

# Firebreaks and Risk-Shifting in Financial Networks

Matthew Elliott  
Cambridge

Co-Pierre Georg  
UCT & Bundesbank

Jonathon Hazell  
MIT

April 3, 2018

# Motivation

- Two main sources of systemic risk:
  - ① correlations in exposures outside the financial system
  - ② counter-party risk
  
- Interaction between sources could be important.

# Motivation

- For example,
  - ▶ correlations in non-financial exposures could create simultaneous losses,
  - ▶ and then financial linkages could propagate failures.
- Policy makers concerned about correlated risks
  - ▶ e.g., Basel III.
  - ▶ but tend to treat interbank and real economy risks as independent (Bandt et al., 2012).

# Portfolio and counterparty choices

Standard view: Diversification motives mean counterparties with less correlated portfolios are preferred.

- For example, Allen and Gale (2000).

## But, in practice...

Those most exposed to sub-prime mortgages traded extensively with each other.

*“Among U.S. bank holding companies, of the notional amount of OTC derivatives, millions of contracts, were traded by just five large institutions (JPMorgan Chase, Citigroup, Bank of America, Wachovia, and HSBC)—many of the same firms that would find themselves in trouble during the financial crisis.”*

—Financial Crisis Inquiry Commission (2011)

# Some anecdotes

Merrill and ACA:

- Merrill was heavily exposed to the subprime crisis.
- Hedged exposure with CDS contracts with monoline insurer ACA.
- ACA was also long the housing market.
- ACA was downgraded by S&P to junk status.
- Merrill taken over by BoA.

Similar patterns at:

- (i) Bear Sterns and Carlyle Capital Group.
- (ii) Wachovia and Lehman.

# This talk

Is there any systematic evidence for banks having counterparties with relatively similar non-financial exposures?

If so, is this bad?

And how could it be explained?

# Preview: Systematic evidence

Would like a setting in which:

- 1 Financial institutions' interdependencies are large and observable (on-book).
- 2 Financial institutions' main non-financial exposures are large and observable (on-book).



# German commercial banking

German commercial banking perfectly fits the bill:

- 1 Substantial, long-term, interbank loans reported to the Bundesbank that generates systemic risk.
  - ▶ Upper and Worms (2004).
- 2 Substantial loans to firms reported to the Bundesbank.

# Empirical question

Do commercial German banks lend more to each other when they have more similar non-bank loan portfolios?

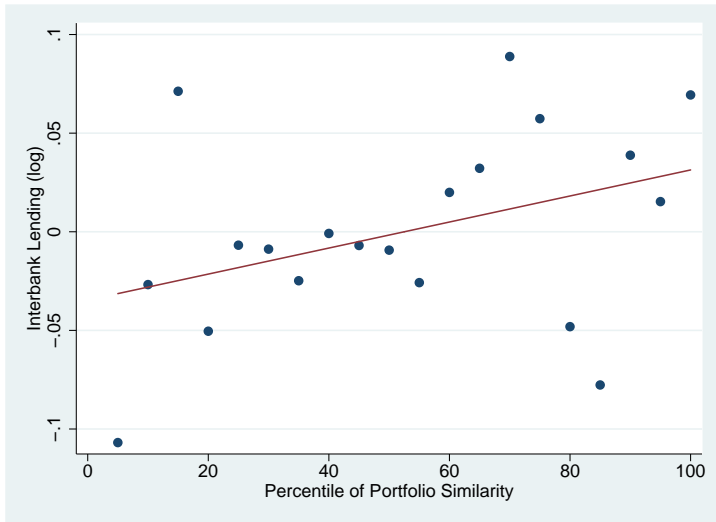
# Empirical question

Do commercial German banks lend more to each other when they have more similar non-bank loan portfolios?

In other words, is there homophily in this network?

# Evidence of homophily

We find a substantial, robust and statistically significant positive relationship.



# Evidence of homophily

In our data, when two banks move from the 25th to the 75th percentile of non-financial portfolio similarity, their net lending to one another grows by roughly 26%.

# Preview: Theory

- Planner would choose uncorrelated underlying exposures and networks with firebreaks.
- But these outcomes are not stable.
- Banks have profitable deviations to make their shocks correlated with their counterparties, to risk-shift.

# Outline

- 1 Stylized Fact: Homophily in Financial Networks
- 2 Parsimonious Theoretical Model
- 3 Social Planner's Solution
- 4 Stable networks
- 5 Conclusions

# Implementation

- German banking system.
  - ▶ 2006/Q1 to 2014/Q4.
- Financial connections: Interbank lending.
  - ▶ Over-the-counter market of secured and unsecured loans generates an Interbank network.
  - ▶ In Germany, about 25-30% of total balance sheet size.
  - ▶ Average loan is long-term (maturity  $> 1$  year).
  - ▶ Network has a core-periphery structure.
- Exposures: Loans to businesses.



# Data

- Quarterly data from the German large credit registry.
  - ▶ All commercial loans
  - ▶ Collected under the German Banking Act.
- Matched with monthly balance sheet statistics (BISTA).
  - ▶ Reported to Bundesbank by all financial institutions located in Germany.

# Computing loan book similarity

Standard Euclidean measure:

- Construct a vector space  $V$  of investments ( $|V| = N$ ).
- Bank  $i$ 's investment in quarter  $t$  is a vector  $v_{i,t}$
- Construct distance measure between the portfolios:

$$\text{Dist}_{ij,t} = \sqrt{\sum_{k=1}^N (v_{i,k} - v_{j,k})^2}$$

- Similarity between banks is high if distance is low.

# Empirical setup

- Empirical setup: Simple panel estimation
- Dependent variable: log of normalized amount of interbank lending from bank  $i$  to bank  $j$  in quarter  $t$ :

$$\log(\text{NormAmount}_{ij,t}) = \beta_{i,T} + \beta_{j,T} + \beta_{ij} + \beta_t + \gamma \log(\text{Dist}_{ij,t}) + \varepsilon_{ij,t}.$$

- But don't care if interbank lending instead causes portfolio changes.
- Standard errors are clustered on borrower, lender, and time level.
- Variation is on the intensive margin.

# Results

$\log(\text{NormAmount}_{ij,t})$	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
$\log(\text{NormDist}_{ij})$	-1.304*** (0.348)		-2.893*** (0.678)		-0.599 (0.393)	
$\log(\text{Dist}_{ij})$		-0.608*** (0.07)		-0.892*** (0.09)		-0.121** (0.05)
Fixed Effects						
Time	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Lender + Borrower	<i>Yes</i>	<i>Yes</i>	-	-	-	-
Time-varying						
Lender + Borrower	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Borrower-Lender	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>Yes</i>
N	33,885	33,885	33,745	33,745	33,048	33,048
$R^2$	0.407	0.423	0.464	0.487	0.660	0.660

Robustness checks: Extensive margin variation, time varying bank controls, sectorial similarity, Amount instead of Norm Amount.

# But...

- Is this correlation necessarily bad?
- What would a social planner choose?
- If it is inefficient, why might banks choose it?

## But...

- Is this correlation necessarily bad?
- What would a social planner choose?
- If it is inefficient, why might banks choose it?

Theory needed to think systematically about them.

# Outline

- 1 Stylized Fact: Homophily in Financial Networks
- 2 Parsimonious Theoretical Model**
- 3 Social Planner's Solution
- 4 Stable networks
- 5 Conclusions

# Hedging

- Banks:  $N = \{1, \dots, n\}$ ;



# Hedging

- Banks:  $N = \{1, \dots, n\}$ ;
- Each bank has an idiosyncratic project, stochastic return  $p_i$ ;

# Hedging

- Banks:  $N = \{1, \dots, n\}$ ;
- Each bank has an idiosyncratic project, stochastic return  $p_i$ ;
- Hedge exposures by writing risk-sharing contracts.

$A_{ij} \in [0, 1]$ :  $i$ 's proportional claim on  $j$ 's project

- Matrix of *dependencies*  $\mathbf{A}$ , non-negative and column stochastic.
- Bank values:  $v_i = \sum_j A_{ij} p_j$       ( $\mathbf{v} = \mathbf{A}\mathbf{p}$ )

# Outside liabilities

- Liabilities to (external) creditors  $\underline{v}$  for all banks.

# Outside liabilities

- Liabilities to (external) creditors  $\underline{v}$  for all banks.
- If  $v_i \geq \underline{v}$  then:
  - ▶ Outside debt holders paid in full.
  - ▶ Equity holders get  $v_i - \underline{v}$ .

# Outside liabilities

- Liabilities to (external) creditors  $\underline{v}$  for all banks.
- If  $v_i \geq \underline{v}$  then:
  - ▶ Outside debt holders paid in full.
  - ▶ Equity holders get  $v_i - \underline{v}$ .
- If  $v_i < \underline{v}$  then:
  - ▶ Outside debt holders force bankruptcy, get  $v_i$ .
  - ▶ Equity holders get 0.

# Bankruptcy costs

- Bankruptcy costs  $\beta \leq \min_j p_j$ .

# Bankruptcy costs

- Bankruptcy costs  $\beta \leq \min_j p_j$ .

- Let

$$b_i(v_i) = \beta \mathbb{I}_{v_i < \underline{v}},$$

$\mathbb{I}_{v_i < \underline{v}}$  is an indicator function.

- Subtracts from proprietary asset returns:

bank value:	$\mathbf{v} = \mathbf{A}(\mathbf{p} - \mathbf{b}(\mathbf{v}))$
equity value:	$\boldsymbol{\pi} = \max\{\mathbf{v} - \underline{\mathbf{v}}, \mathbf{0}\}$
debt value:	$\boldsymbol{\delta} = \min\{\mathbf{v}, \underline{\mathbf{v}}\}$

# Bankruptcy costs

- Bankruptcy costs  $\beta \leq \min_j p_j$ .

- Let

$$b_i(v_i) = \beta \mathbb{I}_{v_i < \underline{v}},$$

$\mathbb{I}_{v_i < \underline{v}}$  is an indicator function.

- Subtracts from proprietary asset returns:

bank value:	$\mathbf{v} = \mathbf{A}(\mathbf{p} - \mathbf{b}(\mathbf{v}))$
equity value:	$\boldsymbol{\pi} = \max\{\mathbf{v} - \underline{\mathbf{v}}, \mathbf{0}\}$
debt value:	$\boldsymbol{\delta} = \min\{\mathbf{v}, \underline{\mathbf{v}}\}$
So:	$\mathbf{v} = \boldsymbol{\pi} + \boldsymbol{\delta}$



# Payment equilibrium

- There is always a *payment equilibrium*, i.e. a vector of consistent market values  $v$ .
- Set of payment equilibria has a lattice structure.
  - ▶ Equilibria partially ordered by which set of banks fail.
  - ▶ Focus on the case where the minimum set of banks fail.

# Shocks

- Rare project-specific shocks (probability  $r$ ).
- Shocks can be large or small

$$\varepsilon = \begin{cases} \varepsilon_L > n(R - \underline{v}) & \text{w.p. } rq \\ \varepsilon_S \in (R - \underline{v}, n(R - \underline{v})) & \text{w.p. } r(1 - q). \end{cases}$$

- Large shocks are
  - ▶ much rarer ( $q < 1/n^2$ ), and
  - ▶ hit in isolation.
- Small shocks can be arbitrarily correlated.

# Small shock correlations

When a small shocks hits:

- Any subset of banks can be hit simultaneously.
- States of the world—power set of all banks.
- Probability distribution over these states such that:
  - ▶ Marginal probability each bank is hit is  $1/n$ .

# Example with 2 banks

Three possible probability distributions over shocks:

## States of the World

<i>e.g.</i>	No Shock	Small Shock				Large Shock	
		No Bank	Bank 1	Bank 2	Banks 1, 2	Bank 1	Bank 2
(a)	$1 - r$	0	$\frac{r(1-q)}{2}$	$\frac{r(1-q)}{2}$	0	$\frac{rq}{2}$	$\frac{rq}{2}$
(b)	$1 - r$	$\frac{r(1-q)}{4}$	$\frac{r(1-q)}{4}$	$\frac{r(1-q)}{4}$	$\frac{r(1-q)}{4}$	$\frac{rq}{2}$	$\frac{rq}{2}$
(c)	$1 - r$	$\frac{2r(1-q)}{2}$	0	0	$\frac{r(1-q)}{2}$	$\frac{rq}{2}$	$\frac{rq}{2}$

# Separate shocks

## Definition

Shocks are *separate* if the probability small shocks hit more than 1 bank at once is 0.

- e.g. (a) had separate shocks.

# Outline

- 1 Stylized Fact: Homophily in Financial Networks
- 2 Parsimonious Theoretical Model
- 3 Social Planner's Solution**
- 4 Stable networks
- 5 Conclusions

# Autarky outcomes

Autarky: Claims are the identity network  $\mathbf{I}$ .

$$v_i(\mathbf{I}) = R - (r/n) (q\varepsilon_L + (1 - q)\varepsilon_S + \beta)$$

We constrain our social planner in two ways

- Knows the probability distribution of returns but not the realization.
- Must respect individual rationality constraints:

$$v_i(\mathbf{A}) \geq v_i(\mathbf{I}) \quad \text{for all } i$$

# Planner's problem

Choose

- 1 a feasible, individually rational network  $\mathbf{A}$ ; and
- 2 a joint shock distribution  $\phi$ ,

to maximize expected equity value plus expected debt value:

$$\mathbb{E} \left[ \sum_{i \in N} (\pi_i(\mathbf{A}) + \delta_i(\mathbf{A})) \right]$$



# Planner's problem

Choose

- 1 a feasible, individually rational network  $\mathbf{A}$ ; and
- 2 a joint shock distribution  $\phi$ ,

to maximize expected equity value plus expected debt value:

$$\mathbb{E} \left[ \sum_{i \in N} (\pi_i(\mathbf{A}) + \delta_i(\mathbf{A})) \right]$$

- Equivalent to minimising the expected number of failures.

# Integer assumptions

Define  $d^*$  to be the unique positive root of

$$d_i^2(R - \underline{v})\beta + d_i((R - \underline{v})(\varepsilon_L - \varepsilon_S) - \varepsilon_S\beta) + \varepsilon_S(n(R - \underline{v}) - \varepsilon_L) = 0.$$

We abstract from the integer problems by assuming:

- (i)  $d^*$  is an integer; and
- (ii)  $n/d^*$  is an integer.

# $d^*$ -clusters

Can partition the banks into  $n/d^*$  groups of  $d^*$  banks.

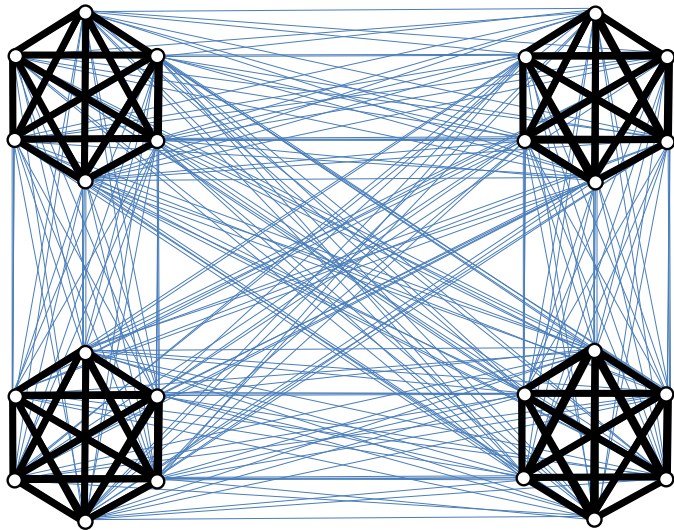
## Definition

The class of networks  $\mathcal{A}^*(d^*)$  are  $d^*$ -clustered, where:

$$\mathcal{A}^*(d^*) := \left\{ \mathbf{A} \in \mathcal{A} : \begin{array}{ll} |G_i| = d^* & \forall i \in N \\ A_{ji}^* = \frac{R-v}{\varepsilon_S} & \forall i, j : G_i = G_j \\ A_{ji}^* = \frac{R-v}{\varepsilon_L + \beta d^*} & \forall i, j : G_i \neq G_j \end{array} \right\},$$

and  $G_i$  is the group that  $i$  belongs to.

# Example



# Socially optimal networks

## Proposition

Under the maintained assumptions as  $r \rightarrow 0$  a network shock distribution pair  $(\mathbf{A}, \phi)$  solve the social planner's problem if and only if  $\mathbf{A} \in \mathcal{A}^*(d^*)$  and there are separate shocks.

# Socially optimal networks

## Proposition

Under the maintained assumptions as  $r \rightarrow 0$  a network shock distribution pair  $(\mathbf{A}, \phi)$  solve the social planner's problem if and only if  $\mathbf{A} \in \mathcal{A}^*(d^*)$  and there are separate shocks.

We then have that:

- No banks fail after a small shock.
- Failures after a large shock are contained within a cluster.
- Weak links between clusters act as firebreaks.

# Proof strategy

- Suppose planner knows which bank will be hit by the large shock, if it occurs.
- Find a lower bound on the number of failures the planner can achieve.
- Also a lower bound when the large shock can hit any bank.
- Show this lower bound can be achieved by all  $d^*$ -clustered network with separate shocks.
- Show no other network-shock distribution pair can achieve it.

# Proof outline

Two observations simplify the problem.

- (i) As  $r \rightarrow 0$ , the individual rationality constraints imply that the social planner must choose a row stochastic network  $\mathbf{A}$ .
  
- (ii) As large shocks are rare relative to small shocks, the planner never chooses a network–shock distribution pair in which:
  - ▶ a bank holds assets that result in at least one failure whenever the small shock hits it.



# Proof outline

- The second observation implies that  $A_{ij}\varepsilon_S \leq R - \underline{v}$  for all  $i, j$ .
- The first observation implies that  $v_i = R$  for all  $i$  when no shock hits.
- Let  $D_i$  be the set of banks that fail following a large shock to  $i$ .
- For all  $j \notin D_i$ ,  $A_{ji}\varepsilon_L + \sum_{k \in D_i} A_{jk}\beta \leq R - \underline{v}$

# Proof outline

Combining these inequalities it can be shown that:

## Lemma

For all doubly stochastic network structures  $\mathbf{A}$  such that there is no bank that holds assets which always result in at least one failure when the small shock hits it,

$|D_i| \geq \lceil d^* \rceil$  where  $d^*$  is the unique positive root of

$$d_i^2 (R - \underline{v}) \beta + d_i ((R - \underline{v})(\varepsilon_L - \varepsilon_S) - \varepsilon_S \beta) + \varepsilon_S (n(R - \underline{v}) - \varepsilon_L) = 0.$$

# Proof outline

$d^*_{qr}$  is a lower bound on the expected number of failures a planner must incur . . .

# Proof outline

$d^*qr$  is a lower bound on the expected number of failures a planner must incur . . .

even when they know which bank a large shock hits.

# Proof outline

$d^*$  is a lower bound on the expected number of failures a planner must incur . . .

even when they know which bank a large shock hits.

However, all networks  $\mathbf{A} \in \mathcal{A}^*(d^*)$  with separate shocks achieve

- exactly  $d^*$  failures following a large shock to *any* bank, and
- no failures following a small shock to *any* bank.

All networks  $\mathbf{A} \in \mathcal{A}^*(d^*)$ , with separate shocks solve the planner's problem.

# Proof outline

Achieving  $d^*$  failures requires several inequalities to bind.

All these inequalities binding implies the network is  $d^*$ -clustered and there are separate shocks.

So only  $d^*$ -clustered networks with separate shocks can be socially optimal.

# Efficient modularity

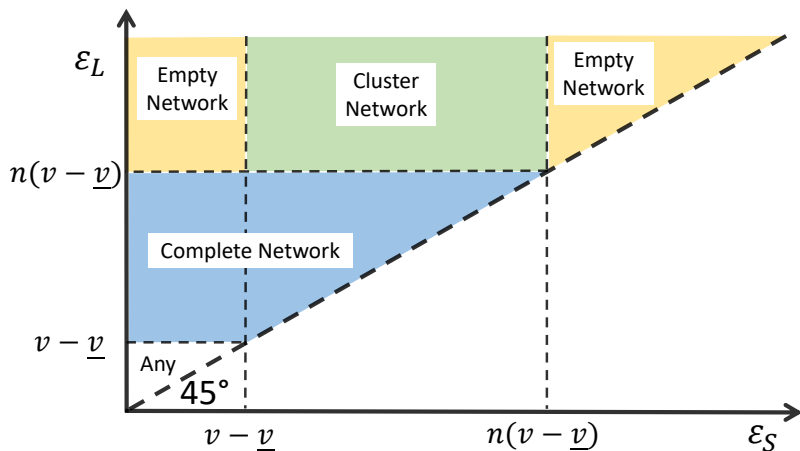
*Al'Qaeda ... operates not as a centralised, integrated organisation but rather as a highly decentralised and loose network of small terrorist cells. ... As events have shown, Al'Qaeda has exhibited considerable systemic resilience in the face of repeated and on-going attempts to bring about its collapse.*

*These two characteristics are closely connected. A series of decentralised cells, loosely bonded, make infiltration of the entire Al'Qaeda network extremely unlikely. If any one cell is incapacitated, the likelihood of this undermining the operations of other cells is severely reduced. That, of course, is precisely why Al'Qaeda has chosen this organisational form. Al'Qaeda is a prime example of modularity and its effects in strengthening systemic resilience.*

*banking ... has many of the same basic ingredients.*

—Haldane (2010)

# Other shock sizes



Acemoglu et al (2015): One shock size (follows the 45 degree line).



# Debt and equity holders

Planner maximizes sum of equity and debt value, but. . .

## Corollary

Suppose there are separate shocks and consider the class of networks  $\mathcal{A}'$  whereby no bank fails under a small shock. Abstracting from integer problems, the socially efficient networks  $\mathcal{A}^* \subset \mathcal{A}'$  have the following properties:

- 1 Any  $A^* \in \mathcal{A}'$  minimises the sum of expected payments to shareholders
- 2 Any  $A^* \in \mathcal{A}'$  maximises the sum of expected payments to external creditors

# Outline

- 1 Stylized Fact: Homophily in Financial Networks
- 2 Parsimonious Theoretical Model
- 3 Social Planner's Solution
- 4 Stable networks**
- 5 Conclusions

# Portfolio and counter-party choices

- Banks maximize expected equity value  $\mathbb{E}[\pi_i]$  by choosing:
  - (i) their financial connections; and
  - (i) how correlated the shocks they face are with others' shocks.

# Portfolio and counter-party choices

Banks maximize expected equity value  $\mathbb{E}[\pi_i]$  by choosing

- (i) their financial connections; and
- (i) how correlated their shock is with others'.

# Portfolio and counter-party choices

Banks maximize expected equity value  $\mathbb{E}[\pi_i]$  by choosing

- (i) their financial connections; and
- (i) how correlated their shock is with others'.

We look for profitable deviations from the planner's solution. For simplicity:

- First we fix the network and look for deviations regarding the correlation structure.
- Then, fix the correlation structure and look for deviations regarding the network.

# Some notation

Denote the possible states of the world by:

$$\Omega = \text{No Shock} \cup \underbrace{2^N}_{\text{Possible Small Shocks}} \cup \underbrace{N}_{\text{Possible Large Shocks}}$$

Let  $\phi(\omega)$  be the probability of state  $\omega \in \Omega$ .

# Choosing the correlation structure

## Definition

A probability distribution  $\phi'$  is *implementable* by bank  $i$  from a probability distribution  $\phi$  if and only if:

- (i) bank  $i$  only changes when it's small shock hits, and not when others' shocks hit; and
- (ii) the overall probability that bank  $i$  is hit by a small shock does not change.

# Choosing the correlation structure—math

## Definition

A probability distribution  $\phi'$  is *implementable* by bank  $i$  from a probability distribution  $\phi$  if and only if:

- (i)  $\phi'(S) + \phi'(S \cup \{i\}) = \phi(S) + \phi(S \cup \{i\})$ ,  
for all  $S \subseteq N \setminus \{i\}$ ; and
- (ii)  $\sum_{S \in 2^N: i \in S} \phi'(S) = \sum_{S \in 2^N: i \in S} \phi(S)$ .



# Portfolio and counter-party choices

## Proposition

For any socially efficient network structure-shock distribution pair, for each bank  $i$  there exist implementable probability distributions that:

- (i) strictly increases  $i$ 's equity value,
- (ii) weakly increases the correlation of  $i$ 's shock with all other banks; and
- (iii) strictly increases the correlation of  $i$  shock with at least one other banks.

# Intuition

## Remark

Bank  $i$ 's equity value can be rewritten as

$$\mathbb{E}[\pi_i] = \underbrace{P(v_i \geq \underline{v})}_{\text{Pr. no failure}} \left( \sum_{j \in N} A_{ij} \left[ \underbrace{\mathbb{E}[p_j | v_i \geq \underline{v}]}_{\text{Conditional value of claims}} \right] \right. \\ \left. - \sum_{j \in N} A_{ij} \left[ \underbrace{\beta P(v_j < \underline{v})}_{\text{Unconditional bankruptcy losses}} \right] - \underbrace{\underline{v}}_{\text{Obligations}} \right)$$

# Intuition

## Remark

Bank  $i$ 's equity value can be rewritten as

$$\begin{aligned} \mathbb{E}[\pi_i] = & \underbrace{P(v_i \geq \underline{v})}_{\text{Pr. no failure}} \left( \sum_{j \in N} A_{ij} \left[ \underbrace{\mathbb{E}[p_j | v_i \geq \underline{v}]}_{\text{Conditional value of claims}} \right] \right. \\ & - \sum_{j \in N} A_{ij} \left[ \underbrace{\beta P(v_j < \underline{v})}_{\text{Unconditional bankruptcy losses}} \right] - \underbrace{\underline{v}}_{\text{Obligations}} \left. \right) \\ & + \underbrace{\beta \sum_{j \in N} A_{ij} \text{Cov} [I_{v_j < \underline{v}}, I_{v_i < \underline{v}}]}_{\text{Bankruptcy losses passed onto debt holders}} \end{aligned}$$

# Intuition

Correlating failures with counter-parties shifts risk.

If  $i$  and  $j$  correlate shocks to fail at the same time:

- 1 Debt holders suffer higher losses.
- 2 Equity holders are not affected—limited liability.

And the probability of no shock increases, so equity values increase.

# Network deviations

- Starting from an efficient network, similar forces can make switching counter-parties profitable too.
- But there is now a countervailing force.
- The trade might induce your counter-party to fail in new states when you do not.
- And this reduces your equity value.
- There is a profitable deviation if and only if bankruptcy costs are below a key threshold.

# Outline

- 1 Stylized Fact: Homophily in Financial Networks
- 2 Parsimonious Theoretical Model
- 3 Social Planner's Solution
- 4 Stable networks
- 5 Conclusions**

# Conclusions

- Anecdotal evidence suggests homophily might have played a role in the financial crisis.
- It is present for German commercial banks.
- In a parsimonious model, this is not what a planner would choose.
- Risk-shifting pushes banks towards homophilous networks.