, frequency of liquidity shocks $\cdots$
  - Cross-section results are not targeted and used to evaluate.

Important Model Targets

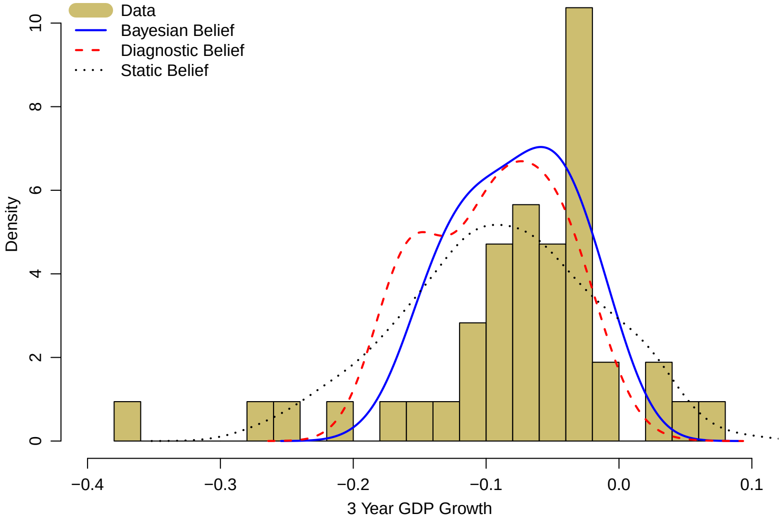
1. Avg 3-year output drop of -9% in financial crises (Schularick and Taylor 2011) $\rightarrow \bar{A} - \underline{A}$
    - Where "financial crisis" $\equiv$ bank credit growth in worst 4% quantile of distribution
2. Average bank leverage of 5 (flow of funds) $\rightarrow \eta$

3. Frequency of illiquidity events $=$ 13% (liquidity premium) $\rightarrow E[\lambda]$
4. Average spike in credit spread in a crisis $=$ 0.7σs (Krishnamurthy and Muir 2020) $\rightarrow \lambda_{H \rightarrow L}$
5. Half-life of credit spread recovery $=$ 2.5 years (Krishnamurthy and Muir 2020) $\rightarrow \lambda_{L \rightarrow H}$
6. Diagnostic parameter (Bordalo, Gennaioli, Shleifer, 2018) $\rightarrow \theta = 0.9$

Mean paths (✗ Benchmark, ✓Bayesian, ✓Diagnostic)



Cross-section: Left-Skewed Distribution of Severity ✓✓✓



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)	
$(\frac{\text{bank credit}}{\text{GDP}})_t$∗crisis$_t$		−1.40		−2.61		−3.48		−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 variation in **credit supply**.

	Dependent variable: Excess return $_{t+1}$			
	Static Belief	Bayesian	Diagnostic	Data
$(\frac{\text{bank credit}}{\text{GDP}})_t$	-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

$\Leftrightarrow$ higher bank leverage and fragility

$\Leftrightarrow$ higher risk premium

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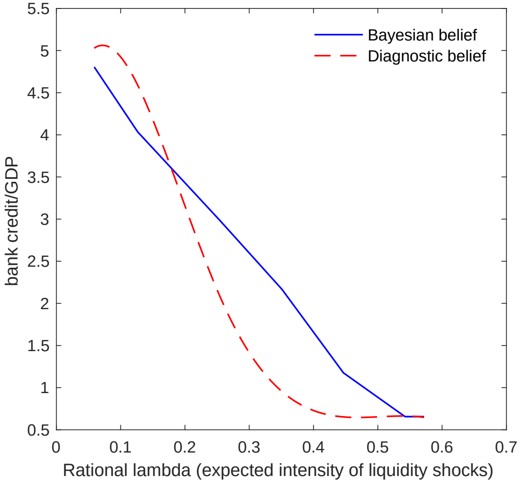
Why the Bayesian model works?



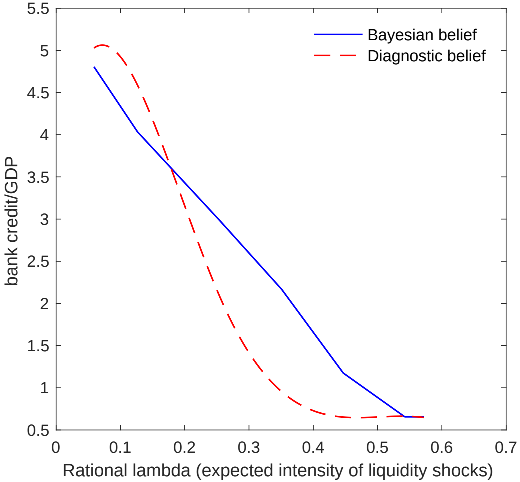
Pre-Crisis Mechanism X ✓ ✓

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

- * crises more likely
- ⇔ 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 credit

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

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

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

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

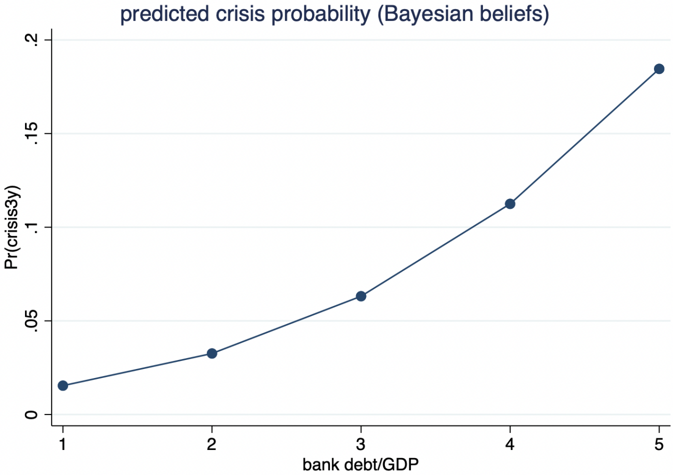
Predicting Crises in Model and Data

	Dependent variable: crisis$_{t+1 \text{ to } t+5}$							
	Static Belief		Bayesian		Diagnostic		Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HighFroth $_t$	-0.76		0.06		0.32		1.76	
							(0.91)	
HighCredit$_t$		-0.90		0.09		0.34		0.55
								(0.46)
Observations							528	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.

Crisis Predictability from Model Simulations

- In both Bayesian and diagnostic models, there is strong crisis predictability. Broadly consistent with Greenwood et al (2022), "Predictable financial crises."



Summary

- This paper bridges the quantitative nonlinear macro-finance models with the empirical crisis literature.
  - 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)

- 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, 2018)