A Dynamic Network Model of the Unsecured Interbank Lending Market

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Money Market Workshop European Central Bank 20-21 October 2014 Model of formation of interbank lending relationships, implications for credit availability and conditions (interest rates and volumes)

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- Monetary policy analysis: role of central bank interest rate corridor

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4. Results

Dutch Interbank Market during Crisis



Before Lehman 08/2008

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



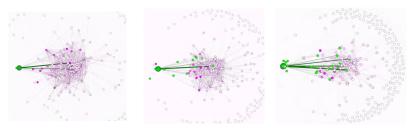


Before Lehman 08/2008

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Dutch Interbank Market during Crisis



Before Lehman 08/2008

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After 3yr LTRO 12/2011

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Relevance of Private Information

Why should central banks not resume the 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."

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→ Key issue: Role of credit risk uncertainty, peer monitoring and private information in the interbank market? In OTC market we need to consider uncertainty as bank-to-bank specific problem!

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Liquidity Shocks

- Network of N banks i = 1, ..., N, time is discrete and infinite
- Banks are hit by liquidity shocks ζ_{i,t}

$$\zeta_{i,t} \stackrel{iid}{\sim} \mathcal{N}(\mu_{\zeta_i}, \sigma_{\zeta_i}^2)$$
 where $\mu_{\zeta_i} \sim \mathcal{N}(\mu_{\mu}, \sigma_{\mu}^2)$ and $\log \sigma_{\zeta_i} \sim \mathcal{N}(\mu_{\sigma}, \sigma_{\sigma}^2)$
and correlation parameter $\rho_{\zeta} := corr(\mu_{\zeta_i}, \log \sigma_{\zeta_i})$

- Banks can smooth liquidity shocks by either
- standing facilities with borrowing rate \bar{r}_t and deposit rate \underline{r}_t , where $\bar{r}_t > \underline{r}_t \frac{OR}{OR}$
- unsecured interbank lending under asymmetric info about counterparty risk
 - counterparty selection
 - bilateral interest rate bargaining

Credit Risk Uncertainty and Peer Monitoring

▶ Perceived financial distress: $z_{i,j,t} = z_{j,t} + e_{i,j,t}$

►
$$z_{j,t} \sim (0, \sigma^2)$$
 is true financial distress of j , true PD: $\mathbb{P}(z_{j,t} > \epsilon)$
► $e_{i,j,t} \sim (0, \tilde{\sigma}_{i,j,t}^2)$ is independent perception error

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- Perceived probability of default

$$\mathbb{P}(\mathbf{z}_{i,j,t} > \epsilon) \le \frac{\sigma^2 + \tilde{\sigma}_{i,j,t}^2}{\sigma^2 + \tilde{\sigma}_{i,j,t}^2 + \epsilon^2} =: P_{i,j,t}$$

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• Evolution of $\tilde{\sigma}_{i,j,t}^2$ (credit risk uncertainty)

$$\log \tilde{\sigma}_{i,j,t+1}^2 = \alpha_{\sigma} + \gamma_{\sigma} \log \tilde{\sigma}_{i,j,t}^2 + \beta_{\sigma} m_{i,j,t} + u_{i,j,t}, \quad u_{i,j,t} \sim \mathcal{N}(0, \sigma_{u,j}^2)$$

where $m_{i,j,t}$ is bank-to-bank monitoring expenditure

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

$$\lambda_{i,j,t} = rac{1}{1 + \exp(-eta_{\lambda}(\mathbf{s}_{i,j,t} - lpha_{\lambda}))}$$

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• If $B_{i,j,t} = 1$, bilateral Nash bargaining about rates

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

where θ is bargaining power of lender, with $\overline{r}_t = r > \underline{r}_t = 0$

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▶ If $r_{i,j,t} \in [0, r]$, loan amount is exogenously given by

$$y_{i,j,t} = \min\{\zeta_{i,t}, -\zeta_{j,t}\}$$

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:

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

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

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

Non-linear policy function for search

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

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

Adaptive expectations using exponentially weighted moving average

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Data

• Observed variables are $I_{i,j,t}$ (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)

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- ▶ 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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- ▶ 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
- 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!

Indirect Inference Estimator

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

$$\hat{ heta} := \operatorname*{argmin}_{ heta \in \Theta} \| \hat{eta}(X) - rac{1}{S} \sum_{s=1}^{S} \hat{eta}(X_s(heta)) \|.$$

• $\hat{\theta}$ is consistent and asymptotically normal, see Gouriéroux et al. (1993)

 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

Auxiliary statistic	Observed $\hat{oldsymbol{eta}}_{\mathcal{T}}$	Simulated $ ilde{eta}_{\mathcal{TS}}(\hat{m{ heta}}_{\mathcal{T}})$
Density (mean)	0.021	0.020
Reciprocity (mean)	0.082	0.060
Stability (mean)	0.982	0.978
Avg clustering (mean)	0.031	0.035

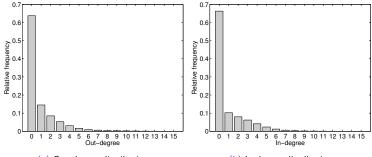
Comparison of Auxiliary Statistics

	Observed	Simulated
Auxiliary statistic	$\hat{\boldsymbol{\beta}}_{T}$	$\tilde{\beta}_{TS}(\hat{\theta}_T)$
Density (mean)	0.021	0.020
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Stability (mean)	0.982	0.978
Avg clustering (mean)	0.031	0.035
$Corr(I_{i,j,t}, \#I_{i,j,t-1}^{rw}) \text{ (mean)}$	0.644	0.586
$\operatorname{Corr}(r_{i,j,t}, \# I_{i,j,t-1}^{rw})$ (mean)	-0.072	-0.123

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 Avg log volume (mean) Std log volume (mean)	4.117 1.690	4.137 1.136
Avg spread (mean) Std spread (mean)	0.286 0.107	1.075 0.112

Simulated Degree Distributions



(a) Out-degree distribution

(b) In-degree distribution

Auxiliary statistic	Observed $\hat{oldsymbol{eta}}_{\mathcal{T}}$	Simulated $ ilde{eta}_{\mathcal{TS}}(\hat{m{ heta}}_{\mathcal{T}})$
Avg degree (mean)	1.038	0.991
Std outdegree (mean)	1.841	1.753
Skew outdegree (mean)	2.882	2.451
Std indegree (mean)	1.600	1.687
Skew indegree (mean)	2.403	2.076

Heterogeneous Liquidity Shock Distributions

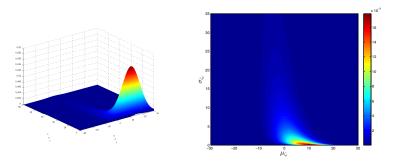


Figure : Joint distribution of mean and standard deviation parameter

$$\zeta_{i,t} \sim \mathcal{N}(\mu_{\zeta_i}, \sigma_{\zeta_i}^2) \quad \text{where} \quad \begin{pmatrix} \mu_{\zeta_i} \\ \log \sigma_{\zeta_i} \end{pmatrix} \sim \mathcal{M}\mathcal{N} \begin{pmatrix} \sigma_{\mu}^2 & \rho \sigma_{\sigma} \sigma_{\mu} \\ \rho \sigma_{\sigma} \sigma \mu & \sigma_{\sigma}^2 \end{pmatrix}$$

Bank Heterogeneity and Trading Relationships

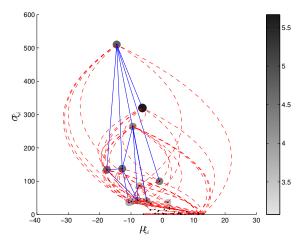
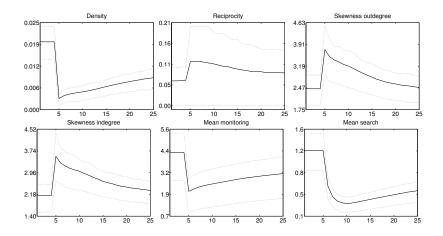
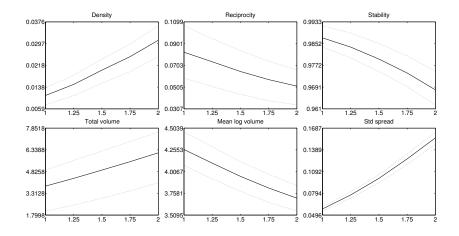


Figure : Five days of simulated interbank trading. Bank *i*'s position in x-y plane given by parameters of its liquidity shock distribution (μ_{ζ_1} , σ_{ζ_1}). Node size scaled and shaded proportional to average loan volume per bank. Directed links are plotted as curved dashed lines (red) with the curvature bending counterclockwise moving away from a node. Solid blue lines represent reciprocal links.

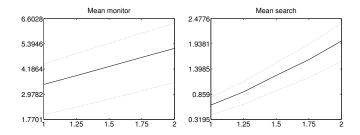
Dynamic Network Responses to Credit Risk Uncertainty Shock



Monetary Policy Analysis: Changes in Interest Rate Corridor



Monetary Policy Analysis: The 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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