A Dynamic Network Model
of the Unsecured Interbank Lending Market

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Formation of interbank lending relationships and associated network structure, implications for credit availability and conditions (interest rates and volumes)
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- Focus on role of credit risk uncertainty and peer monitoring in over-the-counter market
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- Policy analysis: role of central bank corridor
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Dutch Interbank Market during Crisis

Figure: Nodes: banks; links: ON loans; big green node: central bank; small green nodes: banks only relying on central bank; pink nodes: banks without use of central bank facilities, see video 3 Heijmans et al. (2014)
Dutch Interbank Market during Crisis

Before Lehman 08/2008

After Lehman 12/2008

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Relevance of Private Information

- Why should central banks not resume role of central counterparty for money market transactions also in normal times (i.e. non-crisis times)?
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- Efficiency of liquidity allocations, Rochet & Tirole (1996)

"Specifically, in the unsecured money markets, where loans are uncollateralised, interbank lenders are directly exposed to losses if the interbank loan is not repaid. This gives lenders incentives to collect information about borrowers and to monitor them [...] Therefore, unsecured money markets play a key peer monitoring role."

from speech by Benoît Cœuré (ECB Executive Board) in Tourrettes, Provence, 16 June 2012.
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→ **Key issue:** Role of credit risk uncertainty, peer monitoring and private information in the interbank market? We need to consider uncertainty as bank-to-bank specific problem!
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Liquidity Shocks

- Network of \( N \) banks \( i = 1, \ldots, N \), time is discrete and infinite

- Banks are hit by liquidity shocks \( \zeta_{i,t} \)

\[
\zeta_{i,t} \sim \mathcal{N}(\mu_{\zeta_i}, \sigma_{\zeta_i}^2) \quad \text{where} \quad \mu_{\zeta_i} \sim \mathcal{N}(\mu_{\mu}, \sigma_{\mu}^2) \quad \text{and} \quad \log \sigma_{\zeta_i} \sim \mathcal{N}(\mu_{\sigma}, \sigma_{\sigma}^2)
\]

and correlation parameter \( \rho_{\zeta} := \text{corr}(\mu_{\zeta_i}, \log \sigma_{\zeta_i}) \), heterogeneity related to scale of bank’s business \( (\sigma_{\zeta_i}) \) and structural liquidity supply or demand \( (\mu_{\zeta_i}) \)

- Banks can smooth liquidity shocks by either
  - recourse to central bank facilities with borrowing rate \( \bar{r}_t \) and deposit rate \( r_t \), where \( \bar{r}_t > r_t \) OR
  - unsecured interbank lending under asymmetric info about counterparty risk
    - counterparty selection
    - bilateral interest rate bargaining
Credit Risk Uncertainty and Peer Monitoring

- Perceived financial distress $z_{i,j,t}$

$$z_{i,j,t} = z_{j,t} + e_{i,j,t}$$

where $z_{j,t} \sim (0, \sigma^2)$ is true financial distress with true prob of default $P(z_{j,t} > \epsilon)$ and $e_{i,j,t} \sim (0, \tilde{\sigma}^2_{i,j,t})$ is independent perception error
Credit Risk Uncertainty and Peer Monitoring

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- Perceived probability of default is obtained from Chebyshev’s bound as
  \[ P(z_{i,j,t} > \epsilon) \leq \frac{\sigma^2 + \tilde{\sigma}_{i,j,t}^2}{\sigma^2 + \tilde{\sigma}_{i,j,t}^2 + \epsilon^2} =: P_{i,j,t} \]
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- Focus on evolution of log perception error variance (credit risk uncertainty)
  
  $$\log \tilde{\sigma}_{i,j,t+1}^2 = \alpha_{\sigma} + \gamma_{\sigma} \log \tilde{\sigma}_{i,j,t}^2 + \beta_{\sigma} m_{i,j,t} + u_{i,j,t}, \quad u_{i,j,t} \sim \mathcal{N}(0, \sigma_u^2)$$

  where $m_{i,j,t} \in \mathbb{R}_0^+$ are monitoring expenditures
Link Formation, Interest Rates and Loan Volumes

- $B_{i,j,t} \sim \text{Bernoulli}(\lambda_{i,j,t})$ indicates link between bank $i$ and $j$ at time $t$ with

$$\lambda_{i,j,t} = \frac{1}{1 + \exp(-\beta \lambda (s_{i,j,t} - \alpha \lambda))}$$

where $s_{i,j,t} \in \mathbb{R}^+_0$ is the search effort of bank $j$ towards specific lender $i$
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- Upon contact Nash bargaining about rates, Afonso & Lagos (2012); lender surplus over deposit facility: $(1 - P_{i,j,t}) r_{i,j,t} - P_{i,j,t} - r_t$, borrower surplus over lending facility: $\bar{r}_t - r_{i,j,t}$. Solution:

$$r_{i,j,t} = \theta r + (1 - \theta) \frac{P_{i,j,t}}{1 - P_{i,j,t}}$$

where $\theta$ is bargaining power of lender, with $\bar{r}_t = r > r_t = 0$
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- Upon successful bargaining, $r_{i,j,t} \in [0, r]$, the loan volume is exogenously given by

  $$\zeta_{i,j,t} = \min\{\zeta_{i,t}, -\zeta_{j,t}\} \mathbb{I}(\zeta_{i,t} \geq 0) \mathbb{I}(\zeta_{j,t} \leq 0),$$

  where $\zeta_{i,t}$ and $\zeta_{j,t}$ are liquidity shocks specific to each transaction
Dynamic Optimization Problem

- Dynamic optimization problem of each bank $i$:

$$\max_{\{m_{i,j,t}, s_{i,j,t}\}} \mathbb{E}_t \sum_{s=t}^{\infty} \left( \frac{1}{1+r} \right)^{s-t} \left( \sum_{j=1}^{N} \bar{R}_{i,j,t} y_{j,i,t} + (r - r_{j,i,t}) y_{j,i,t} - m_{i,j,t} - s_{i,j,t} \right)$$

s.t. constraints; where $\bar{R}_{i,j,t} = (1 - P_{i,j,t}) r_{i,j,t} - P_{i,j,t}$, no default occurs!
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- Optimal linearized policy rules for monitoring
  \[
  m_{i,j,t} = a + b \hat{\sigma}_{i,j,t}^2 + c \mathbb{E}_t \hat{\sigma}_{i,j,t+1}^2 + d \mathbb{E}_t \lambda_{i,j,t+1} + e \mathbb{E}_t y_{i,j,t+1}
  \]
  \( \rightarrow \) depends on current uncertainty and expected future uncertainty, loan volume and link probability

- Non-linear policy function for search
  \[
  s_{i,j,t} = f(\mathbb{E}_t (r - r_{j,i,t}) y_{j,i,t}) \quad f' \geq 0
  \]
Dynamic Optimization Problem

- Dynamic optimization problem of each bank $i$:

$$
\max_{\{m_{i,j,t}, s_{i,j,t}\}} \sum_{s=t}^{\infty} \left( \frac{1}{1+r} \right)^{s-t} \left( \sum_{j=1}^{N} \tilde{R}_{i,j,t} y_{i,j,t} + (r - r_{j,i,t})y_{j,i,t} - m_{i,j,t} - s_{i,j,t} \right)
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- Optimal linearized policy rules for monitoring

$$
m_{i,j,t} = a + b\tilde{\sigma}^2_{i,j,t} + c\mathbb{E}_t\tilde{\sigma}^2_{i,j,t+1} + d\mathbb{E}_t\lambda_{i,j,t+1} + e\mathbb{E}_t y_{i,j,t+1}
$$

→ depends on current uncertainty and expected future uncertainty, loan volume and link probability

- Non-linear policy function for search

$$
s_{i,j,t} = f(\mathbb{E}_t(r - r_{j,i,t})y_{j,i,t}) \quad f' \geq 0
$$

- Banks have adaptive expectations and compute expectations $\mathbb{E}_t\hat{\lambda}_{i,j,t+1}$ as EWMA
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Data

- Estimation based on Dutch overnight interbank loan-level dataset constructed from TARGET2 payment records using refined version of Furfine algorithm, see Heijmans et al. (2011), Arciero et al. (2013) de Frutos et al. (2014) for evaluation
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- Compared to data obtained from US fedwire and other payments systems three advantages:
  - TARGET2 payments have flag for interbank credit transactions
  - information on actual sender and recipient bank (not settlement banks)
  - cross-validation with EONIA panel, Italian (e-MID) and Spanish (MID) official transaction level data!
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Observed variables are $l_{i,j,t}$ (link/loan indicator), $y_{i,j,t}$ (volumes) and $r_{i,j,t}$ (spreads), for loans between $N = 50$ most active Dutch banks at daily frequency from 01-02-2008 to 30-04-2011, $T = 810$, volumes and spreads only for granted loans; three $N\times N \times T$ arrays (with missings)
Indirect Inference Estimator

- Idea: characterize data $X$ by vector of auxiliary statistics $\beta$ in a way that identifies structural parameters $\theta$, then simulate $s = 1, \ldots, S$ different datasets $X_s$ and choose $\hat{\theta}$ as

$$\hat{\theta} := \arg\min_{\theta \in \Theta} \| \hat{\beta}(X) - \frac{1}{S} \sum_{s=1}^{S} \hat{\beta}(X_s(\theta)) \|.$$ 

- $\hat{\theta}$ is consistent and asymptotically normally distributed estimator, see Gourieroux et al. (1993)
- We use quadratic form with diagonal weight matrix related to identity, $S = 24$ simulated networks with each $T^* = 3000$, and restrict parameter space $\Theta$ to ensure stability of reduced form
- Network statistics (e.g. density, reciprocity, stability, degree distribution, RL measures) and moments of volumes and spreads as auxiliary statistic, see Blasques and Bräuning (2014)
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Comparison of Auxiliary Statistics

<table>
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<td>Corr($r_{i,j,t}$, $#l_{i,j,t-1}^{rw}$) (mean)</td>
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<td>Avg log volume (mean)</td>
<td>4.117</td>
<td>4.137</td>
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<td>Std log volume (mean)</td>
<td>1.690</td>
<td>1.136</td>
</tr>
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<td>Avg spread (mean)</td>
<td>0.286</td>
<td>1.075</td>
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Simulated Degree Distributions

(a) Out-degree distribution

(b) In-degree distribution

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<td>Avg degree (mean)</td>
<td>1.038</td>
<td>0.991</td>
</tr>
<tr>
<td>Std outdegree (mean)</td>
<td>1.841</td>
<td>1.753</td>
</tr>
<tr>
<td>Skew outdegree (mean)</td>
<td>2.882</td>
<td>2.451</td>
</tr>
<tr>
<td>Std indegree (mean)</td>
<td>1.600</td>
<td>1.687</td>
</tr>
<tr>
<td>Skew indegree (mean)</td>
<td>2.403</td>
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</tbody>
</table>
Heterogeneous Liquidity Shock Distributions

Figure: Joint distribution of mean and standard deviation parameter

\[ \zeta_{i,t} \sim \mathcal{N}(\mu\zeta_i, \sigma^2\zeta_i) \]

where

\[
\begin{pmatrix}
\mu\zeta_i \\
\log \sigma\zeta_i
\end{pmatrix} \sim \mathcal{M}\mathcal{N}
\begin{pmatrix}
\sigma^2\mu \\
\rho\sigma\sigma\mu \\
\rho\sigma\sigma\mu \\
\sigma^2\sigma
\end{pmatrix}
\]
Bank Heterogeneity and Trading Relationships

Figure: Five days of simulated interbank trading. Bank $i$'s position in x-y plane given by parameters of its liquidity shock distribution ($\mu_{\zeta_i}, \sigma_{\zeta_i}$). Node size scaled and shaded proportional to average loan volume per bank. Directed links are plotted as curved dashed lines (red) with the curvature bending counterclockwise moving away from a node. Solid blue lines represent reciprocal links.
Figure: Simulated network responses to changes in persistence of credit risk uncertainty
Dynamic Network Responses to Credit Risk Uncertainty Shock

Figure: Simulated network responses to changes in persistence of credit risk uncertainty
Responses of Credit Conditions, Monitoring and Search

- **Mean log volume**
- **Mean spread**
- **Mean monitoring**
- **Mean search**

Graphs showing changes in mean log volume, mean spread, mean monitoring, and mean search over time (5 to 25).
Monetary Policy Analysis

- What’s the role of monetary policy on interbank network structure?
- Focus on width of interest rate corridor as key parameter
Changes in Central Bank Interest Rate Corridor
Multiplier Effect of Monitoring

Changes in Lending Network are driven by two effects:

- **Direct effect** on interbank lending activity by altering outside options
- **Indirect multiplier effect** through changes in monitoring and search efforts
Conclusion

▶ We introduce and estimate structural interbank network model where banks monitor and search counterparties for bilateral bargaining
▶ Estimated model matches well sparse core-periphery structure of Dutch market and existence of relationship lending
▶ Dynamic analysis reveals importance of monitoring and search as driver behind prolonged market downturn after shock to uncertainty
▶ Changes in discount window lead to direct effect on interbank lending and indirect multiplier effect through altered monitoring and search efforts
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