# Banks' syndicated interconnectedness and global shock propagation

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# Motivation: Importance from global systemic perspective

- **Volatility:** Syndicated loan market sensitive to bank balance sheet constraints and subject to rapid adjustments (Chui, Domanski, Kugler and Shek, 2010). During the crisis market collapsed from USD 800 to 300 billion in quarterly issuance volume, back to pre-crisis levels by 2011 (Gadanecz, 2011).

- **Transmission of shocks globally:** By 2007, international syndicated loans made up 40% of all cross-border funding to US and more than 2/3 of cross-border flows to EMEs (De Haas and Van Horen, 2012)

- **Transmission of shocks to the real economy:** One example is the collapse in trade following the subprime crisis (yr/yr decline of 25% in Q1 2009, largest ever documented, Antonakakis (2012)).

# Motivation: the 2008 syndicated loan market collapse

- Market almost halved in size during the first year of the crisis alone
  - Volume of loans contracted by approximately 43% in 2008 relative to previous year
- Most of the adjustment took place along the extensive (about 4/5) rather than intensive margin (about 1/5)
  - Total number of unique tranches declined from 15,070 to 11,556.
  - Average tranche size declined by 13% from $ 305 to 266 million
- The lion share of lending contraction came from banks not responsible for originating the loan
  - Average loan share of lead arrangers actually increased from 28 to 30%

# Motivation: Understand which of market features amplify shock transmission

Upper (2011) points out a shortcoming in studies of systemic risk in that most of them abstract from ex ante bank behaviour, simply treating banks as passive transmitters of exogenous shocks.

**Aim of this work:**

- Build a **micro-founded model** of syndicated lending in to (a) match key features of the market and (b) to calibrated with empirical data
- Look at systemic consequences of bank behaviour in a network setting, with balance sheet constraints and risk of insolvency as drivers

$\Rightarrow$ **Implications for global shock propagation and systemic risk**

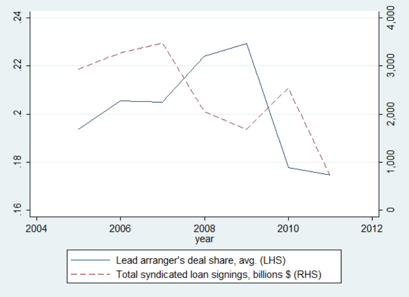
# Example: Implication for LOLR policy

Even in a rational expectations setting (whereby banks take into account borrower credit risk, own equity risk, and network externalities of syndicated lending) “tail risk” does not affect the bank portfolio very much. Hence, a CB backstop against tail risk would not affect bank behavior.

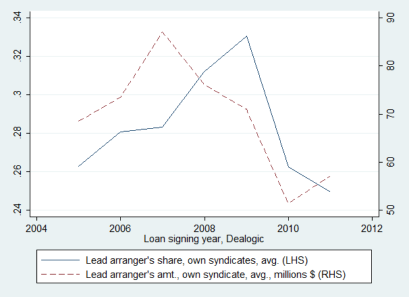
$\Rightarrow$ LOLR would NOT lead to “moral hazard” at least in a homogeneous setup

Unless, market dominated by few large players. Then LOLR turns into bank subsidy.

# Market feature I: Interaction between lead arrangers and other lenders




Inverse relation of lead arrangers' share to total lending




Asymmetric exposure of lead arrangers

Ivashina and Scharfstein (2010, AER) attribute such rise in lead share to dominance of bank capital shocks over shocks to borrower collateral.

# Market feature II: Network externalities

Measure of syndicated interconnectedness based on Cai, Saunders, and Steffen (2011).

$w_{i,j}$ – the weight bank $i$ invests in syndicate $j$

For each bank: $\sum_{j=1}^{J} w_{i,j} = 1$, where $J$ is the number of deals in year $t$.

Compute the Euclidean distance between bank $m$ and bank $n$ in the $J$-dimensional space:

$$d_{m,n} = \sqrt{\sum_{j=1}^{J} (w_{m,j} - w_{n,j})^2} \quad (1)$$

$deg_m = \sum_{n \neq m}^{N} d_{m,n}$ – degree of connectedness for bank $m$ with other banks through participation in common syndicates in year $t$.

## Market feature II: Network externalities

The amplification effect of interconnectedness in the propagation of bank equity shocks:

$$D_{i,t} = \gamma_0 + \phi(deg_i \times \bar{D}_{\neq i,t}) + \gamma_1 deg_i + \gamma_2 \bar{D}_{\neq i,t} + \beta \mathbf{X}_{i,t} + \epsilon_{i,t}, \qquad (2)$$

$D_{i,t}$ – bank $i$'s default likelihood
$\bar{D}_{\neq i,t}$ – average of default likelihoods of all other banks excluding bank $i$
$\mathbf{X}_{i,t}$ – vector of bank level controls: bank capital, reliance on market-based funding sources, liquidity ratio, and risk exposure in syndicated loans market (following Brei and Gadanecz, 2012)
$\phi$ –captures any amplification of bank distress propagation due to interconnectedness.

# Market feature II: Network externalities

Table : Network amplification of bank default likelihood (levels)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $deg_i \times \bar{D}_{\neq i,t}$ | 0.022** | 0.021** | 0.020* | 0.020* | 0.017 |
| | (0.011) | (0.010) | (0.010) | (0.010) | (0.012) |
| $\bar{D}_{\neq i,t}$ | 1.079** | 1.024** | 1.030** | 1.036** | 1.116** |
| | (0.485) | (0.474) | (0.481) | (0.481) | (0.555) |
| $deg_i$ | 0.001 | -0.003 | -0.002 | -0.002 | 0.001 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) |
| capital | | -0.107*** | -0.094*** | -0.097*** | -0.121*** |
| | | (0.026) | (0.033) | (0.033) | (0.040) |
| market funding | | | 0.003 | 0.004 | 0.001 |
| | | | (0.006) | (0.006) | (0.006) |
| leveraged loans | | | | 0.005 | 0.004 |
| | | | | (0.005) | (0.006) |
| liquidity | | | | | -0.017* |
| | | | | | (0.009) |
| $\gamma_0$ | -0.002 | 0.864** | 0.646 | 0.454 | 1.042 |
| | (0.284) | (0.347) | (0.522) | (0.553) | (0.653) |
| observations | 306 | 305 | 291 | 291 | 252 |
| R-squared | 0.263 | 0.302 | 0.292 | 0.294 | 0.303 |

Notes: *, **, and *** indicate coefficients significant at 10%, 5%, and 1% level respectively; robust standard errors in parentheses; 2005 through 2011 time sample.

# Market feature II: Network externalities

Table : Network amplification of bank default likelihood (first differences)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $deg_i \times \bar{D}_{\neq i,t}$ | 0.024** | 0.020** | 0.021** | 0.022** | 0.022* |
| | (0.010) | (0.010) | (0.010) | (0.011) | (0.012) |
| $\bar{D}_{\neq i,t}$ | 1.024** | 0.865* | 0.735 | 0.706 | 0.808 |
| | (0.455) | (0.451) | (0.462) | (0.464) | (0.542) |
| $deg_i$ | -0.003 | -0.001 | -0.002 | -0.002 | -0.002 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| capital | | -0.302*** | -0.342*** | -0.341*** | -0.345*** |
| | | (0.098) | (0.104) | (0.104) | (0.117) |
| market funding | | | -0.011 | -0.011 | -0.003 |
| | | | (0.023) | (0.023) | (0.027) |
| leveraged loans | | | | 0.007 | 0.009 |
| | | | | (0.010) | (0.011) |
| liquidity | | | | | 0.005 |
| | | | | | (0.027) |
| $\gamma_0$ | 0.135 | 0.123 | 0.141 | 0.145 | 0.191 |
| | (0.262) | (0.259) | (0.263) | (0.263) | (0.305) |
| observations | 259 | 258 | 246 | 246 | 209 |
| R-squared | 0.337 | 0.361 | 0.349 | 0.351 | 0.354 |

Notes: *, **, and *** indicate coefficients significant at 10%, 5%, and 1% level respectively; robust standard errors in parentheses; 2005 through 2011 time sample.

# Model

Build a micro-founded model of syndicated lending that accounts for the structural features of the market:

- Risk neutral banks maximize returns subject to a VaR constraint
- Banks can trade a share of a loan, and, hence, benefit from risk-sharing
- Each project is financed by a lead arranger, who in effect underwrites the loan
- The probability distribution of aggregate withdrawals is endogenous and depends on the network structure

# Model: Benchmark without risk sharing

- $N$ investment projects: $X_1, \ldots, X_N$
- Bank equity (common across banks): $e$
- Return to the project: $R_j \sim \mathcal{N}\ (R,\ \sigma^2)$
- Risk neutral banks invest subject to VaR constraint: $\Pr(R_j X_j < -e) \leq \alpha$

$\Rightarrow \Phi((-e - R_j X_j)/(\sigma X_j)) \leq \alpha$ where $\Phi$ denotes the standard normal

distribution function. Define $\phi$ such that $\Phi(-\phi_\alpha) = \alpha$. Then the VaR constraint is expressed as:

$$\frac{e + E(R_j X_j)}{\sqrt{V(R_j X_j)}} \geq \phi_\alpha \tag{3}$$

# Model: Benchmark without risk sharing

$$Max_{X_j} \ E(R_j X_j)$$

$$\text{s.t } (e + RX_j)^2 \geq \phi^2 \sigma^2 X_j^2$$

$\Rightarrow$

$$X^* = e/(\sigma\phi - R)$$

$NX^*$: Total lending in autarky

# Model: Risk sharing through syndicated lending

- Return to the project: $R_j \sim \mathcal{N}\ (R,\ \sigma^2)$
- Fee for participating in the syndicate: $f$
- Lending to project $j$ by lead bank $j$: $a_j$
- The set of banks who lead projects that bank $j$ joins as a participant: $\Omega_j$ (size of $\Omega_j$ is $l_j$)
- banks can trade a share of a loan: $s$
- Total lending amount committed to the firm undertaking the investment project $j$: $X_j = a_j + \sum_{i \in \Omega_j} l_i s$

Bank $j$'s future wealth is

$$W_j' = R_j a_j + \sum_{i \in \Omega_j} (R_i - f)s \tag{4}$$

# Model: Risk sharing through syndicated lending

Hence, banks diversify idiosyncratic project risk by choosing optimal participation in the syndicates of others:

$$E(W_j') = Ra_j + (R - f)sl_j \tag{5}$$

and

$$V(W_j') = \sigma^2(a_j^2 + l_j s^2). \tag{6}$$

# Model: Risk sharing through syndicated lending

Maximize $E(W_j')$ by choosing $a_j, l_j$ subject to a VaR constraint

$$\frac{e + E(W_j')}{\sqrt{V(W_j')}} \geq \phi_\alpha \tag{7}$$

In a symmetric case, the amount of lending for project $j$ is $X = a + ls$.
Total amount of lending is $N(a + ls) > Ne/(\sigma\phi_\alpha - R)$.

# Model: Risk sharing through syndicated lending

**Numerical example:**

Calibrate the model parameters as follows. $R = 0.1$, $e = 1$, $s = 0.1$, $\sigma = 0.3$, $\sigma_c = 0.01$, $\phi = 2.33$, and $f = 0.0672$, the optimal portfolio is $a_j^* = 1.51$ and $l_j^* = 5$:

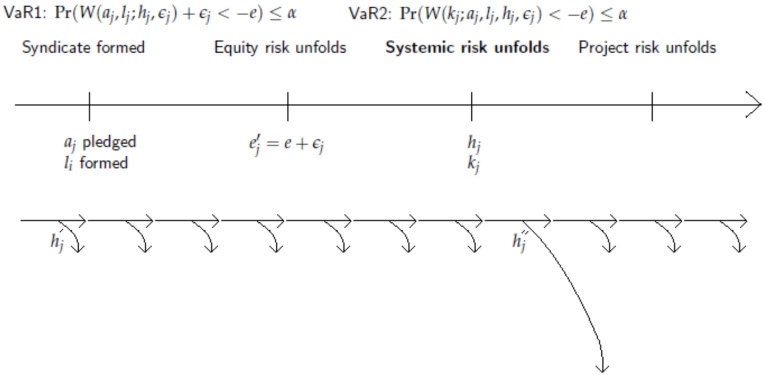
- Aggregate lending: $NX = 201$
- Expected wealth (net of fees): $NE(W') = 16.7$

Autarky:

- Aggregate lending: $NX = 167$
- Expected wealth: $NE(W') = 16.7$.

Thus, the aggregate investment enjoys an increase by 20% by the syndicated loan market.

# Model: Addition of bank capital shocks



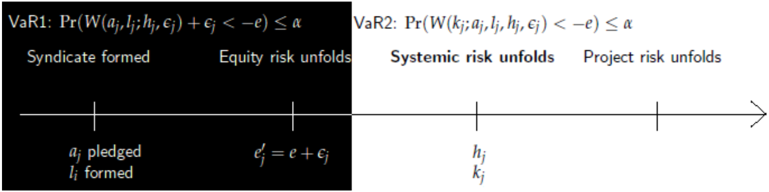

- $h_j$: number of participants who withdraw from the loan arranged by $j$
- $k_j$ : number of syndicated loans withdrawn by bank $j$

# Model: Addition of bank capital shocks

Banks' policy functions $k_j(a_j, l_j, h_j, \epsilon_j)$:

- Compute the bank's policy as a threshold function of $\epsilon_j$
- $\bar{\epsilon}(k, h)$ is the minimum $\epsilon_j$ such that $k_j(a_j, l_j, h, \epsilon) = k$

# Model: Addition of bank capital shocks




Second stage wealth conditional on $h_j$ and $\epsilon_j$:

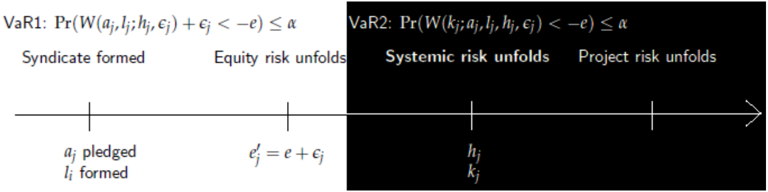
$$W(k_j; a_j, l_j, h_j, \epsilon_j) = R_j(a_j + sh_j) + \sum_{i \in \Omega_j \setminus \Omega_{j,0}} (R_i - f)s$$

$$E(W'_j | a_j) = R(a_j + h_j s) + (R - f)s(l_j - k_j)$$

$$V(W'_j | a_j) = \sigma^2((a_j + h_j s)^2 + (l_j - k_j)s^2)$$

where $\Omega_{j,0}$ denote the set of projects that $j$ decides to withdraw from, its size is $k_j$

# Model: Addition of bank capital shocks




A bank's problem in the first stage (before $\epsilon_j$ realizes) is:

$$\max_{a_j, l_j, k_j(h_j, \epsilon_j)} E(W(a_j, l_j; h_j, \epsilon_j)) \text{ s.t. } \Pr(W_j' + \epsilon_j < -e) \leq \alpha \qquad (8)$$

- $a_j$ is determined by the VaR constraint with equality holding, and the maximization determines integer $l_j$
- $W(a_j, l_j; h_j, \epsilon_j)$ determined from the optimal threshold policy for withdrawals conditional on $\epsilon_j$ and $h_j$

# Model: Addition of bank capital shocks

**Rational expectations equilibrium**

An equilibrium is the probability distribution $p(h_j)$ and the policy functions $a_j(e), l_j(e)$ and $k_j(a_j, l_j, h_j, \epsilon_j)$ such that the policy functions solve the bank's maximization problem given $p(h_j)$, and $p(h_j)$ is consistent with the bank's policy functions, the distributions of shocks $\epsilon_j$ and the network structure.

The equilibrium maps a realization of $\epsilon$ to an outcome $h$ and $k$. Thus, the equilibrium fluctuations of $h$ and $k$ are well defined.

**Rare-event risk**

The tail part of the distribution of $\sum_j k_j$ signifies the endogenous rare-event risk in the syndicated loan market that arises from the propagation effects of bank capital shocks.

# Model simulations

Calibrate model parameters to match important aspects of the syndicated loan market:

| | | |
|---|---|---|
| mean excess return | $R$ | 0.05 |
| standard deviation of returns | $\sigma$ | 0.15 |
| equity (normalized) | $e$ | 1 |
| standard deviation of the equity shock | $\sigma_e$ | 1/2.33 |
| VaR confidence level set to 99% | $\alpha$ | 0.01 |
| loan amount per participant | $s$ | 0.28 |
| average number of participants observed the dataset | $\bar{l}$ | 6 |

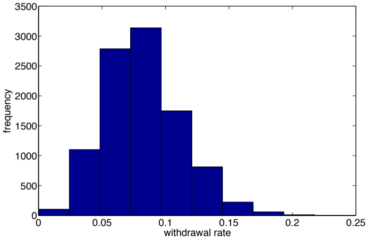
- $\sigma$ set to 15%, which corresponds to 2% default risk of the investment project $j$
- $\sigma_e$ set to $1/2.33$, which yields bank default risk $\Pr(e + \epsilon_j < 0)$ of 1%
- $s = 0.28$ yields the fraction of a participant's share of a syndicated loan of about 17% in equilibrium, which matches the data

# Model computation

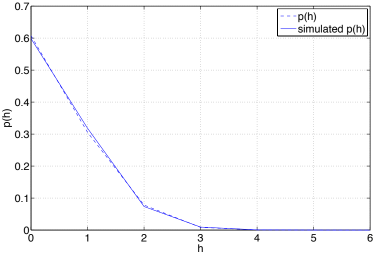
- Given a withdrawal hazard function $p(h)$, compute banks' optimal plans:
  - $a_j$ and thresholds for $k(a_j, l_j; h_j, \epsilon_j)$
  - Check if $l_j$ is better than $l_j - 1$
- Draw a network of syndicates with 100 banks
- Simulate $\tilde{p}(h)$ in the equilibrium outcomes by 10,000 Monte-Carlo runs
- Iterate until $p(h)$ and $\tilde{p}(h)$ coincide

# Model simulations: No common equity shocks

Rate of withdrawals $\sum_{j=1}^{N} h_j / (N\bar{l})$



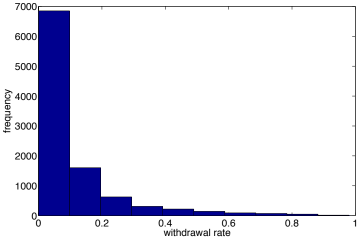

Withdrawal hazard per project



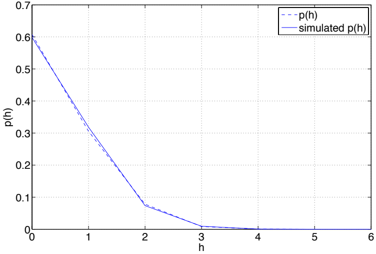
# Model simulations: Common equity shocks

Equity shock $\epsilon_j$ has an idiosyncratic and a common component with the same contribution to overall variance $\sigma^2$. Banks know shock distribution, but cannot identify what portion of $\epsilon_j$ is idiosyncratic or common.

Rate of withdrawals $\sum_{j=1}^{N} h_j/(N\bar{l})$




Withdrawal hazard per project

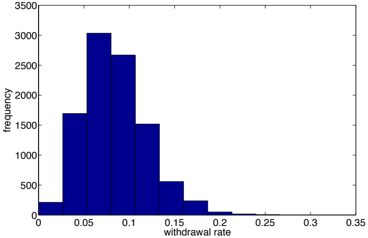


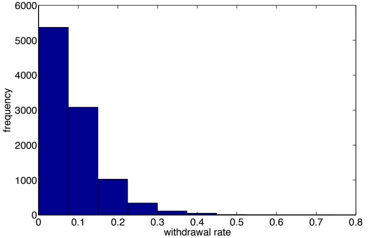

$\Rightarrow$ Observe a long tail in the dissolution distribution

# Model simulations: Common equity shocks

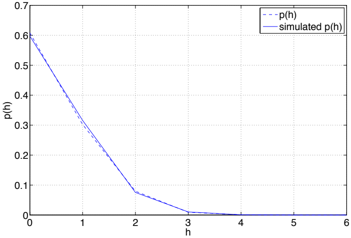
Above: 1% of equity risk is common across banks; Below: 10%

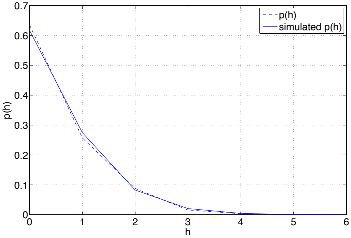
## Rate of withdrawal




## Withdrawal hazard



# Model simulations: Common equity shocks

| common shock ratio | 0 | 0.01 | 0.1 | 0.3 |
|---|---|---|---|---|
| withdrawal $> 0.3$ | 0 | 0 | 0.0183 | 0.0899 |
| $(h = l$ event$) > 0.3$ | 0 | 0 | 0 | 0.0048 |
| $(h = l$ event$) > 0.1$ | 0 | 0 | 0.0001 | 0.0135 |
| mean common shock on rare events | - | - | -0.4092 | -2.5260 |

# Summary

- Develop micro-founded model of syndicated lending
  - Optimal amount of syndication mediated by market price
  - Complementarity of syndication decisions a structural feature of the market
  - Whether or not risk sharing benefits materialize depends on the coordination among banks
  - Efficiency – stability trade-off
- Model calibrated using market data can be used to quantify systemic risk in the market
- Possible policy implications for LOLR and bank capital regulation
- Future extensions: bank heterogeneity & network topology