Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment

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The Financial (Banking) Crisis Cycle: Mean Path

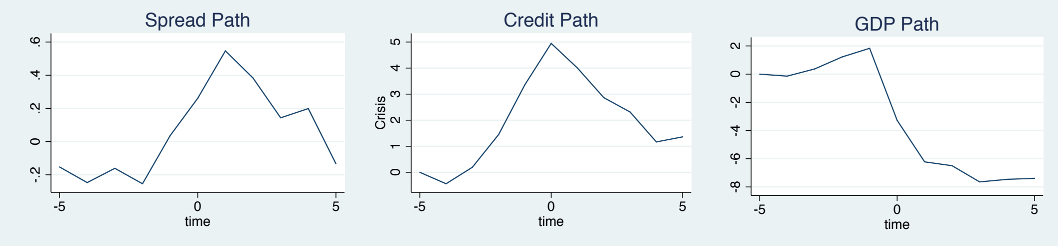


Figure: Mean paths of credit spread, bank credit, and GDP of 41 financial crises, 1870-2014.

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).

Crisis Cycle Facts: Cross-section

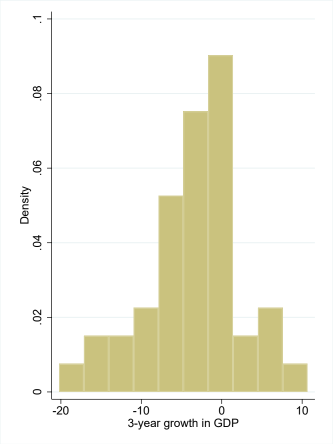


Figure: Distribution of 3-Year GDP Growth after a Crisis

- Crisis skewness in GDP growth and credit spreads, in cross-section
- Relation between pre-crisis credit quantity, credit spreads, and crisis GDP growth
- Predictive relationships:

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

- Higher credit growth predicts more crises (Schularick and Taylor 2012) and equity crashes (Baron and Xiong 2017), AND lower expected excess equity return/risk premium (Baron and Xiong 2017)

Financial Crises Cycle Research

1. Transition to financial crisis: sharp fall in asset prices, rise in risk premia, bank runs, disintermediation, contraction in credit.
   (Reinhart and Rogoff 2009; Schularick and Taylor 2012; Muir 2017)

2. Aftermath of crisis: slow recovery in macro aggregates
   (Reinhart and Rogoff 2009; Schularick and Taylor 2012)

3. Pre-crisis: credit supply expansion and low risk spreads
   - Conditioning on crisis at time t: Low credit spread + high credit growth before crises (Krishnamurthy and Muir 2017).
   - Predictability: Higher credit growth predicts more crises (Schularick and Taylor 2012) and equity crashes (Baron and Xiong 2017), AND lower expected excess bank equity return/risk premium (Baron and Xiong 2017)

Mechanisms?

1. Financial intermediation
   - Losses reduced equity capital
   - Disintermediation and fire sales
   - 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: Greenwood, Hanson, and Jin (2019), Maxted (2019)

This Paper

- **Qualitative and quantitative assessment of these two mechanisms.**
- We build a model with both mechanisms. Turn on and off features to understand what is needed to match the data.
- Strategy: incrementally increase model complexity to match data.

Agents and Preferences

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

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

  and bankers transit to households at rate η.

- Bankers raise only demandable debt, and only have inside equity.
- Both bankers and households invest in productive capital.
- "A-K" production technology: productivity per unit of capital is $\bar{A}$ for bankers, but $\underline{A}$ for households, with $\underline{A} < \bar{A}$.
- 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/financial distress Poisson shock dN_t with intensity λ_t.
  - Exogenous shock triggers household funding withdrawals and sales of capital by banks; drop in output/capital price is endogenous
  - Capital liquidation: illiquidity discount α^0 and endogenous capital price decline.
  - See Li (2019)

Beliefs

- The intensity of dN_t is a continuous-time Markov process $\tilde{\lambda}_t$ with two states, $\{\lambda_H, \lambda_L = 0\}$, and switching intensity $\lambda_{H\to L}$ and $\lambda_{L\to H}$.

- Agents do not observe $\tilde{\lambda}_t$, but only the realizations dN_t. Differences of models arise in the expected intensity $\lambda_t = E_t[\tilde{\lambda}_t]$.

  (1) Benchmark model: constant intensity with $\lambda_t = const.$, no transition.

  (2) Bayesian (rational) belief λ_t:

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

  (3) Diagnostic (non-rational) expectation λ_t^θ:

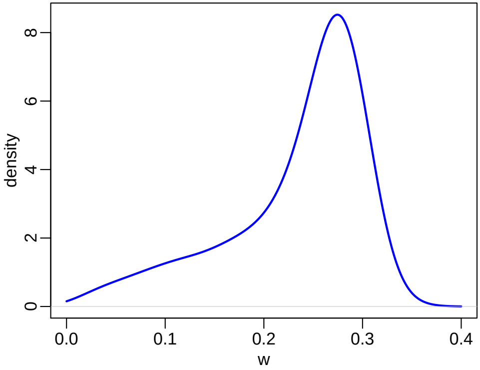
$$\lambda_t^\theta = \lambda_t + \underbrace{f(\lambda_t, \lambda_{t-t_0}; \theta)}_{\text{non-rational component}}$$

Key feature: overweight of recent observations.

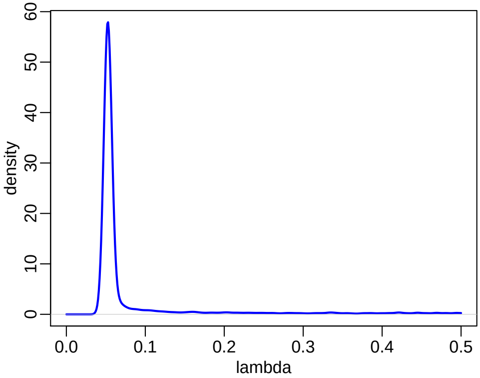
Exogenous Shocks, State Variables, and Endogenous Variables

- Two driving shocks: dB_t (gains/losses in capital), dN_t (illiquidity shocks)
- State variables:
  - w_t: banker wealth share
  - λ_t: intensity of illiquidity shock
  - K_t: scale of the economy
- Endogenous outcome variables:
  - Output: "AK" technology
  - Price of capital $= p(w_t, \lambda_t)$
  - Credit: Borrowing of banker from household
  - Credit spread: we define a zero-net supply defaultable bond, calibrated to match BAA bond characteristics and price this bond using the banker's pricing kernel

Steady State Distribution

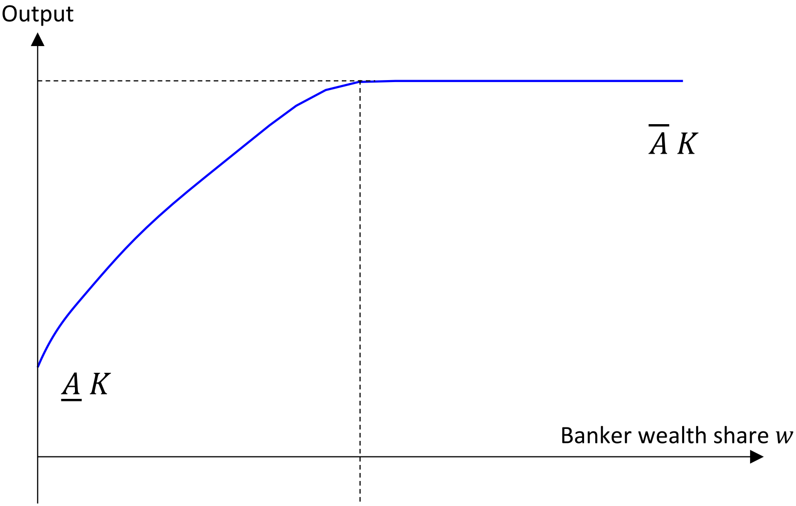


(a) w density of Bayesian model

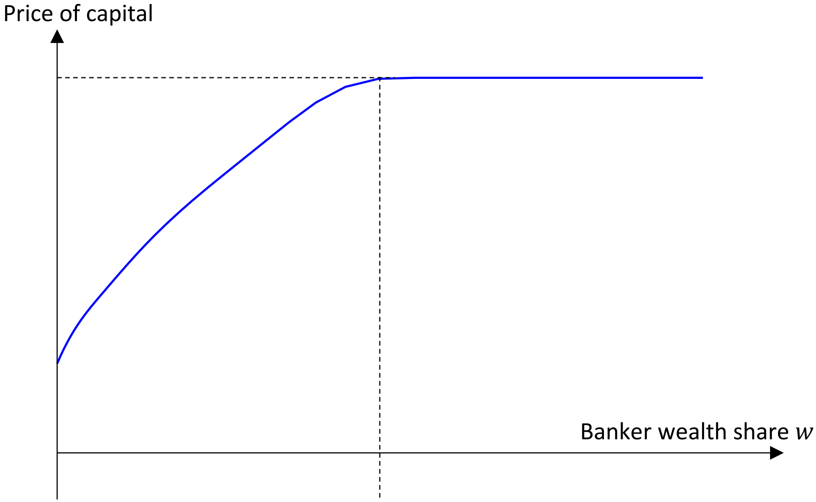


(b) λ density of Bayesian model

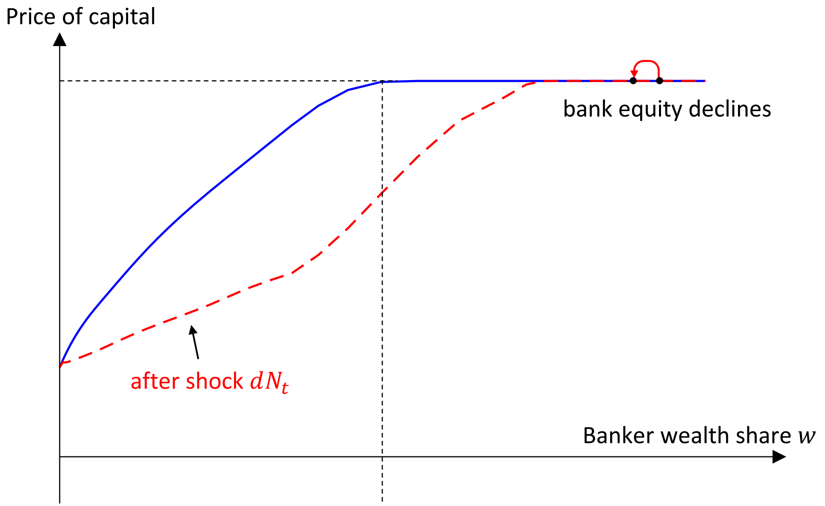
Financial Amplification Mechanism (Output)



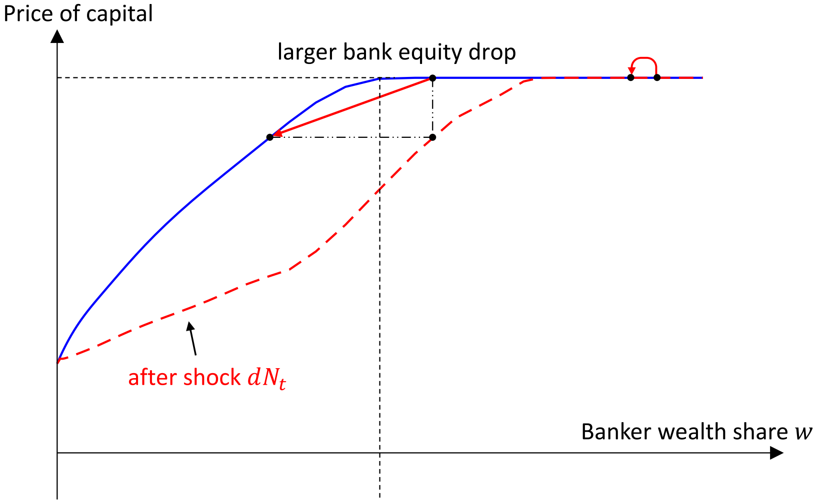
Financial Amplification Mechanism (Asset Price)



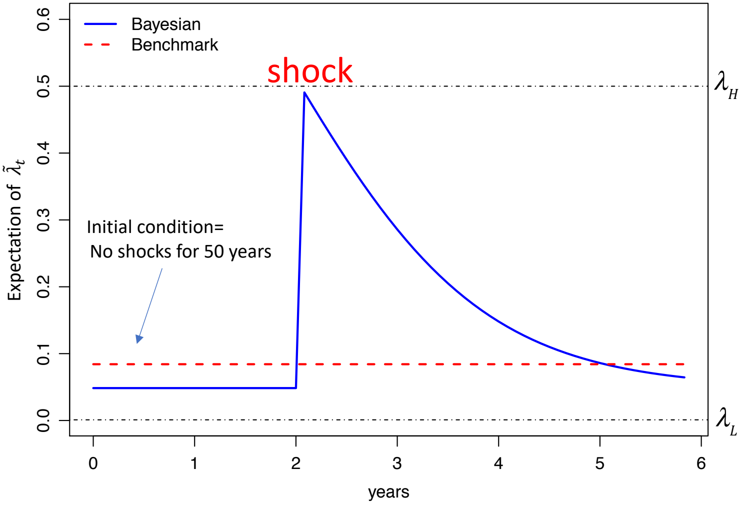
Financial Amplification Mechanism (With Illiquidity Shock)



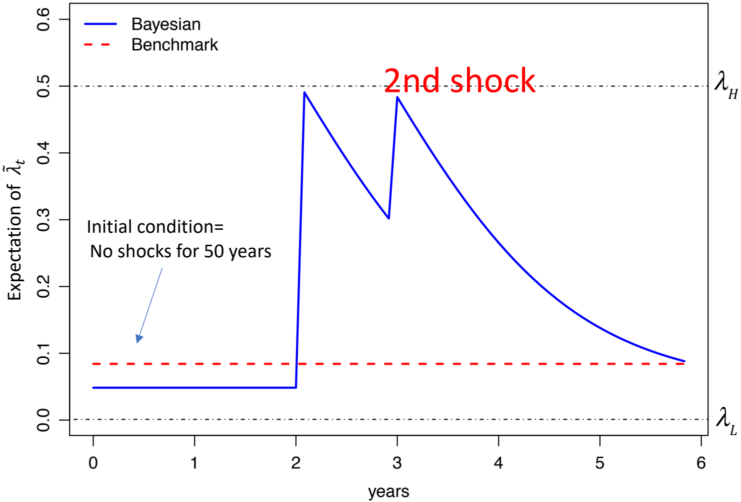
Financial Amplification Mechanism (Conditional Response)



Example to Illustrate Belief Mechanism



Belief Mechanism: Smaller Response to Second Shock



Parameters to be Estimated

Parameters	Benchmark Model	Bayesian Belief Model	Diagnostic Belief Model
σ^K	✓	✓	✓
$\bar{A}+\underline{A}$	✓	✓	✓
$\bar{A}-\underline{A}$	✓	✓	✓
η	✓	✓	✓
λ_H	✓	✓	✓
$\lambda_{H\to L}$	–	✓	✓
$\lambda_{L\to H}$	–	✓	✓
θ	–	–	✓

This table lays out the set of estimated parameters in different models. "–" indicates not having the parameter, while "✓" indicates having the parameter.

Model Targets

1. Output growth volatility of 4% (flow of funds) $\rightarrow \sigma^K$
2. Investment/capital ratio of 14% (flow of funds) $\rightarrow$ weighted average of $\bar{A}$, $\underline{A}$
3. Avg 3-year output drop of -9% in financial crises (Schularick and Taylor 2011) $\rightarrow \bar{A} - \underline{A}$
   - Where "financial crisis" $\equiv$ output growth in a given year is lower than 4% quantile of yearly output growth distribution
4. Average bank leverage of 5 (flow of funds) $\rightarrow \eta$

Related to belief parameters $(\lambda_H, \lambda_{H\rightarrow L}, \lambda_{H\rightarrow L}, \theta)$

5. Frequency of illiquidity events = 13% (Baron and Xiong 2017) $\rightarrow E[\lambda]$
6. Average spike in credit spread in a crisis $= 0.7\sigma$s (Krishnamurthy and Muir 2017) $\rightarrow \lambda_{H\rightarrow L}$
7. Half-life of credit spread recovery = 2.5 years (Krishnamurthy and Muir 2017) $\rightarrow \lambda_{L\rightarrow H}$
8. Pre-crisis credit spread $= -.34\sigma$s (Krishnamurthy and Muir 2017) $\rightarrow \theta$

Table: Comparison of Model Target and Moment

	Data	Benchmark	Bayesian	Diagnostic
1. Output growth volatility	4%	3%	4%	5%
2. Investment/capital ratio	14%	14%	18%	14%
3. Avg 3-year output drop in crises	-9%	-8%	-12%	-10%
4. Average bank leverage	5.0	5.2	4.8	5.2
5. Frequency of illiquidity events	13%	13%	12%	13%
6. Avg credit spread change in crises	0.70	0.11	0.63	0.49
7. Half-life of credit spread recovery (years)	2.5	2.3	3.2	2.2
8. Pre-crisis credit spread	-0.34			-0.34

We choose parameters to minimize sum of absolute deviations between model moment and targets.

Mean Path Around Model-defined Crisis ✓✓

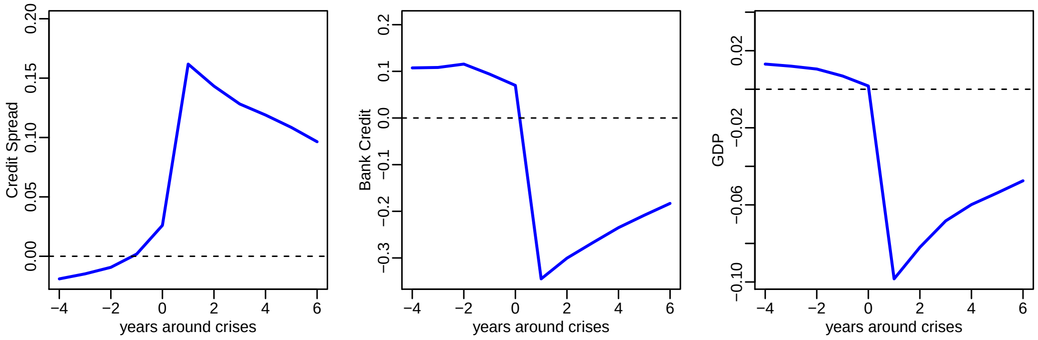


Figure: Dynamics of the Benchmark Model Around Crises. Credit spread and bank credit are measured as standard-deviations from the mean value. For example, credit spread raising to 0.2 means that it is larger than the value at year 0 by 0.2σs. GDP is measured in terms of percentage deviation from the long-run mean value.

Distribution of Output Growth in 3 Years after Crisis Date ✓✓

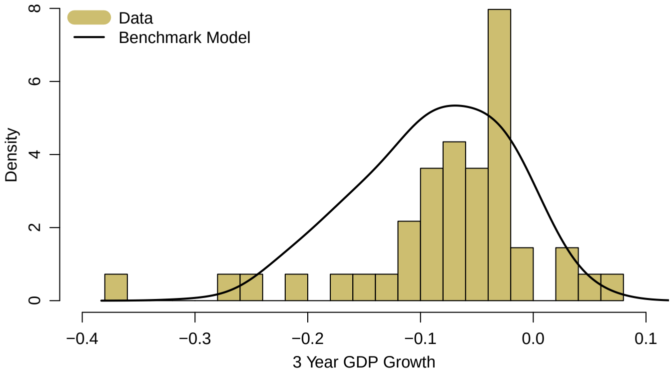


Figure: Distribution of Output Growth 3 Years after Crisis: Benchmark Model and Data

Credit and Output ✓✓

Table: GDP Growth and Credit Spread in the Benchmark Model

	Dependent variable: GDP Growth from t to t + 3			
	Model Simulations		Data	
	(1)	(2)	(3)	(4)
$(\frac{\text{bank credit}}{\text{GDP}})_t{*}\text{crisis}_t$	−1.40		−0.95 (0.30)	
$\Delta\text{credit spread}_t{*}\text{crisis}_t$		−6.19		−7.46 (0.16)
Observations			641	641

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

Credit growth and future equity returns ✓✓

- Baron and Xiong (2017): high credit growth $\Rightarrow$ low future equity returns
  (low credit growth $\Rightarrow$ high future returns)

Table: Bank Credit Predicting Equity Excess Return in the Benchmark Model

	Dependent variable:	
	Average realized excess return $_{t+1}$	
	(1) Model Simulations	(2) Data
$\left(\frac{\text{bank credit}}{\text{GDP}}\right)_t$	-0.02	-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 the excess equity index return 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.

Pre-Crisis Behavior X

- Krishnamurthy and Muir (2017): credit spread is unusually low in the pre-crisis period
- Model fails to match pre-crisis spreads. Sign is wrong!

Table: Credit Spread Before Crises in the Benchmark Model

	Dependent variable: credit spread$_t$	
	Model Simulations	Data
	(1)	(2)
pre-crisis indicator	0.21	−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.

Why a belief state variable is needed?

$\Rightarrow$ The benchmark model matches the crises dynamics well, but fails to match pre-crisis behavior

- Failure is due to only one state variable, w, driving credit and risk-taking of banks
- Beliefs that vary over time, λ_t, adds another state variable and resolves the problem.
- Model has 2 more parameters; recalibrated to best match calibration targets (slide 14)

Pre-Crisis Behavior ✓

- Condition on crisis at t, what are spreads before t?

Table: Credit Spread Before Crises in the Bayesian Model

	Dependent variable: credit spread$_t$	
	Model Simulations	Data
	(1)	(2)
pre-crisis indicator	-0.13	-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.

Mechanism: Bayesian Beliefs about Liquidity Risk and Leverage

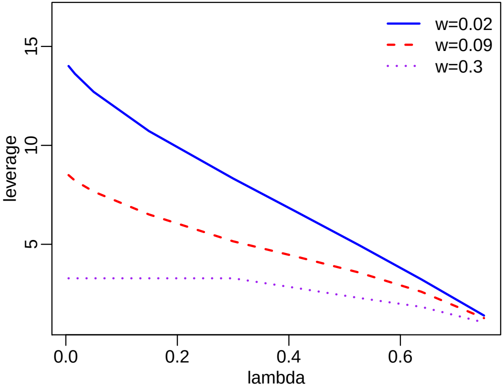
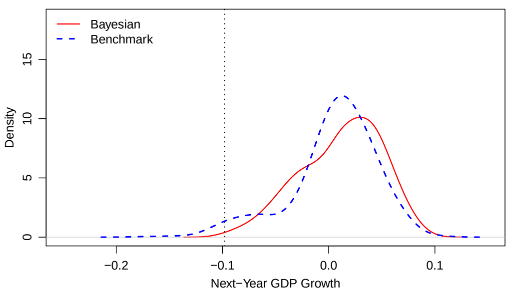
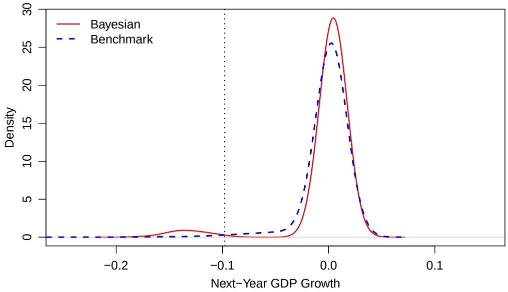


Figure: Leverage and Lambda. This figure plots the leverage of banks as a function of state variable λ, given different levels of w, the other state variable.

Predictive Results: Risk-taking when Credit Growth is High



(a) Conditioning on Low Bank Credit



(b) Conditioning on High Bank Credit

Figure: Density of Next-Year GDP Growth Conditional on Bank Credit/GDP. Cutoffs are 30% quantile and 90% quantile of bank credit/GDP.

Predicting Crises ~

Table: Predicting Crises in the Bayesian Model

	Dependent variable: crisis$_{t+1 \text{ to } t+5}$			
	Model Simulations		Data	
	(1)	(2)	(3)	(4)
HighFroth$_t$	0.05		1.76 (0.91)	
HighCredit$_t$		0.08		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.

Diagnostic Beliefs

⇒ Summarizing: Adding the second state variable, beliefs, helps to match the pre-crisis dynamics qualitatively

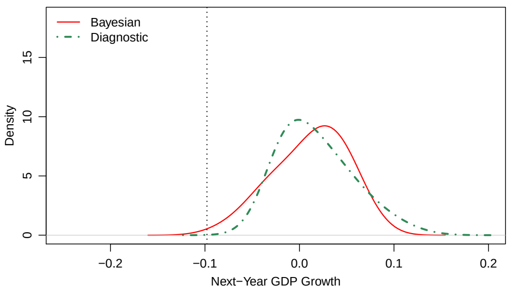
– Even the most "surprising" one: High credit growth predicts more crises **AND** lower excess returns.

- But quantitatively, the model has room to improve
- Diagnostic (non-rational) expectation λ_t^θ:

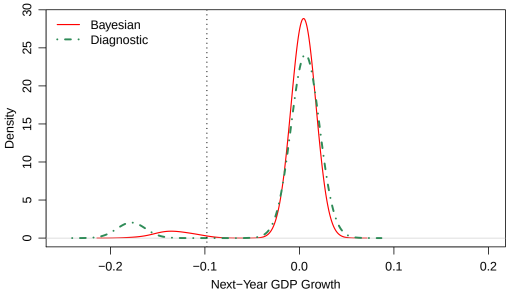
$$\lambda_t^\theta = \lambda_t + \underbrace{f(\lambda_t, \lambda_{t-t_0}; \theta)}_{\text{non-rational component}}$$

Key feature: overweight of recent observations.

Mechanism: Over-optimism and Risk-taking when λ is low



(a) Conditioning on Low Bank Credit/GDP



(b) Conditioning on High Bank Credit/GDP

Figure: Density of Next-Year GDP Growth in Bayesian and Diagnostic Models Conditional on Bank Credit/GDP. Cutoffs are 30% quantile and 90% quantile of bank credit/GDP.

Pre-Crisis Behavior ✓✓

Table: Credit Spread Before Crises in the Diagnostic Model

	Dependent variable: credit spread$_t$	
	Model Simulations	Data
	(1)	(2)
pre-crisis indicator	−0.34	−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.

Predicting Crises ✓✓

Table: Predicting Crises in the Diagnostic Model

	Dependent variable: crisis$_{t+1\ to\ t+5}$			
	Model Simulations		Data	
	(1)	(2)	(3)	(4)
HighFroth$_t$	0.41		1.76	
			(0.91)	
HighCredit$_t$		0.41		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.

Conclusions

Conclusion 1: Two state variable model works!

- Minimal model with two state variables, one that governs financial frictions and one that governs beliefs, can match the crisis cycle facts.
- Our analysis shows that these variables can have the "right" dynamics under both Bayesian and diagnostic belief updating.

Conclusion 2: Non-rational beliefs help quantitatively, not qualitatively

- Simple Bayesian model gets the patterns qualitatively right.
- Is there a more complex version that gets it quantitatively right?