Financial networks over the business cycle

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Motivation

- Years prior to financial crisis saw growing financial interconnectedness
  - Credit risk pooling (securitization), loan portfolio overlap, derivatives (CDS), interbank lending, etc. Measures
- Financial architecture shapes systemic risk
  - ‘Robust-yet-fragile’ property: Risk sharing vs correlated failures

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  - 'Robust-yet-fragile' property: Risk sharing vs correlated failures
- This paper: a dynamic model with interlinked financial sector

1. How does systemic risk build up over time?
2. Why do systemic financial crises happen at the end of credit booms?

Framework

- Interconnectedness is due to common portfolio holdings
  - Asset commonality is a crucial source of systemic risk
    e.g., Borio (2003), Elsinger et al. (2006)
  - Tractable, yet captures essential trade-off
    e.g., Allen et al. (2012), Cabrales et al. (2017)

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  - Risk sharing: individual default risk ↓; joint default probability ↑
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  - Risk-sharing links are costly to form
- Main novelty: **time-varying** and **endogenous** interconnectedness
  - Incentives to form links change over the credit cycle
  - Systemic risk is governed by evolving density of financial links

Main results

- Positive analysis: Systemic risk is built up during 'good' times
  - Systemic crises occur at the end of credit booms
  - Credit is abundant but real investment is not productive
  - Strong asset commonality due to active risk sharing
- Welfare analysis: Inefficiently high systemic risk

Literature

- Fragility of financial networks
  - Allen and Gale (2000), Allen, Babus, and Carletti (2012), Elliott, Golub, and Jackson (2014), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Babus (2016), Cabrales, Gottardi, and Vega-Redondo (2017), Farboodi (2017)
  - Portfolio overlap and systemic risk: Shaffer (1994), Acharya (2009), Stiglitz (2010), Wagner (2010, 2011), Ibragimov, Jaffe, and Walden (2011), Liu (2018)

  Difference: dynamic model of systemic risk and financial fragility

- Macro models with financial frictions
  - Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999), He and Krishnamurthy (2012), Brunnermeier and Sannikov (2014), Gertler and Kiyotaki (2015), Boissay, Collard, and Smets (2017)

  Difference: role of financial links for shock propagation and aggregate fluctuations

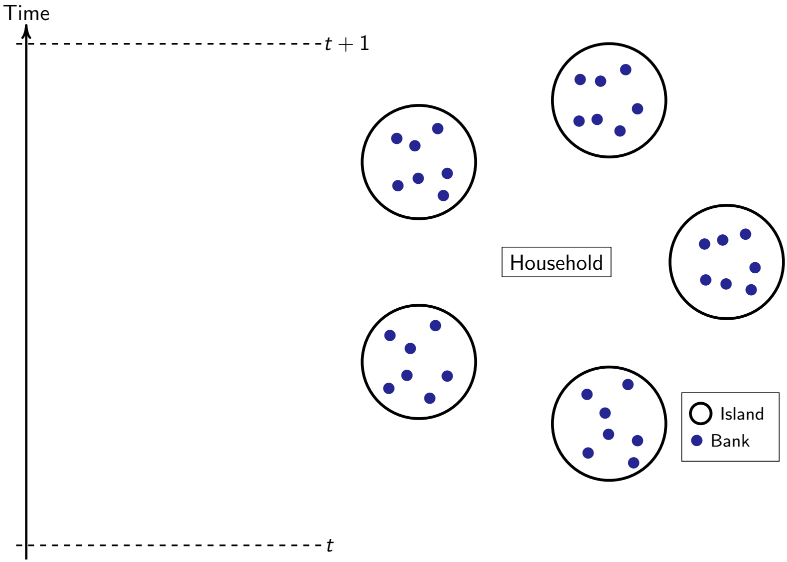
- Interconnectedness and systemic risk: Empirics
  - Elsinger, Lehar, and Summer (2006), Diebold and Yilmaz (2009, 2014), Billio, Getmansky, Lo, and Pelizzon (2012), Adrian and Brunnermeier (2016), Cai, Eidam, Saunders, and Steffen (2018)

I. Model

Model: Overview

- Closed economy, infinite horizon
- Two types of agents: households and banks
- Long-lived representative household
  - Owns all assets but relies on banks for real investment (no HH-banks frictions)
  - Makes intertemporal consumption/savings decision
- One-period banks
  - Raise funds from households, extend credit to real economy

The structure of the economy



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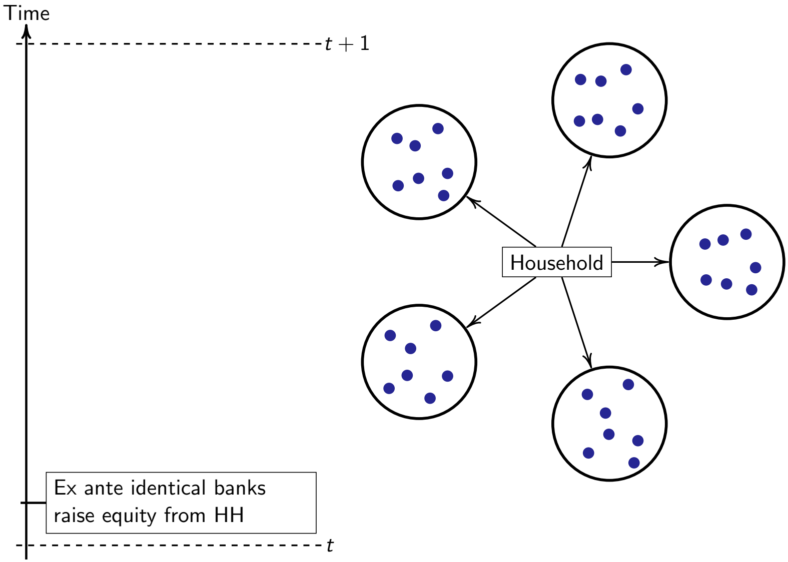

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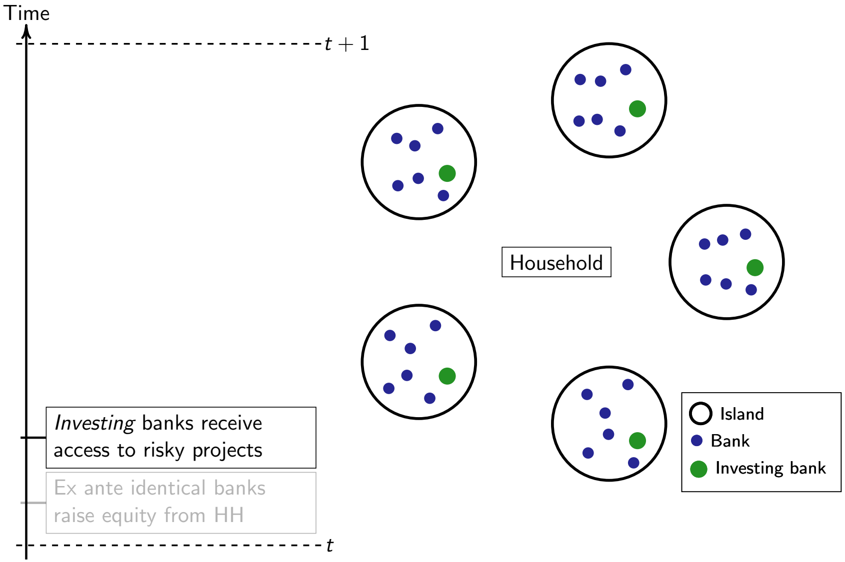

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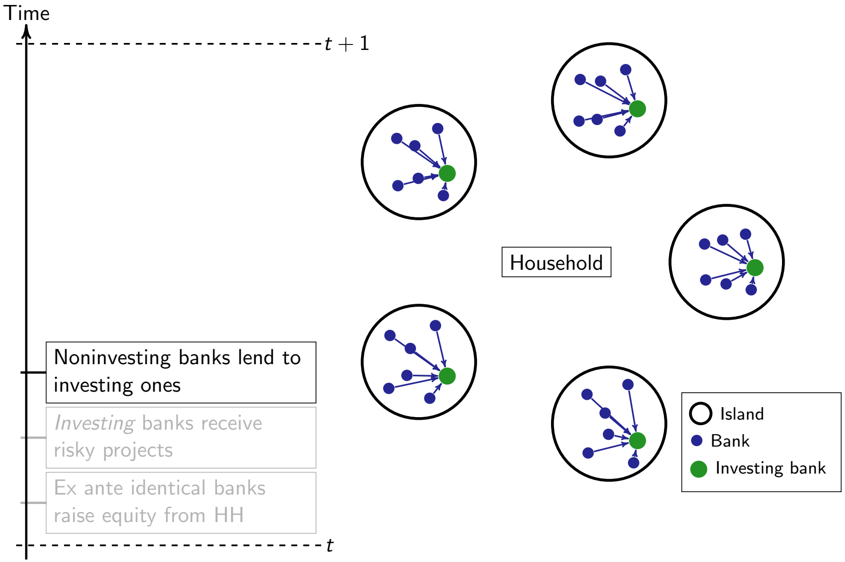

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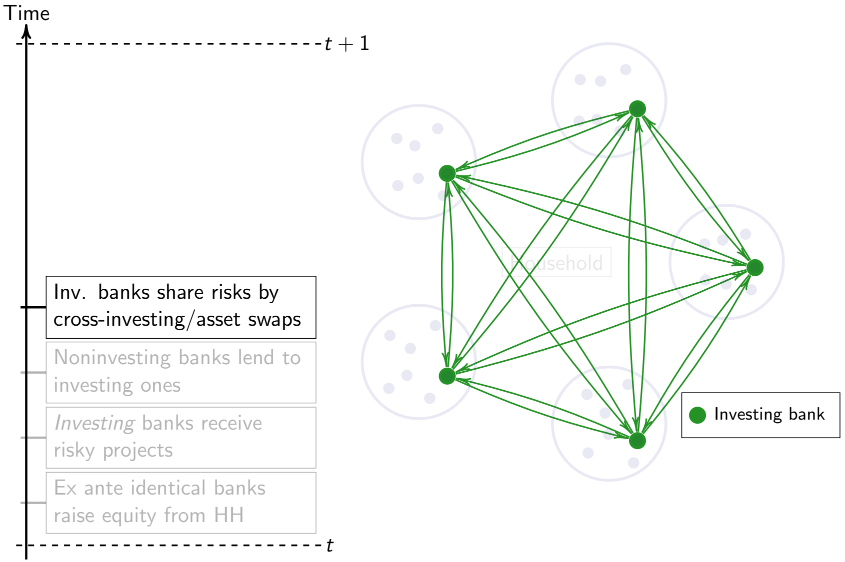

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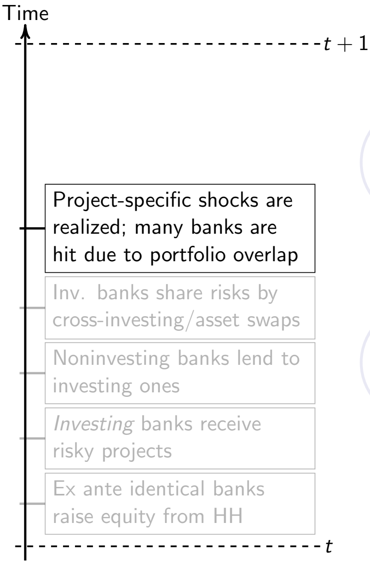

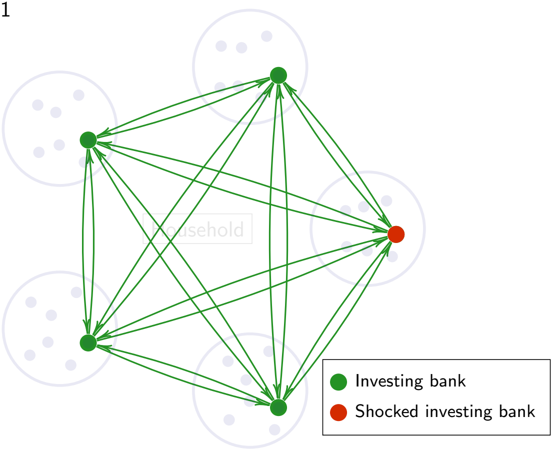

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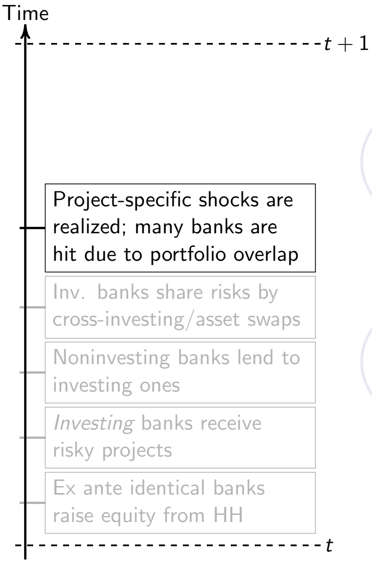

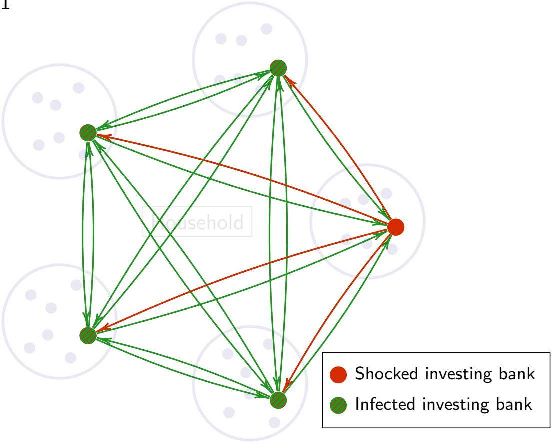

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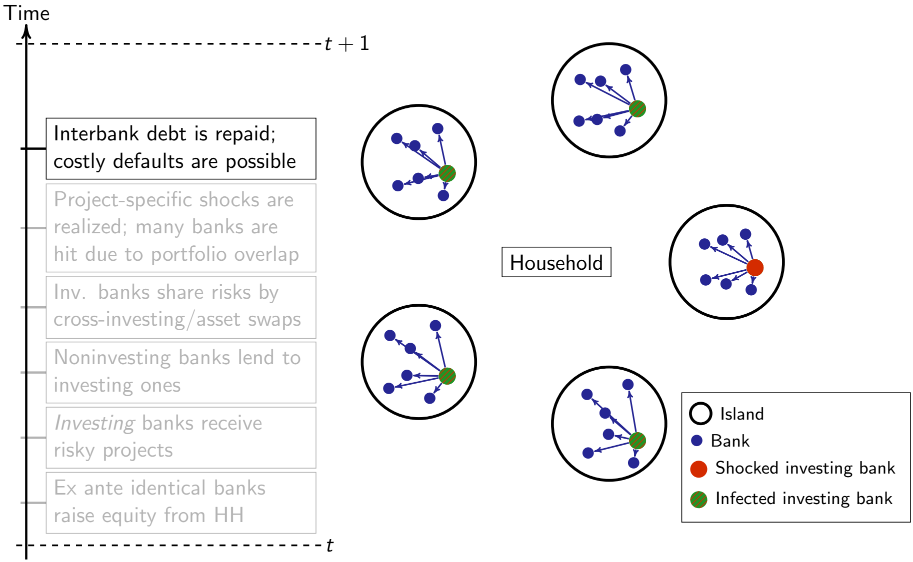

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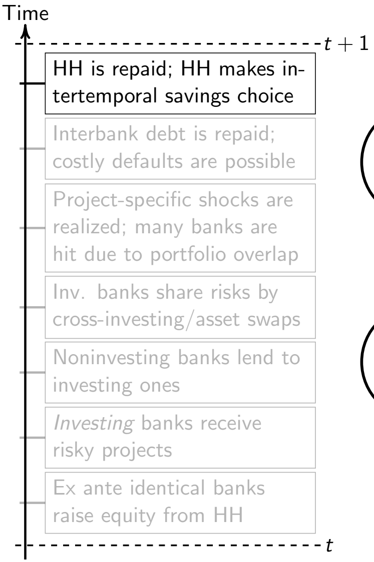

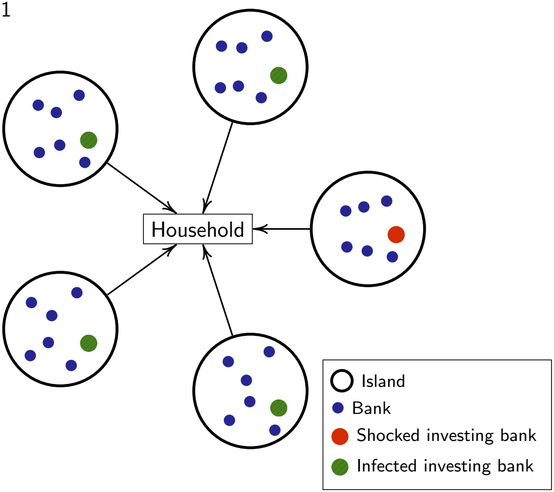

Problem of investing banks

- Investing bank i maximizes its expected earnings

$$\max_{\mu,\rho,\{\omega_{ij}\}_{j=1}^{N}} \underbrace{\frac{a_0}{1-\mu}}_{\text{Assets}} \times \left[\underbrace{\frac{1}{N}\sum_{j=1}^{N}\int_{\underline{x}}^{\frac{R-\rho\mu}{\omega_{ij}}} (R-\omega_{ij}x-\rho\mu)d\Phi(x)}_{\text{Expected net returns}} - \underbrace{f\sum_{j\neq i}\omega_{ij}}_{\text{Linking costs}} \right]$$

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- ρ makes noninvesting banks break even

$$\rho_s = \underbrace{\rho \frac{1}{N} \sum_{j=1}^{N} \Phi\left(\frac{R-\rho\mu}{\omega_{ij}} \right)}_{\text{No default}} + \underbrace{\frac{1}{\mu} \frac{1}{N} \sum_{j=1}^{N} \int_{\frac{R-\rho\mu}{\omega_{ij}}}^{\infty} (R - \omega_{ij} x - \overbrace{\theta}^{\text{Default loss}}) d\Phi(x)}_{\text{Default}}$$

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- Borrowing capacity: $\mu \leq \bar{\mu} \equiv \frac{M-1}{M}$, where each island has M banks
  - Assumed to be binding in the theoretical analysis

Portfolio structure

Proposition

Portfolio $\{\omega_{ij}\}_{i=1}^{N}$ *of investing bank i has the following form:*

	Project $j < i$	Project i	Project $k > i$
Bank i	$\omega_{ij} = \frac{1-\alpha}{N-1}$	$\omega_{ii} = \alpha > \frac{1}{N}$	$\omega_{ik} = \frac{1-\alpha}{N-1}$

- All projects generate the same diversification benefit
- Projects $j \neq i$ are costly to invest $\Rightarrow$ portfolio is tilted toward project i

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Define *financial interconnectedness* as $IC = \dfrac{1-\alpha}{1-1/N} \in [0,1]$

Interconnectedness and systemic risk

- Systemic crisis: simultaneous defaults of all investing banks

$$p^d_{syst} = 1 - \Phi\left(N \times \frac{R - \rho\mu}{IC}\right)$$

Interconnectedness and systemic risk

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Proposition

- *Profit margin $R - \rho\mu$* **increases** *in projects' return R; interconnectedness IC and probability of systemic crisis p^d_{syst}* **decrease** *in R;*
- *R* **decreases** *in total amount of assets A and* **increases** *in aggregate productivity z.*

Systemic risk measure | Comparative statics | Details

Household

- Representative household solves

$$V(A,z,x) = \max_{C,K',L} \left[\frac{1}{1-\psi} \left(C - \frac{L^{1+\nu}}{1+\nu} \right)^{1-\psi} + \beta \mathbb{E} V(A',z',x') \right]$$

$$\text{s.t. } A' = rA + wL - C + \chi$$

$$\log z' = \rho_z \log z + \sigma_z \epsilon'_z, \; \epsilon_z \sim \mathcal{N}(0,1)$$

- Return on assets r is

$$r = R - \frac{1}{N}x - \frac{N^d(R,x)}{N}\theta - \frac{1}{A}\chi$$

  - N^d is the number of defaulted banks
  - χ is total risk-sharing costs

Stylized policy

II. Numerical analysis

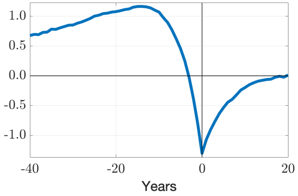
Parameters

Parameter	Value	Source/Target
Preferences		
IES	$1/\gamma = 0.2$	Standard
Frisch elasticity	$1/\nu = 1$	Standard
Time discounting	$\beta = 0.97$	Standard
Production technology		
Capital share	$\eta = 0.33$	Standard
Capital depreciation	$\delta = 0.087$	10% annually (x shocks)
Aggregate shocks		
Persistence	$\rho_z = 0.83$	US postwar data [Moments]
St.dev. of innovations	$\sigma_z = 0.019$	US postwar data
Banking sector		
Number of islands	$N = 10$	Source
Risk-sharing cost	$f = 0.005$	Craig and Ma (2018)
Default loss	$\theta = 0.1$	BGG (1999)
Storage technology	$\rho_s = 1.009$	$\frac{\text{Int Income}}{\text{Assets}} - \frac{\text{Int Expense}}{\text{Liabilities}}$
Number of banks per island	$M = 670$	$\frac{\text{Net Interest Income}}{\text{Assets}}$
Pareto project-specific shocks, $\Phi(x) = 1 - (\underline{x}/x)^{\gamma}$		
Tail index	$\gamma = 3$	Gabaix (2009)
Minimum value	$\underline{x} = 0.088$	Financial crises frequency

Typical systemic crisis

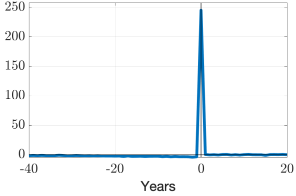
Aggregate productivity, z

[% dev. from mean]



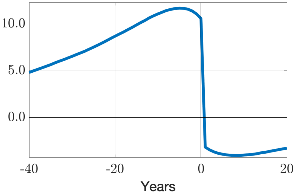
Project-specific shock, x

[% dev. from mean]



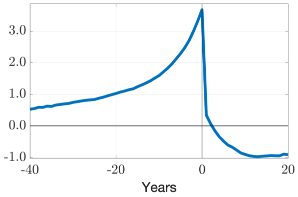
Total assets, A

[% dev. from mean]



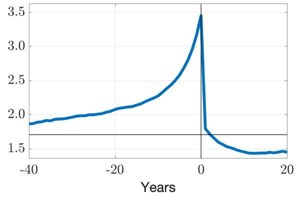
Interconnectedness, IC

[% dev. from mean]



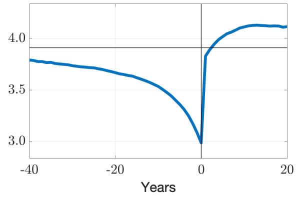
Systemic crisis prob., p^d_{syst}

[%]



Profit margin, $R - \rho\mu$

[%]



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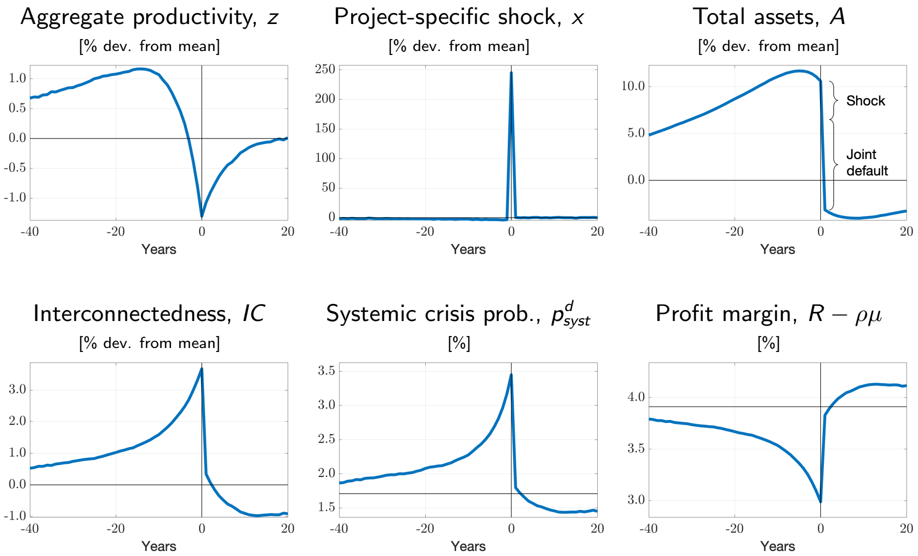
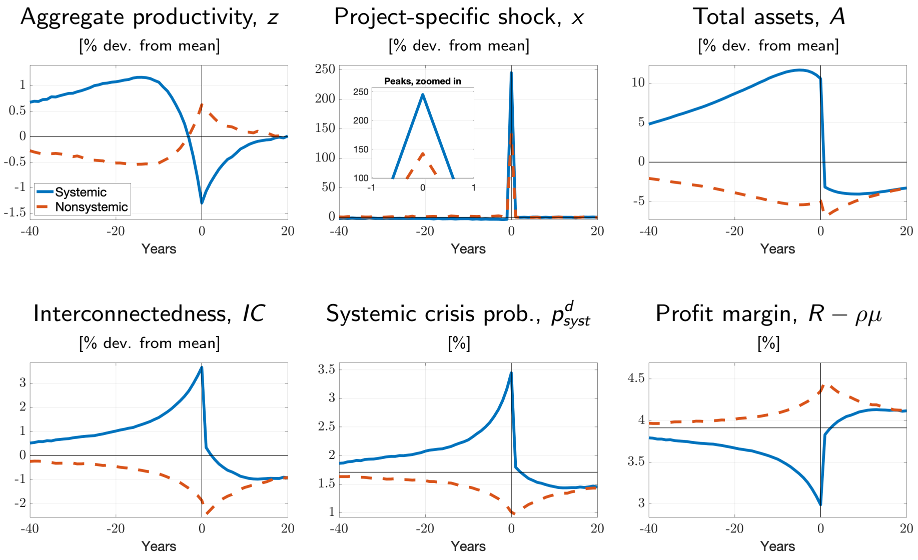


Credit, productivity, lending distance | Interconnectedness | Housing and diversification | Spreads | Shocks and crises

Financial crises: Systemic vs nonsystemic



IC and crises

Financial crises: Statistics

	Model		Data: Romer and Romer (2017)	
	All	Systemic	All	Systemic
Credit boom	1.75	3.04	1.36**	2.85***
Credit bust	– 3.27	– 5.95	– 1.96***	– 2.77***
Output boom	1.00	1.21	1.34***	1.35*
Output bust	– 1.94	– 3.12	– 2.20***	– 2.70***
Frequency	4.2	1.7	4.4	1.8

All numbers are in %. Boom/bust is defined as an average 2 years growth of HP-filtered credit/output prior to/after crises. ***,**,* denote whether the value is statistically different from zero at 1%, 5% and 10% levels, respectively.

Financial crises: Statistics

- Systemic crises are preceded by large credit booms
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Financial crises: Statistics

- Systemic crises are preceded by large credit booms
  - The model matches the frequency of systemic crises (targeted)
- Credit booms are less pronounced prior to nonsystemic crises
  - The model matches the frequency of nonsystemic crises (not targeted)

	Model		Data: Romer and Romer (2017)	
	All	Systemic	All	Systemic
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JST sample | RR definition | Crisis prediction | K/Y path

III. Welfare analysis

Inefficiencies

- Incomplete markets (interbank debt financing) and real default losses
- Pecuniary externality: agents do not internalize their impact on $R \Rightarrow$ overaccumulation of assets, too high systemic risk

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- Incomplete markets (interbank debt financing) and real default losses
- Pecuniary externality: agents do not internalize their impact on $R \Rightarrow$ overaccumulation of assets, too high systemic risk
- (Constrained) planner takes this into account by reducing credit extension in booms

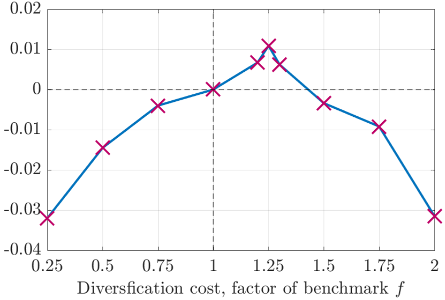
	A	C	L	Y	IC	p^d_{syst}	$p^d_{nonsyst}$	$\kappa^{DE \to SB}$
DE	4.26	1.27	1.08	1.71	0.941	1.7%	2.5%	.
SB	4.00	1.25	1.06	1.65	0.928	1.1%	2.9%	0.05%

Policy DE problem SB problem FB problem Transitional dynamics Role of rebate Aligned preferences

Welfare impacts of financial innovations

- Recent financial innovations (securitization) facilitated risk sharing
- A decline in risk-sharing cost f leads to:
  - Lower expected default losses due to better risk sharing
  - Further increase in investment in the risky technology

Welfare gain, $\kappa^{DE \to DE^f}$



	DE	SB	$DE^{optimal\ f}$
A	4.26	4.00	4.20
IC	0.941	0.928	0.927
p^d_{syst}	1.7%	1.1%	1.5%
$p^d_{nonsyst}$	2.5%	2.9%	3.4%
$\kappa^{DE \to i}$	.	0.05%	0.01%

Aligned preferences | Financial innovation

IV. Concluding remarks

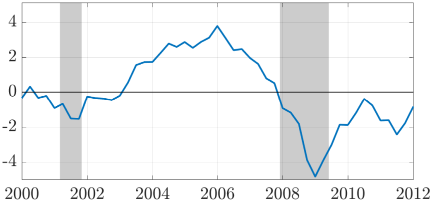
Conclusion

- A dynamic GE model of robust-yet-fragile financial systems
- Financial fragility endogenously changes over the credit cycle
  - Systemic banking crises burst at the end of credit booms
- Decentralized eq'm: overconnected networks, too frequent crises
- Financial innovations are destabilizing: number of systemic crises $\uparrow$
  - ...but welfare implications are generally ambiguous

Appendix

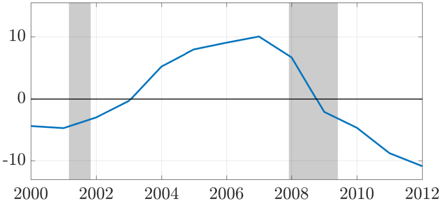
Credit and aggregate productivity

Total factor productivity
[% dev. from linear trend]



Source: Fernald (2014).
Trend is constructed starting from 1990

Loans to nonfinancial private sector
[% dev. from linear trend]



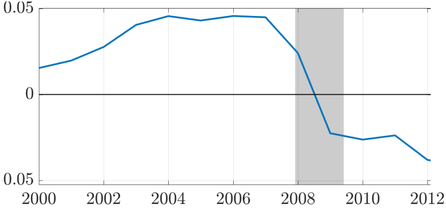
Source: Jorda, Schularick, and Taylor (2017).
Trend is constructed starting from 1990

- TFP around financial crises: Gorton and Ordonez (2018)
- Credit around financial crises: Jorda, Schularick, and Taylor (2017)

Back

Credit and aggregate productivity: UK

Total factor productivity
[% dev. from linear trend]



Source: FRED.
Trend is constructed starting from 1990

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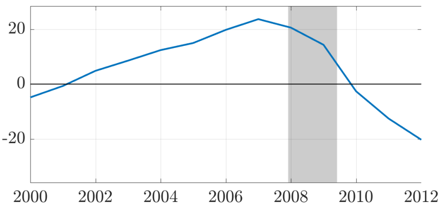

Source: Jorda, Schularick, and Taylor (2017).
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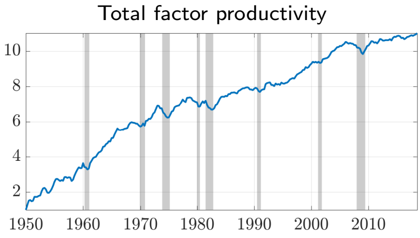
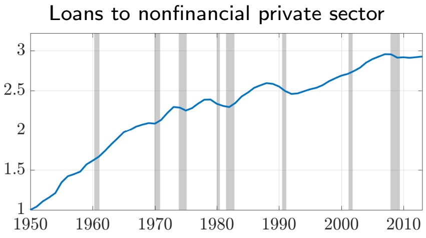
Credit and aggregate productivity: Full series



Source: Fernald (2014)



Source: Jorda, Schularick, and Taylor (2017)

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Mortgages and geographic diversification

- Geographic diversification is used to mitigate risks by mortgage investors (Cotter, Gabriel, and Roll, 2014)
  - Freddie Mac's 2007 annual report: "A key characteristic of our credit risk portfolio is diversification along a number of critical risk dimensions [such as] product mix, LTV ratios and *geographic concentrations*..."
  - Substantial pre-crisis decline in share of geographically concentrated mortgage lenders (Loutskina and Strahan, 2011)
- Geographic concentration is significantly *negatively* associated with proportion of RMBS deal rated AAA (Nadauld and Sherlund, 2009; Ashcraft, Goldsmith-Pinkham, and Vickery, 2010)

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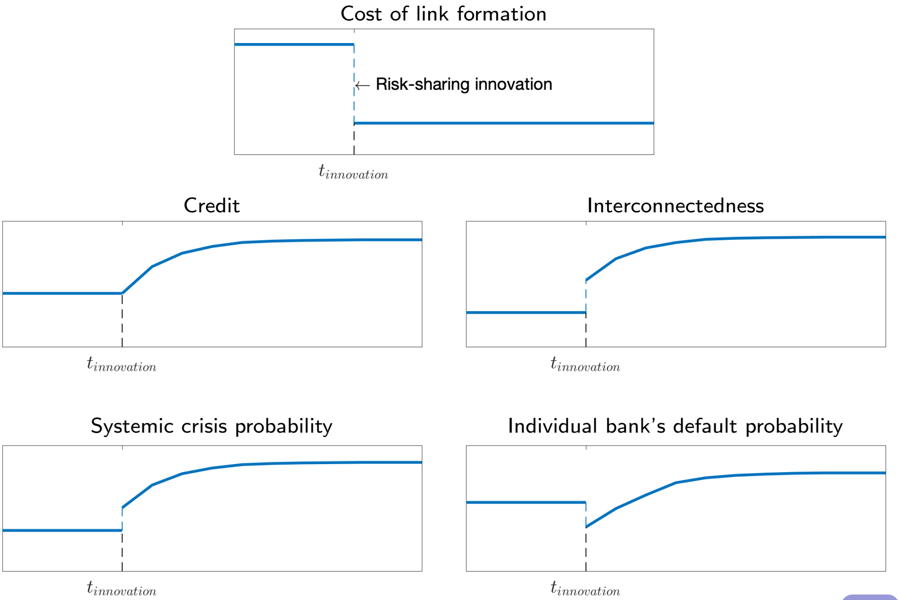
Financial innovation: Reduction in cost of link formation



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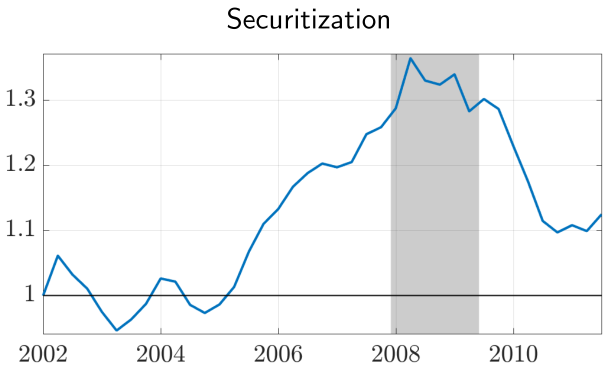
Interconnectedness: Measures I



$$\frac{\text{Nonagency MBS} + \text{ABS}}{\text{Assets}}$$

100 largest US BHC (FR Y-9C)

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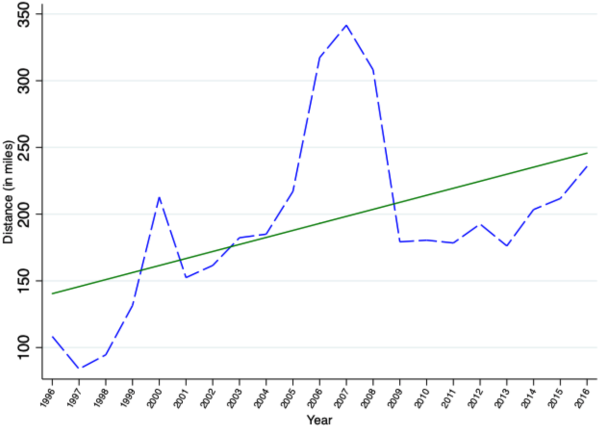
Interconnectedness: Measures II

Average banks' lending distance



Granja, Leuz, and Rajan (2019)

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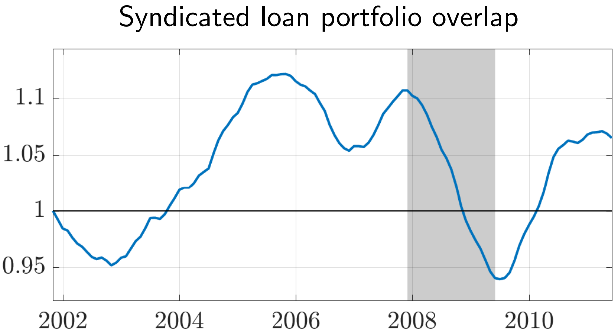
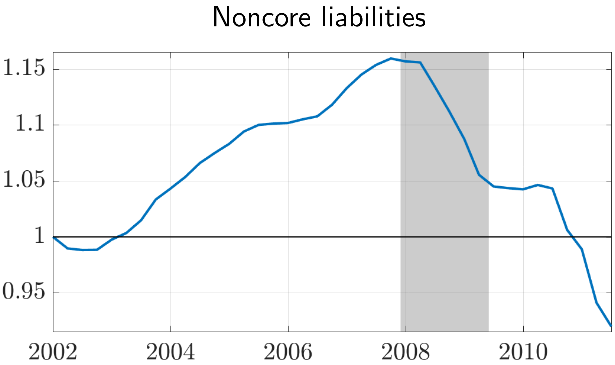
Interconnectedness: Measures III



Cai, Eidam, Saunders, and Steffen (2018)

Hedging Back

Interconnectedness: Measures IV



$$\frac{\text{Liabilities} - \text{Deposits}}{\text{Assets}}$$

Source: Barattieri et al. (2018), 100 largest US BHC (FR Y-9C)

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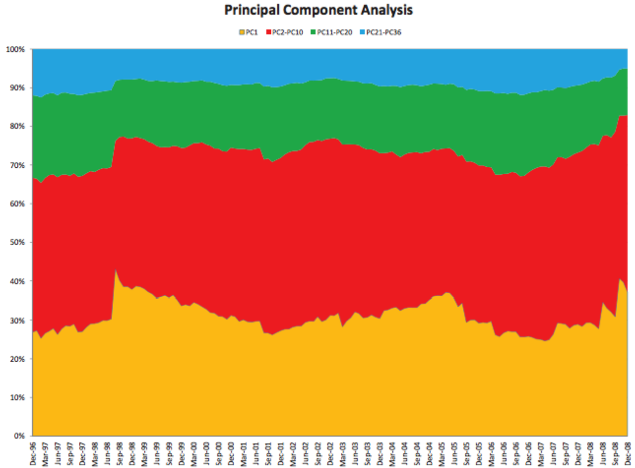
Interconnectedness: Measures V

- PCA of banks', hedge funds', broker/dealers', insurance firms' returns



Source: Billio, Getmansky, Lo, and Pelizzon (2012)

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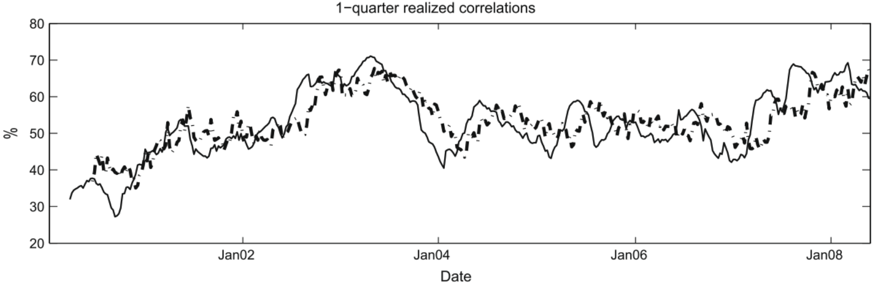
Interconnectedness: Measures VI

- Average equity returns correlation across 12 major U.S. banks



Source: Huang, Zhou, and Zhu (2009)

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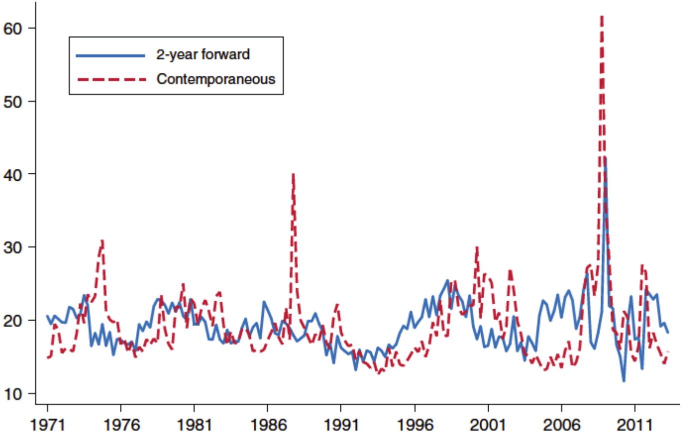
Interconnectedness: Measures VII

- Procyclicality of *forward-*$\Delta CoVaR$



Source: Adrian and Brunnermeier (2016)

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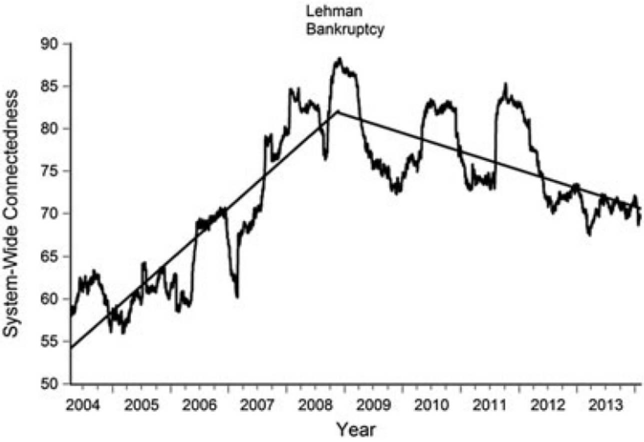
Interconnectedness: Measures VIII

- Volatility interconnectedness between major international banks



Source: Demirer, Diebold, Liu, and Yilmaz (2016)

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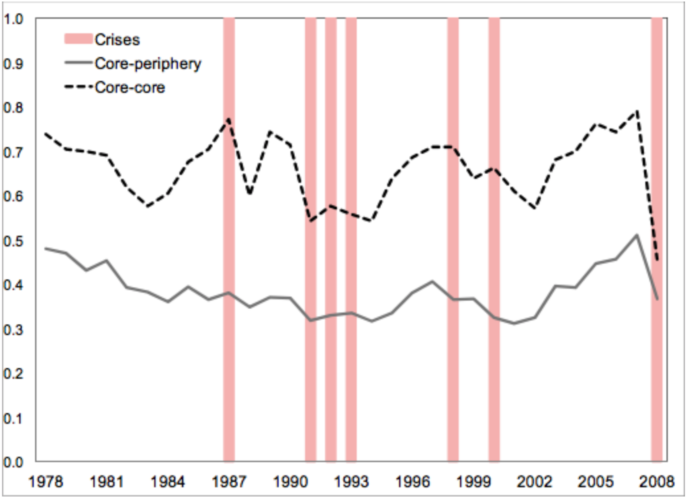
Interconnectedness: Measures IX

- Country-level interbank flows network: fraction of all possible links established



Source: Minoiu and Reyes (2013)

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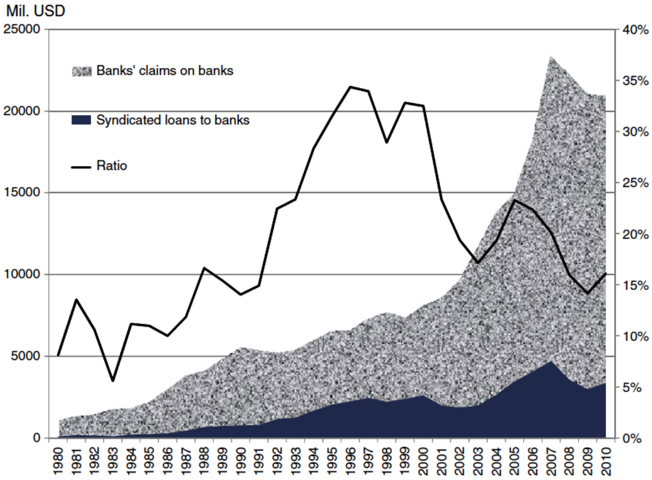
Interconnectedness: Measures X

- International interbank syndicated loans



Source: Hale (2012)

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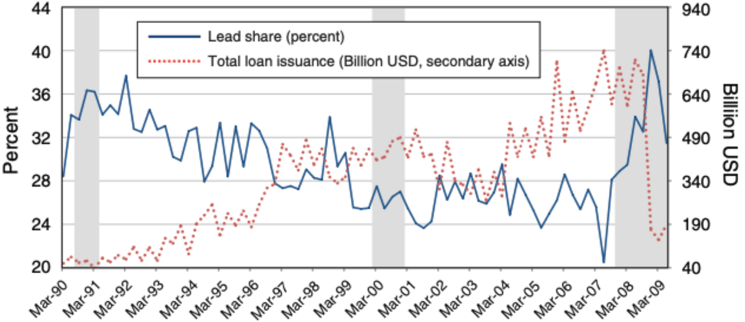
Interconnectedness: Measures XI

- US syndicated loans: Loan share retained by the originating bank and total loan issuance



Source: Ivashina and Scharfstein (2010)

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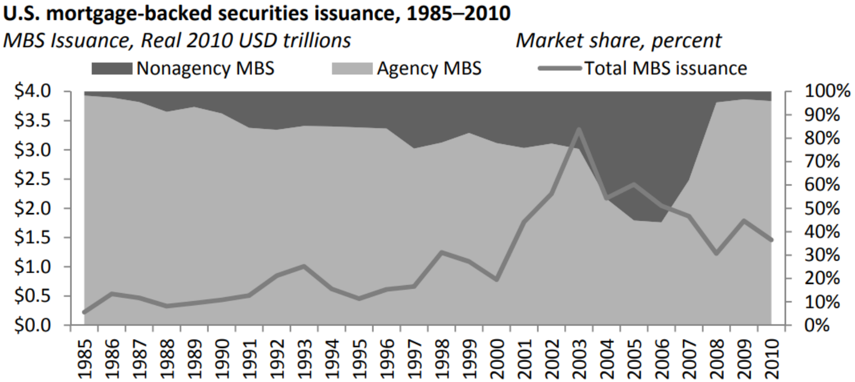
Securitization: Agency vs private



Source: Simkovic (2013)

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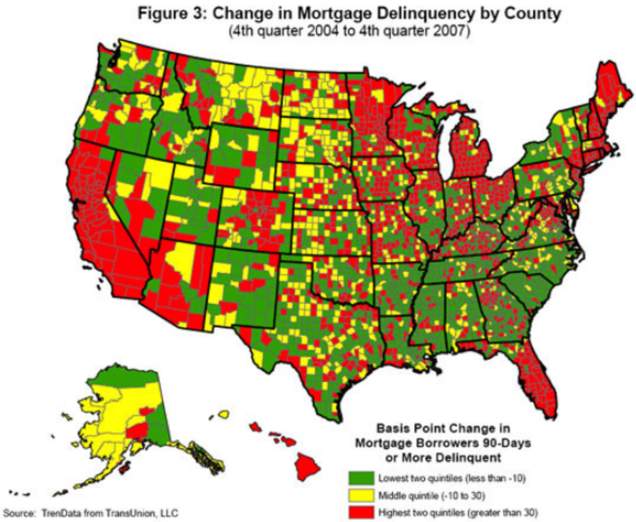
Mortgage crisis: Regional pattern



Source: Bernanke (2008)

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Measure of systemic risk

- Systemic risk: tail comovement between individual institutions and the whole system
  - *CoVaR* measure of Adrian and Brunnermeier (2016)

$$SR = \mathbb{P}\left[\text{All banks default} \middle| \text{Bank } i \text{ defaults}\right]$$

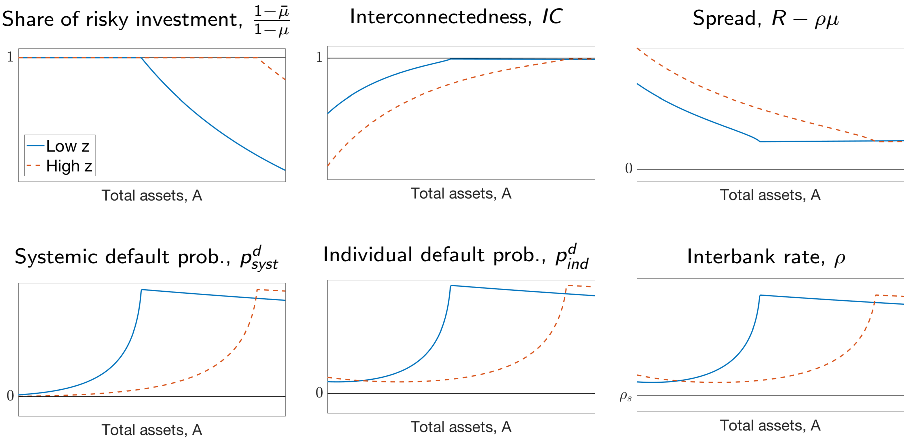
$$SR = \frac{\left(\frac{1-\alpha}{N-1}\right)^{\gamma}}{\frac{1}{N}\alpha^{\gamma} + \frac{N-1}{N}\left(\frac{1-\alpha}{N-1}\right)^{\gamma}}$$

- $\frac{\partial SR}{\partial \alpha} < 0$: higher systemic risk in densely connected systems

Back

Comparative statics: Summary

- Regime 1: high projects' return R, no investment in storage, $\mu = \bar{\mu}$
- Regime 2: low R, nonzero investment in storage, $\mu < \bar{\mu}$



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Interconnectedness and systemic risk: Derivation details

- Denote profit margin $\xi = R - \rho\bar{\mu}$. Then bank's problem can be written as

$$\max_{\rho,\alpha} \frac{a_0}{1-\bar{\mu}} \left[R - \rho_s\bar{\mu} - \theta g_1(\alpha,\xi) - \frac{1}{N}\mathbb{E}_x\tilde{x} - f(1-\alpha) \right],$$
$$\text{s.t. } \rho_s = \rho - \frac{1}{\bar{\mu}}\left(\theta g_1(\alpha,\xi) + g_2(\alpha,\xi)\right).$$

- First order conditions imply

$$B(\alpha,\xi) = \frac{\frac{\partial g_1}{\partial \alpha} + \frac{\partial g_1}{\partial \alpha}\frac{\partial g_2}{\partial \xi} - \frac{\partial g_1}{\partial \xi}\frac{\partial g_2}{\partial \alpha}}{1 + \theta\frac{\partial g_1}{\partial \xi} + \frac{\partial g_2}{\partial \xi}} - \frac{f}{\theta} = 0.$$

- Under sufficiently thin tailed project-specific shocks

$$\frac{\partial B}{\partial \alpha} > 0, \quad \frac{\partial B}{\partial \xi} < 0.$$

- Hence, optimal α and ξ move in the same direction.

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Number of islands

- In the benchmark analysis we use $N = 10$
  - Results are largely unchanged if N is increased (and $\underline{x}$ is recalibrated)
- Number of two-digit SIC industries (Cai et al., 2018)
- 10 largest BHCs account for 70% of total assets (FR Y-9C)
- 10 PCs explain $\approx$ 80% of financial firms' return variation (Billio et al., 2012)

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Number of islands

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  - Results are largely unchanged if N is increased (and $\underline{x}$ is recalibrated)
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- 10 largest BHCs account for 70% of total assets (FR Y-9C)
- 10 PCs explain $\approx$ 80% of financial firms' return variation (Billio et al., 2012)
- Main asset classes of BHCs:

	Weight		Weight
Residential RE Loans	14.12%	Residual Securities	3.21%
C&I Loans	9.69%	Treasuries	2.27%
Repo	9.02%	Equities	2.02%
Agency MBS	8.80%	Nonagency MBS	1.74%
Consumer Loans	8.36%	Agency Securities	1.32%
Cash	7.55%	Municipal Securities	1.28%
Commercial RE Loans	6.55%	Lease Financing	1.13%
ABS and Other Debt Securities	6.46%	Other RE Loans	0.92%
Residual Loans	4.62%	Residual Assets	10.97%

100 largest BHCs from FR Y-9C, 2001-2017

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Macroeconomic moments

- Aggregate productivity: $\log z' = \rho_z \log z + \sigma_z \epsilon'_z,\ \epsilon'_z \sim \mathcal{N}(0,1)$
  - σ_z and ρ_z are chosen to match persistence and st.dev. of Solow residuals

	Output	Hours	Consumption	Investment
Data	1.98	1.70	0.74	5.06
Model	2.23	1.60	1.71	4.16

Standard deviations of macro variables: Model vs postwar US data (1950-2017). All series are HP-filtered with the smoothing parameter of $\lambda = 6.25$.

- x shocks and occasional financial crises generate excess kurtosis and negative skewness of output
  - Data: $\text{Skew}(Y) = -0.57$, $\text{Kurt}(Y) = 3.52$
  - Model (benchmark): $\text{Skew}(Y) = -0.16$, $\text{Kurt}(Y) = 3.64$
  - Model (no default losses): $\text{Skew}(Y) = -0.02$, $\text{Kurt}(Y) = 3.14$

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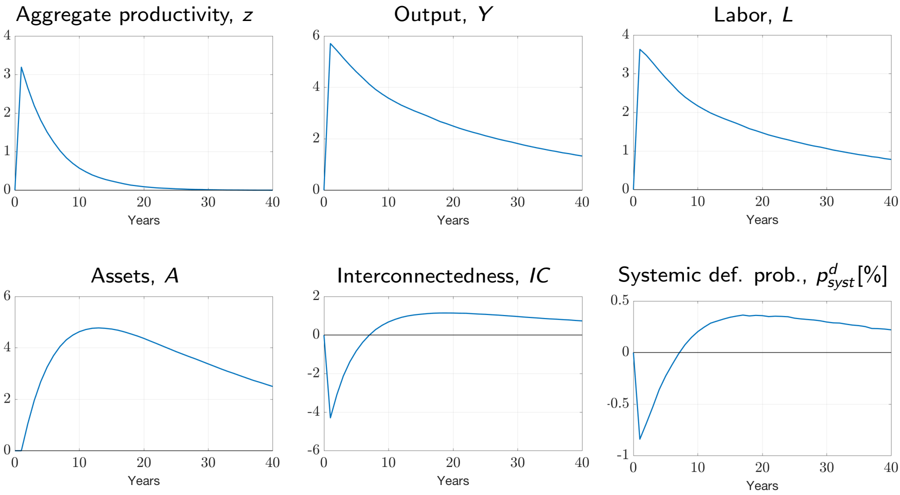
Impulse response functions: Shock to z



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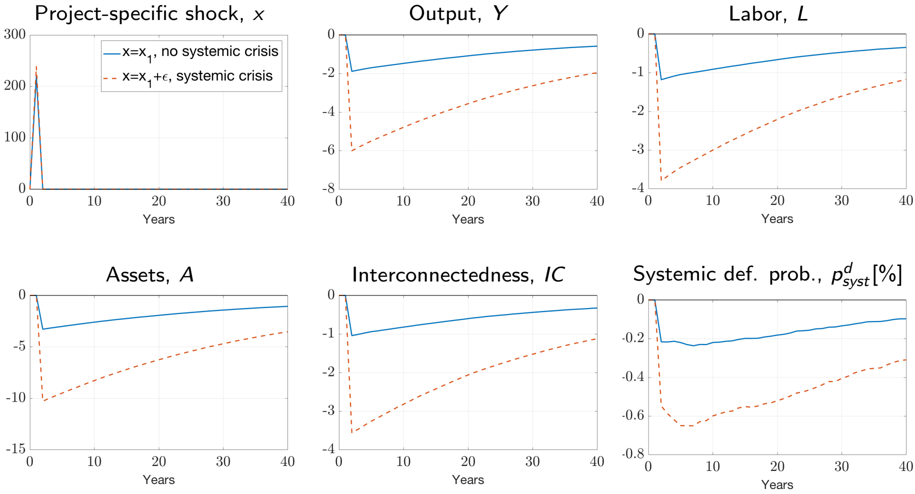
Impulse response functions: Shock to x



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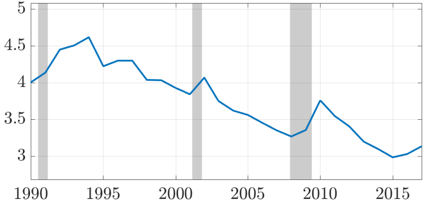
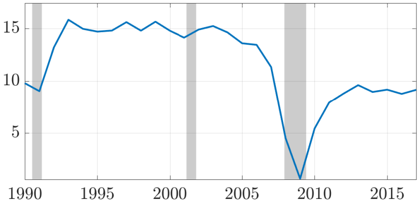
Banks' returns

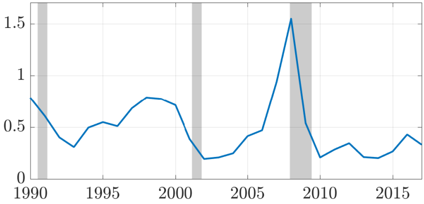
Net interest margin for all U.S. banks [%]



Return on equity for all U.S. banks [%]



TED spread [%]



- Source: FRED

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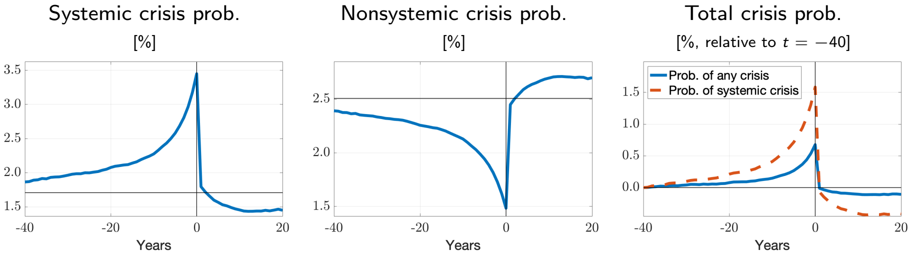
Crises probabilities

- Run-up of a systemic financial crisis:
  - Banks become more alike ⇒ less likely to default in isolation
  - Probability of *some* financial distress grows only marginally (≈CDX, top tranche)



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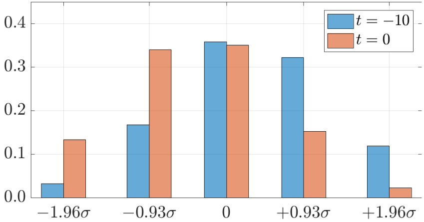
Shocks leading to systemic crises

- Aggregate productivity z:
  - High in the run-up of credit booms
  - Low right prior to systemic crises

Aggregate productivity, z



$$\sigma = \frac{\sigma_z}{\sqrt{1-\rho_z^2}}$$

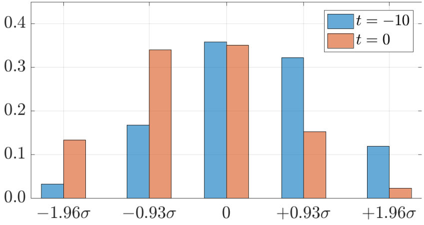
$t = 0$: systemic crisis

$t = -10$: ten periods before systemic crisis

Shocks leading to systemic crises

- Aggregate productivity z:
  - High in the run-up of credit booms
  - Low right prior to systemic crises

Aggregate productivity, z



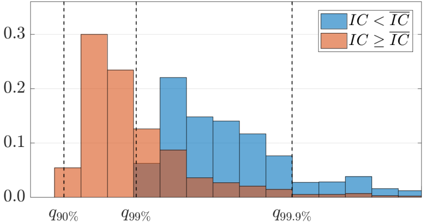
$$\sigma = \frac{\sigma_z}{\sqrt{1-\rho_z^2}}$$

$t=0$: systemic crisis

$t=-10$: ten periods before systemic crisis

- Systemic crises burst in densely connected networks
  - 88% occur when $IC \geq \overline{IC}$

Project-specific shock x at the moment of systemic crisis



$$\mathbb{P}\left[x \leq q_{p\%}\right] = p\%$$

$IC < \overline{IC}$: below average connectedness

$IC \geq \overline{IC}$: above average connectedness

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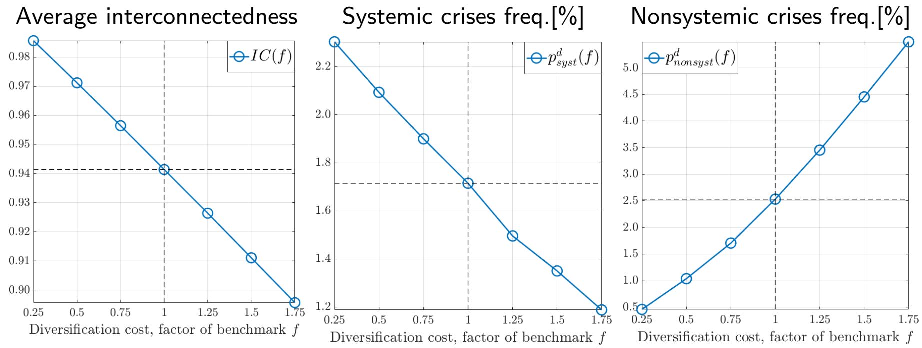
Inspecting the mechanism: Interconnectedness and crises

- $f \downarrow \Rightarrow IC \uparrow$ and $A \uparrow \Rightarrow p^d_{syst} \uparrow$, $p^d_{nonsyst} \downarrow$



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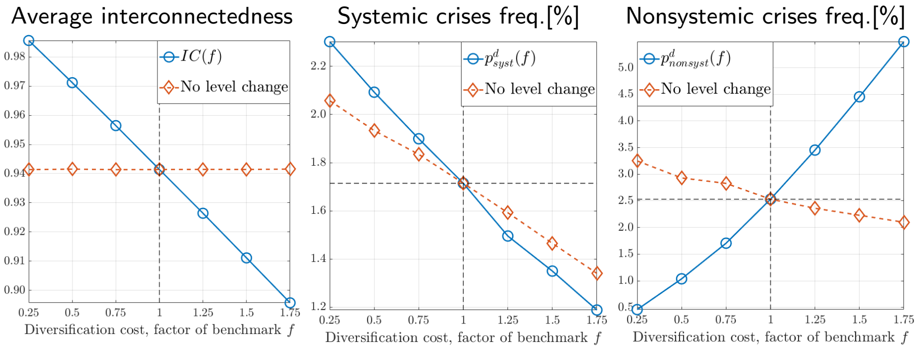
Inspecting the mechanism: Interconnectedness and crises

- $f \downarrow \Rightarrow IC \uparrow$ and $A \uparrow \Rightarrow p^d_{syst} \uparrow$, $p^d_{nonsyst} \downarrow$
- *Level* effect: same change in f holding average IC fixed



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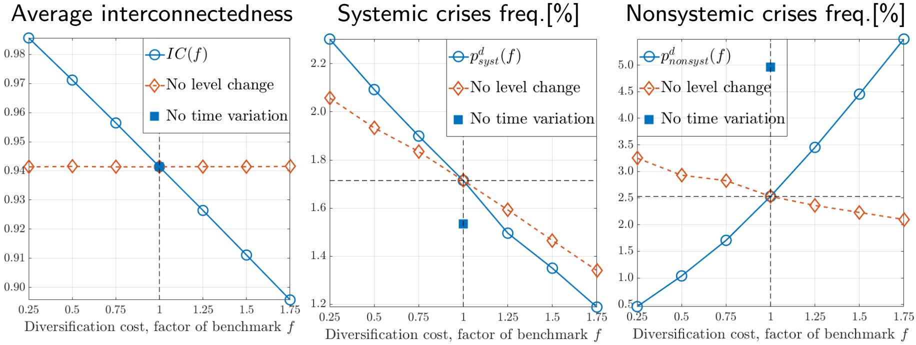
Inspecting the mechanism: Interconnectedness and crises

- $f \downarrow \Rightarrow IC \uparrow$ and $A \uparrow \Rightarrow p^d_{syst} \uparrow$, $p^d_{nonsyst} \downarrow$
- *Level* effect: same change in f holding average IC fixed
- *Time variation* effect: fixed IC over the business cycle



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Financial crises: Statistics

	Model		Data: RR		Data: JST	
	All	Systemic	All	Systemic	RR sample	Full sample
Credit boom	1.75***	3.04***	1.36**	2.85***	3.02***	3.18***
Credit bust	−3.27***	−5.95***	−1.96***	−2.77***	−1.32*	−3.14***
Output boom	1.00***	1.21***	1.34***	1.35*	1.77***	1.33***
Output bust	−1.94***	−3.12***	−2.20***	−2.70***	−2.76***	−2.49***
Frequency	4.2	1.7	4.4	1.8	3.1	4.0

All numbers are in %. Boom/bust is defined as an average 2 years growth of HP-filtered credit/output prior to/after crises. 'JST' and 'RR' stand for Jorda, Schularick, and Taylor (2016) and Romer and Romer (2017), respectively. ***,**,* denote whether the value is statistically different from zero at 1%, 5% and 10% levels, respectively.

Back

Romer and Romer (2017): Crises definition

- Financial distress in 24 OECD countries, 1967-2012
  - Consistent narrative source: OECD Economic Outlook
- *Nonsystemic crisis* should at most involve "...significant problems in the financial sector that are not so severe [to be] central to recent macroeconomic developments or to the economy's prospects"
  - Examples: Australia (2008), Canada (2008), France (1996)
- *Systemic crisis*, at a minimum, should "...involve problems in the financial sector that are widespread and severe, central to the performance of the economy as a whole"
  - Examples: USA (2007-2009), Japan (1997-1999), Sweden (1993)

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Systemic crises: Prediction

- Prediction of model-implied probability of systemic crisis

	OLS: $\log p^d_{syst,t+1}$			
$\log(z_t)$	-8.3	.	.	-12.0
$\log(A_t)$	.	4.4	.	4.3
$\log(IC_t)$	.	.	19.2	4.4
R^2	7.4%	52.7%	72.0%	78.9%

Based on 1,000,000 simulations. All coefficients are significant at 1% level

- Early warning signals for systemic crises

	Logit: $\mathbb{I}\{\text{systemic crisis}\}_{t+1}$			
	(z_t)	(A_t)	(IC_t)	(z_t, A_t, IC_t)
R^2_{pseudo}	0.6%	4.2%	6.5%	6.8%
Type I error	100%	85.9%	60.5%	69.7%
Type II error	0%	5.2%	13.5%	10.0%
# of signals	0	53,930	139,854	103,632

Based on 1,000,000 simulations and 17,170 realizations of systemic crises. Threshold is chosen to have Type II error of 10% for specification (z_t, A_t, IC_t)

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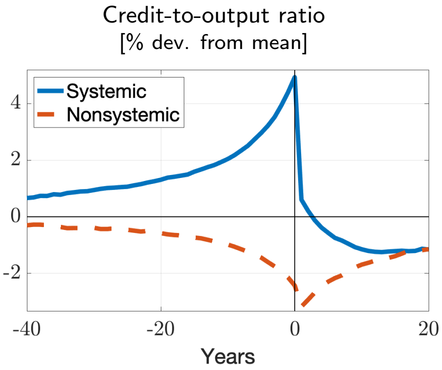
Credit-to-output ratio



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Decentralized equilibrium: Recursive formulation

- The household solves

$$V^{DE}(a, A, z, x) = \max_{c,l,a'} \frac{1}{1-\psi}\left(c - \frac{l^{1+\nu}}{1+\nu}\right)^{1-\psi} + \beta \mathbb{E} V^{DE}(a', A', z', x'),$$

$$\text{s.t. } a' + c = r(A, z, x)a + w(A, z)l + \chi(\alpha(R(A, z))),$$

$$r(A, z, x) = R(A, z) - \frac{1}{N}x - \frac{N^d(R(A, z), x)}{N}\theta - \frac{1}{A}\chi(\alpha(R(A, z))),$$

$$R(A, z) = \eta z A^{\eta-1} L(A, z)^{1-\eta} + 1 - \delta,$$

$$w(A, z) = (1-\eta) z A^{\eta} L(A, z)^{-\eta},$$

$$A' = A'(A, z, x).$$

- $N^d(R, x)$ and $\alpha(R)$ solve interbank problem
- Labor market clears: $l(A, A, z) = L(A, z)$
- Goods market clears: $C + A' = zA^{\eta}L^{1-\eta} + A\left(1 - \delta - \frac{1}{N}x - \frac{N^d}{N}\theta\right)$
- Aggregate law of motion is consistent with individual choice: $a'(A, A, z, x) = A'(A, z, x)$

Back

Constrained planner: Recursive formulation

- The planner makes saving decisions for the household and allows labor and interbank markets to operate like in the DE case
- The planner internalizes that over-accumulation of assets leads to a fragile financial system. It also internalizes that linking costs are rebated to the household

$$V^{SB}(A,z,x) = \max_{C,A'} \frac{1}{1-\psi}\left(C - \frac{L(A,z)^{1+\nu}}{1+\nu}\right)^{1-\psi} + \beta \mathbb{E} V^{SB}(A',z',x'),$$

$$\text{s.t. } A' + C = zA^{\eta}L(A,z)^{1-\eta} + A\left(1 - \delta - \frac{1}{N}x - \frac{N^d(R(A,z),x)}{N}\theta\right).$$

- $N^d(R(A,z),x)$ solves interbank problem
- $L(A,z)$ solves $L(A,z)^{\nu} = (1-\eta)zA^{\eta}L(A,z)^{-\eta}$
- $R(A,z) = \eta z A^{\eta-1}L(A,z)^{1-\eta} + 1 - \delta$

Back

First best allocation: Recursive formulation

- In the first best, defaults are not costly ($\theta = 0$) and the economy reduces to a standard RBC model

$$V^{FB}(A,z,x) = \max_{C,L,A'} \frac{1}{1-\psi}\left(C - \frac{L^{1+\nu}}{1+\nu}\right)^{1-\psi} + \beta \mathbb{E} V^{FB}(A',z',x'),$$

$$\text{s.t. } A' + C = zA^{\eta}L^{1-\eta} + A\left(1 - \delta - \frac{1}{N}x\right).$$

	K	C	L	Y	IC	p^d_{syst}	$p^d_{nonsyst}$	$\kappa^{DE\to i}$
DE	4.26	1.27	1.08	1.71	0.941	1.7%	2.5%	.
SB	4.00	1.25	1.06	1.65	0.928	1.1%	2.9%	0.05%
FB	4.67	1.34	1.12	2.81	.	.	.	0.78%

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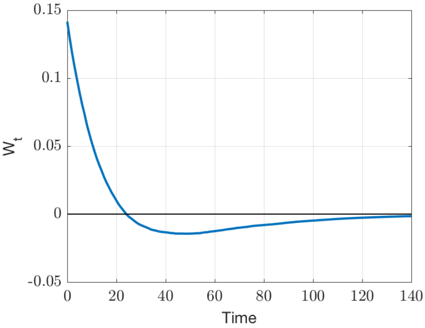
Transitional dynamics: $DE \rightarrow SB$

$$\Delta W = \sum_{t=0}^{\infty} W_t, \text{ where } W_t = \beta^t \mathbb{E}_0 \left[u(C_t^{SB}, L_t^{SB}) - u(C_t^{DE}, L_t^{DE}) \right]$$



- Dissaving at the initial stages of transition $\Rightarrow$ welfare gains
- (Discounted) welfare losses at a lower steady state later on
  - Fewer painful systemic crises in the new steady state

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Cost of intertemporal inefficiencies

No rebate externality

- Consider an economy where linking costs are *not* rebated to the hh

	A	C	L	Y	IC	p^d_{syst}	$p^d_{nonsyst}$	$\kappa^{DE \to SB}$
				Benchmark case				
DE	4.26	1.27	1.08	1.71	0.941	1.7%	2.5%	.
SB	4.00	1.25	1.06	1.65	0.928	1.1%	2.9%	0.05%
				No rebate externality				
$DE^{no\ rebate}$	4.25	1.25	1.08	1.70	0.941	1.7%	2.5%	.
$SB^{no\ rebate}$	3.80	1.21	1.04	1.61	0.913	0.9%	3.1%	0.12%

- Rebate and oversaving externalities work against each other
- *DE* and *SB* allocations get further from each other

Back

Aligned risk preferences

- Benchmark case: risk-averse households, risk-neutral banks
- What if preferences are aligned?
  - No analytical results, more complicated numerical algorithm
  - Results are affected marginally

	A	C	L	Y	IC	p^d_{syst}	$p^d_{nonsyst}$	$\kappa^{DE\to SB}$
				Benchmark case				
DE	4.26	1.27	1.08	1.71	0.941	1.7%	2.5%	.
SB	4.00	1.25	1.06	1.65	0.928	1.1%	2.9%	0.05%
				Aligned risk preferences				
$DE^{aligned\ pref.}$	4.27	1.27	1.08	1.71	0.938	1.7%	3.0%	.
$SB^{aligned\ pref.}$	3.99	1.24	1.06	1.65	0.924	1.1%	3.3%	0.05%

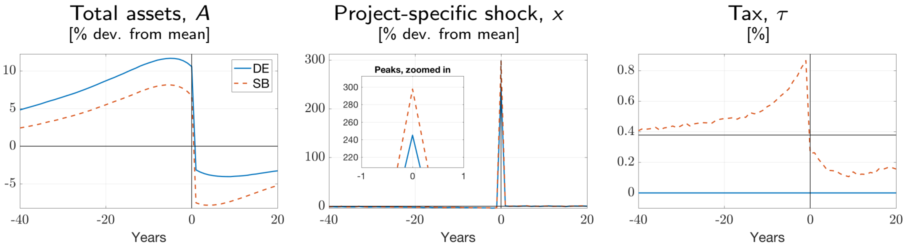
Back

Optimal policy: Savings tax

- Policy to reach *SB* allocation: state-contingent tax on savings A'

$$1+\tau(A,z,x)=\beta\mathbb{E}\left[\left(\frac{C'_{SB}-\frac{1}{1+\nu}L'^{1+\nu}_{SB}}{C_{SB}-\frac{1}{1+\nu}L^{1+\nu}_{SB}}\right)^{-\psi}\times r(A'_{SB},z',x')\right]$$

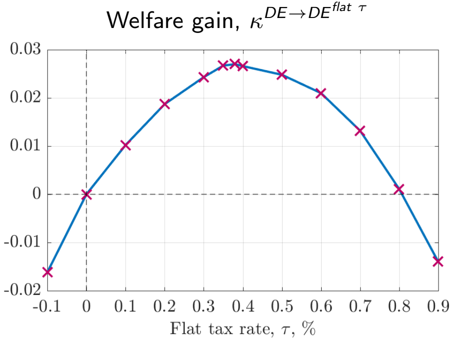
- Tax is positive on average (0.38%)
- Tax prevents large credit booms and speeds up post-crises recoveries



Flat tax Back

Flat tax on savings

- State-contingent tax might be challenging to implement
- Flat tax corrects the steady state but not business cycle fluctuations



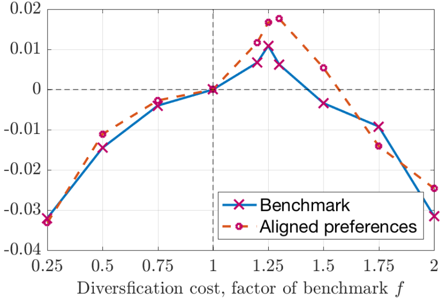
	DE	SB	$DE^{flat\ \tau}$
A	4.26	4.00	4.00
IC	0.941	0.928	0.925
p^d_{syst}	1.7%	1.1%	1.2%
$p^d_{nonsyst}$	2.5%	2.9%	2.9%
$\kappa^{DE \to i}$	.	0.05%	0.03%

Back

Financial innovations: Aligned risk preferences

- Benchmark case: risk-averse households, risk-neutral banks
- Systemic crises are more painful for hhs $\Rightarrow$ too many connections?
  - Might be important for welfare impacts of financial innovations
- Aligned preferences: risk-sharing cost, not risk aversion, limits *IC*
  - Minor impact of preferences misalignment on the welfare analysis

Welfare gain, $\kappa^{DE \to DE^f}$



	DE	SB	$DE^{optimal\ f}$
A	4.27	3.99	4.19
IC	0.938	0.924	0.921
p^d_{syst}	1.7%	1.1%	1.5%
$p^d_{nonsyst}$	3.0%	3.3%	3.9%
$\kappa^{DE \to i}$	.	0.05%	0.02%

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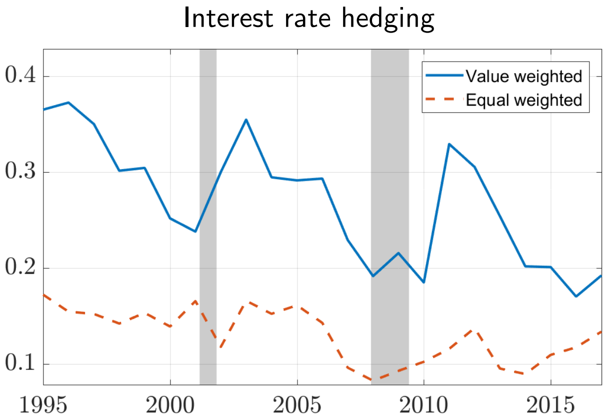
Hedging: Interest rate derivatives



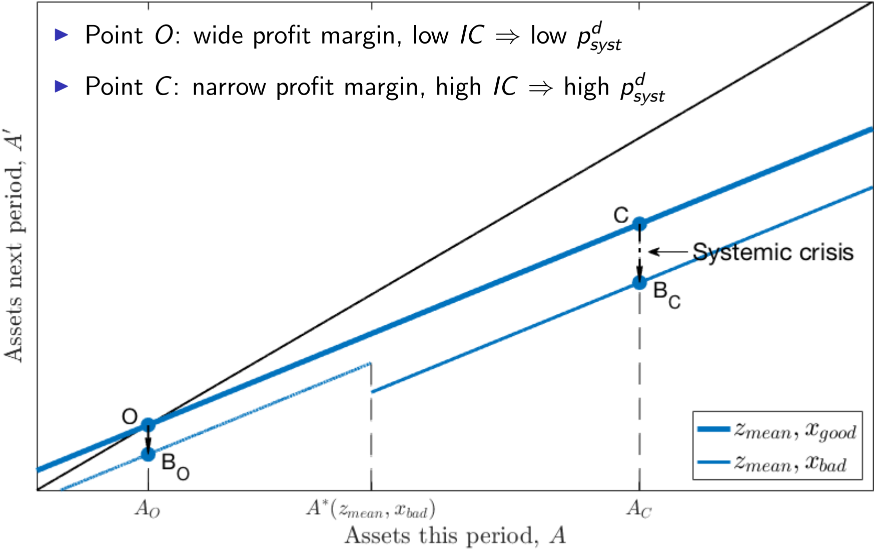
$$\frac{\text{Interest rate derivatives held not for trading}}{\text{Assets}}$$

Source: Rampini et al. (2017), 100 largest US BHC (FR Y-9C)

Back

Asset accumulation policy: State-dependent fragility

- Point O: wide profit margin, low $IC \Rightarrow$ low p^d_{syst}
- Point C: narrow profit margin, high $IC \Rightarrow$ high p^d_{syst}



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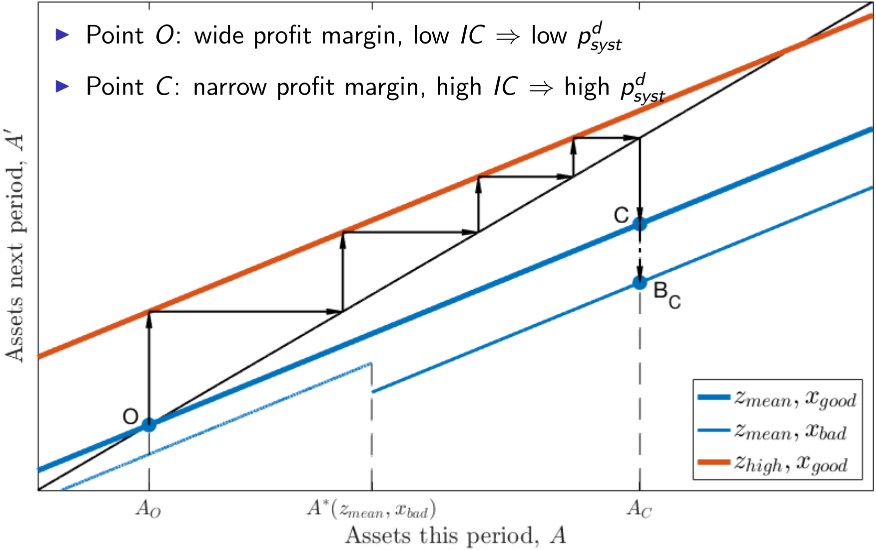

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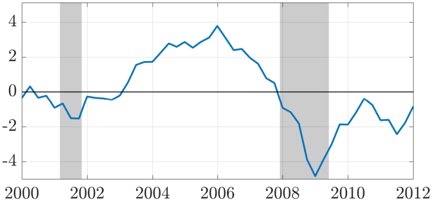
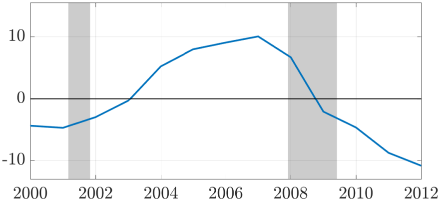
Credit, aggregate productivity, and lending distance

Total factor productivity
[% dev. from linear trend]



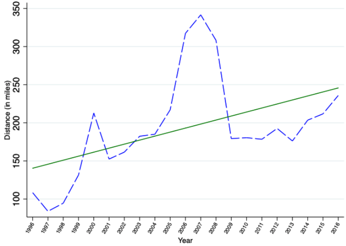
Source: Fernald (2014)

Loans to nonfinancial private sector
[% dev. from linear trend]



Source: Jorda, Schularick, and Taylor (2017)

Average banks' lending distance



Source: Granja, Leuz, and Rajan (2019)

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