

A Dynamic Network Model of the Unsecured Interbank Lending Market

Falk Bräuning^a Francisco Blasques^a Iman van Lelyveld^b

^aVU University Amsterdam & Tinbergen Institute

^bDe Nederlandsche Bank & Bank for International Settlements

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- ▶ Estimation of structural model parameters using Dutch interbank lending data 2008-2011
- ▶ Policy analysis: role of central bank corridor

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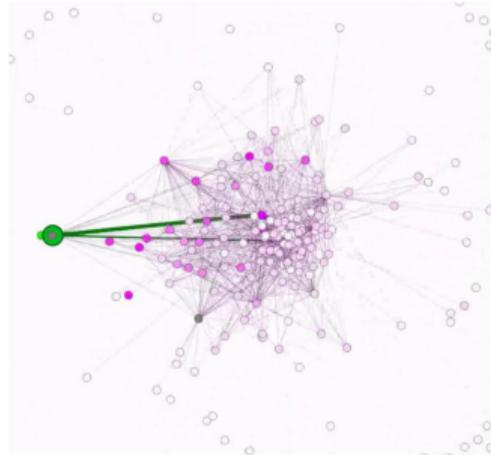
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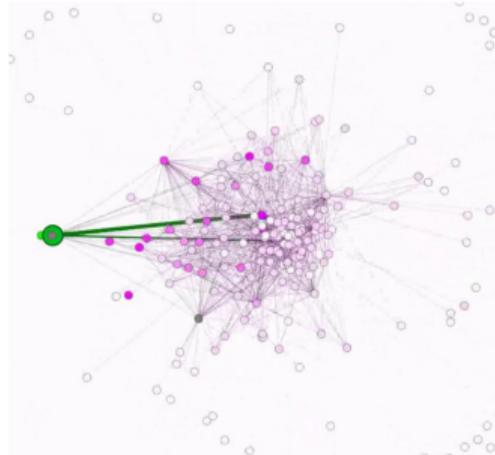
Dutch Interbank Market during Crisis



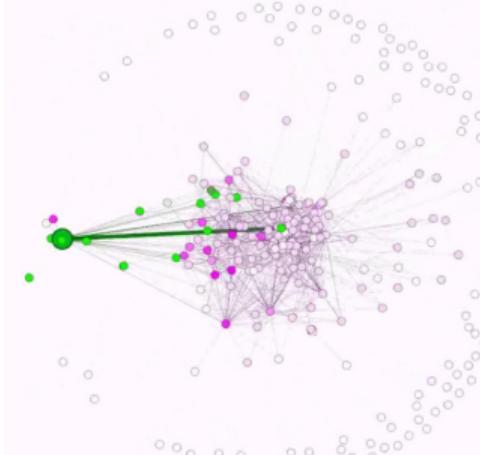
Before Lehman 08/2008

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

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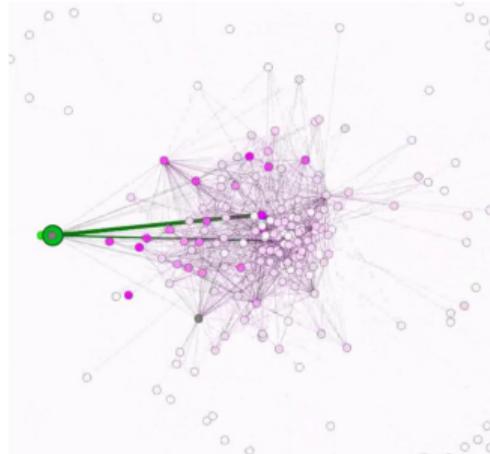
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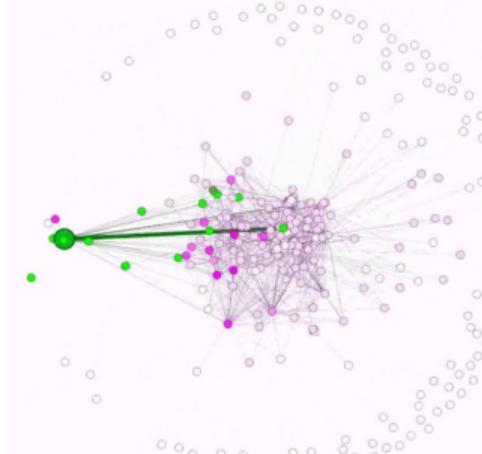
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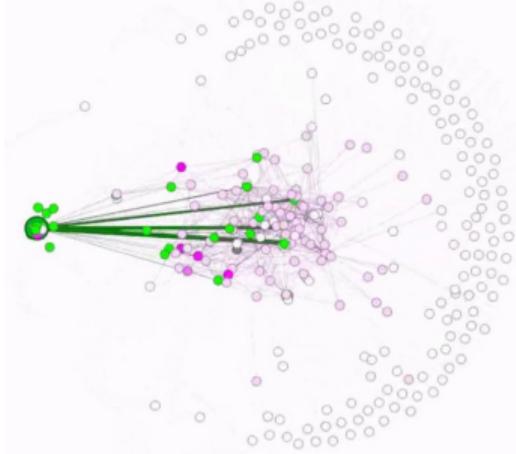
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Before Lehman 08/2008



After Lehman 12/2008



After 3yr LTRO 12/2011

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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."

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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 $i = 1, \dots, N$, time is discrete and infinite
- ▶ Banks are hit by liquidity shocks $\zeta_{i,t}$

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

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

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

- ▶ 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 $\mathbb{P}(z_{j,t} > \epsilon)$ and $e_{i,j,t} \sim (0, \tilde{\sigma}_{i,j,t}^2)$ is independent perception error

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- ▶ Perceived probability of default is obtained from Chebyshev's bound as

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

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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: $(1 - P_{i,j,t})r_{i,j,t} - P_{i,j,t} - \underline{r}_t$, 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 θ is bargaining power of lender, with $\bar{r}_t = r > \underline{r}_t = 0$

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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 :

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

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

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

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

- ▶ Non-linear policy function for search

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

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

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

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 - ▶ *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)

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

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

- ▶ $\hat{\theta}$ 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 Θ 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

Auxiliary statistic	Observed $\hat{\beta}_T$	Simulated $\tilde{\beta}_{TS}(\hat{\theta}_T)$
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
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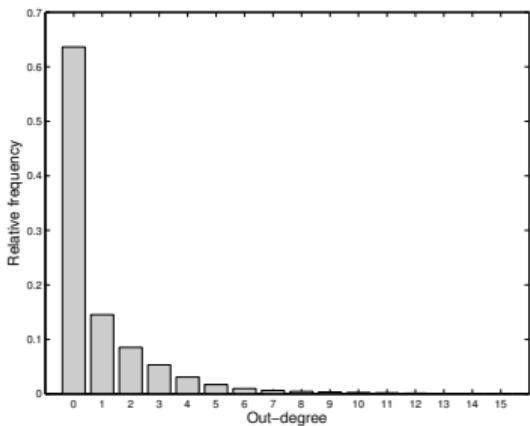
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$\text{Corr}(l_{i,j,t}, \#l_{i,j,t-1}^{rw})$ (mean)	0.644	0.586
$\text{Corr}(r_{i,j,t}, \#l_{i,j,t-1}^{rw})$ (mean)	-0.072	-0.123
...		

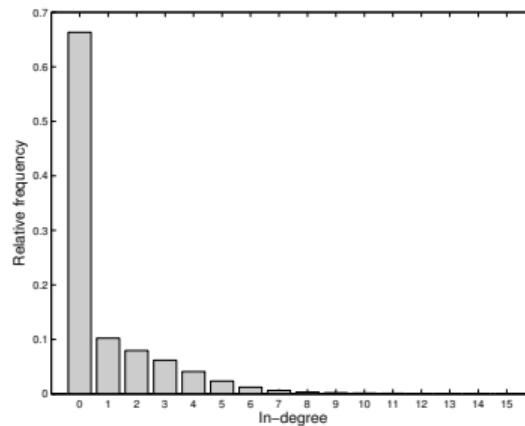
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Corr($r_{i,j,t}$, $\#I_{i,j,t-1}^{rw}$) (mean)	-0.072	-0.123
...		
Avg log volume (mean)	4.117	4.137
Std log volume (mean)	1.690	1.136
Avg spread (mean)	0.286	1.075
Std spread (mean)	0.107	0.112

Simulated Degree Distributions



(a) Out-degree distribution



(b) In-degree distribution

Auxiliary statistic	Observed $\hat{\beta}_T$	Simulated $\tilde{\beta}_{TS}(\hat{\theta}_T)$
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

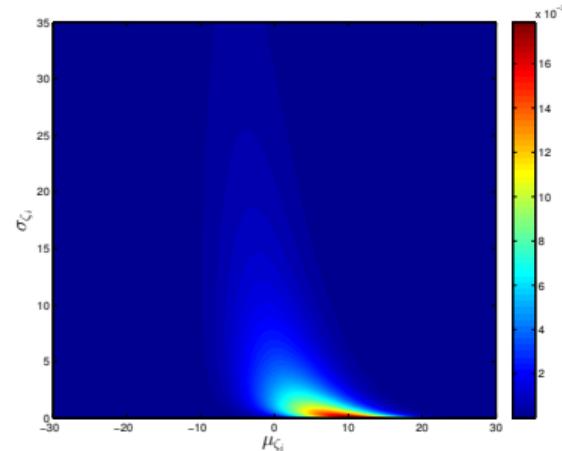
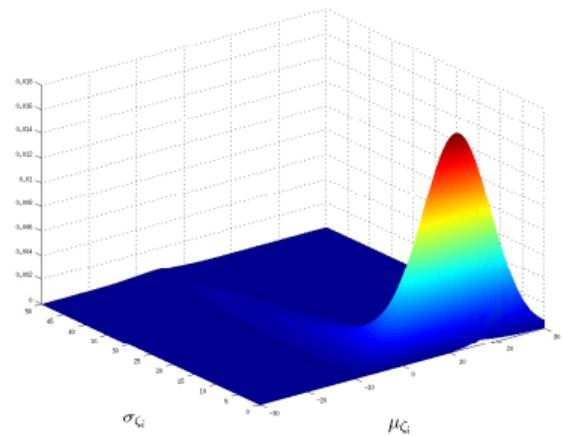


Figure : Joint distribution of mean and standard deviation parameter

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

Bank Heterogeneity and Trading Relationships

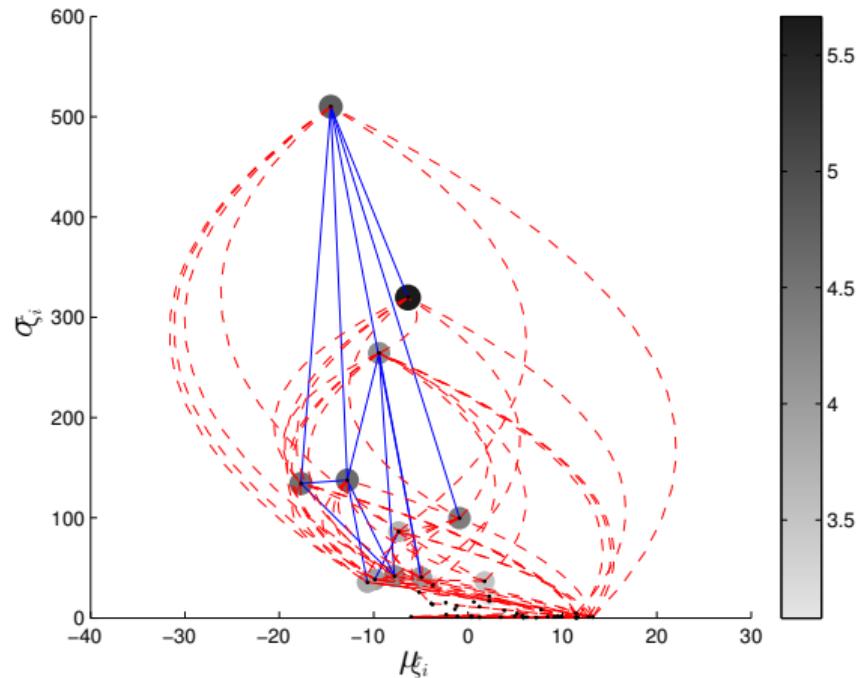


Figure : Five days of simulated interbank trading. Bank i 's position in x-y plane given by parameters of its liquidity shock distribution $(\mu_{\xi_i}, \sigma_{\xi_i})$. Node size scaled and shaded proportional to average loan volume per bank. Directed links are plotted as curved dashed lines (red)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

Comparative Statics of Network Measures

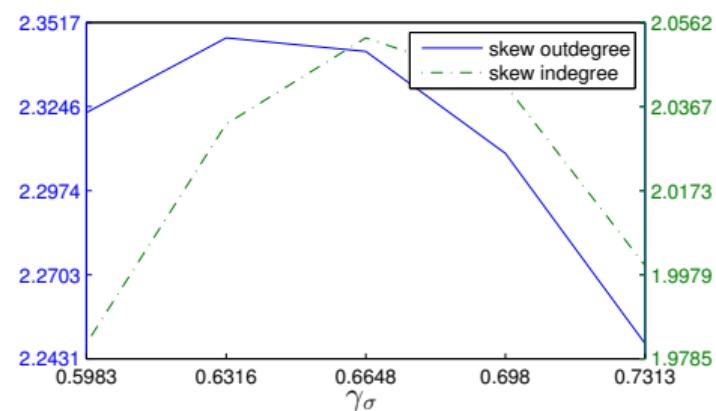
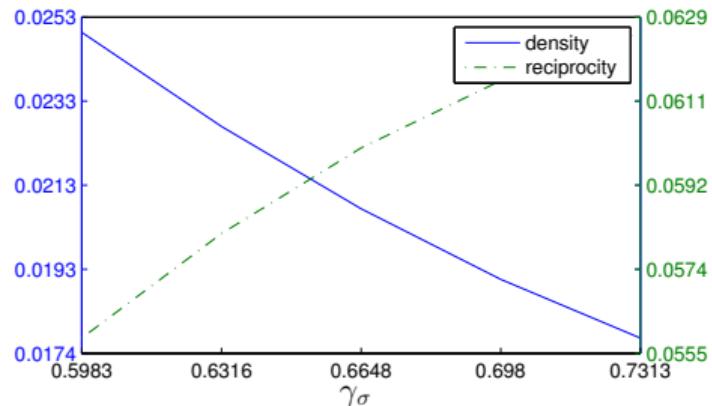


Figure : Simulated network responses to changes in persistence of credit risk uncertainty

Dynamic Network Responses to Credit Risk Uncertainty Shock

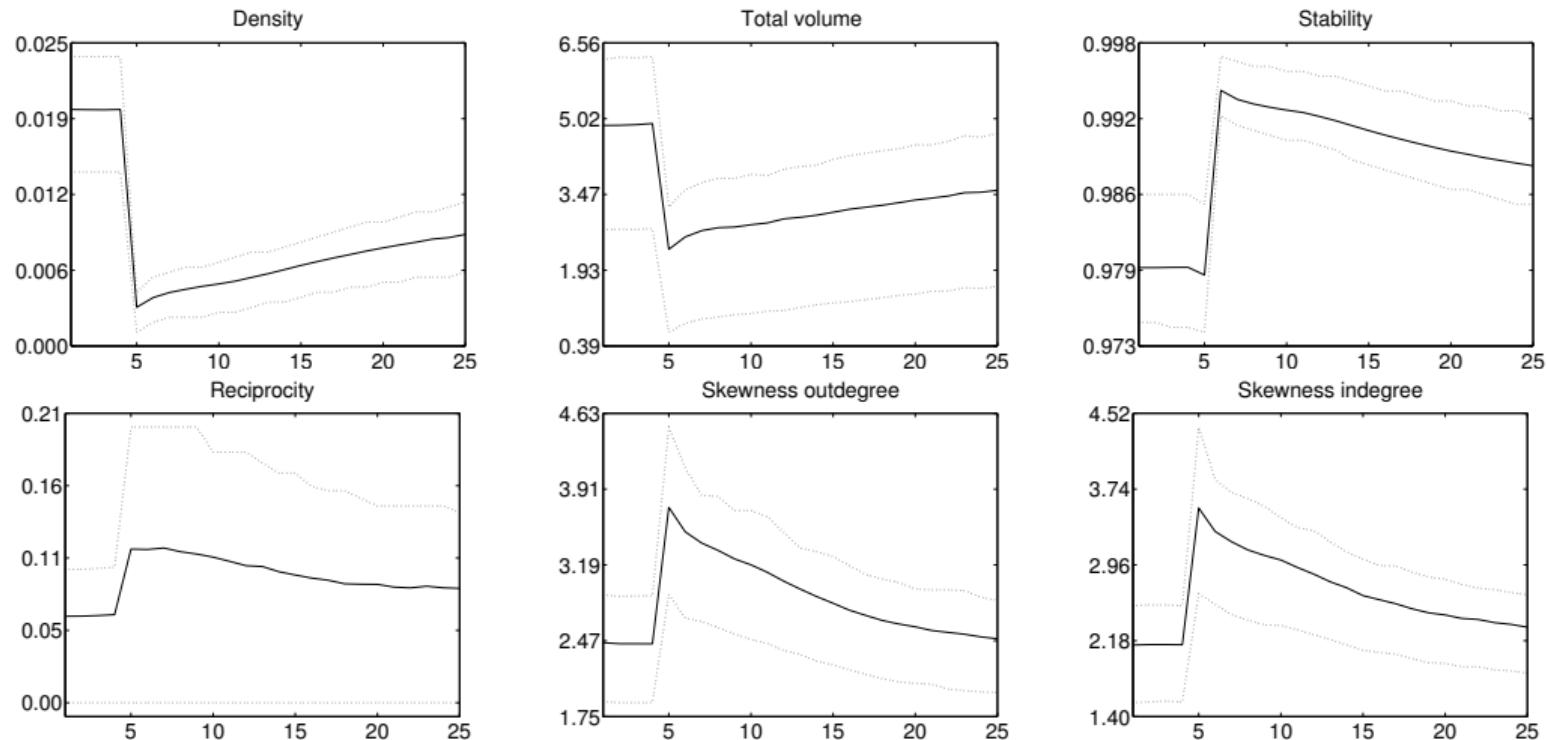
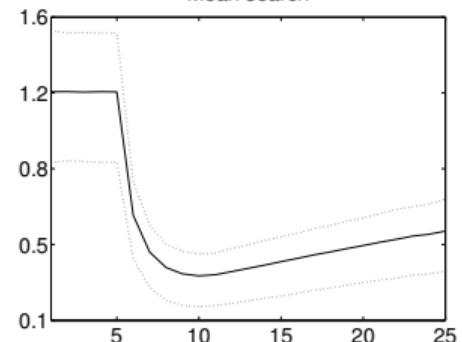
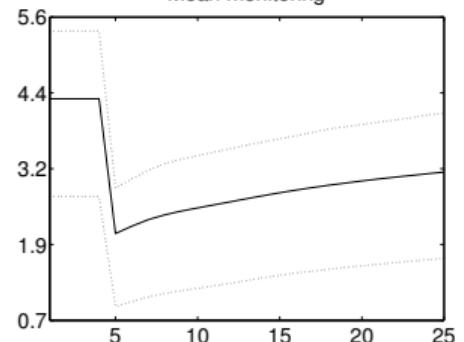
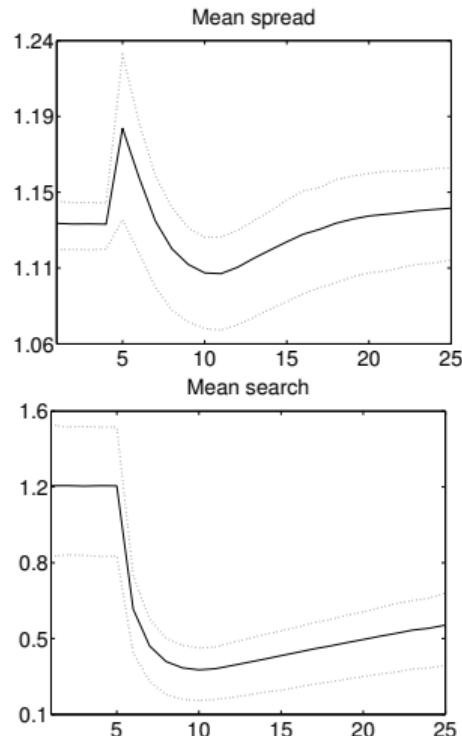
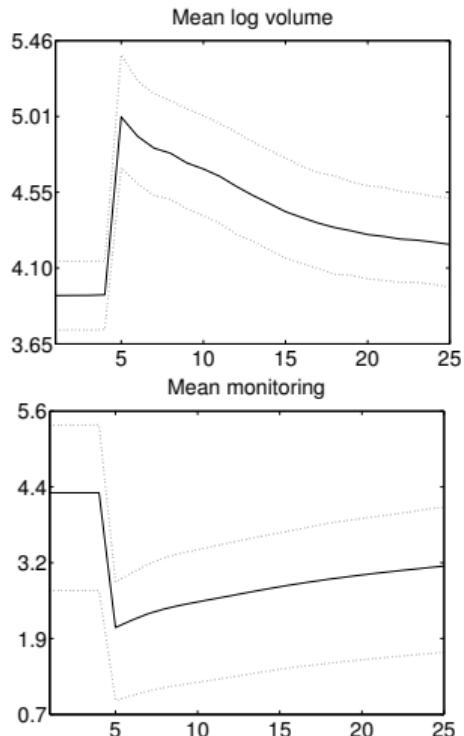


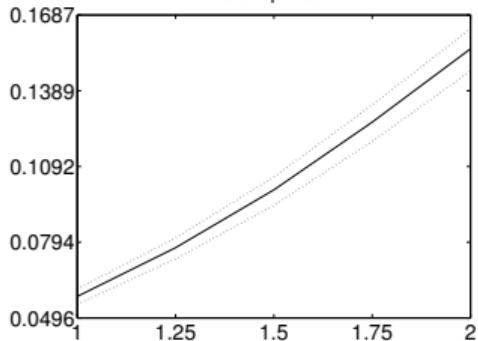
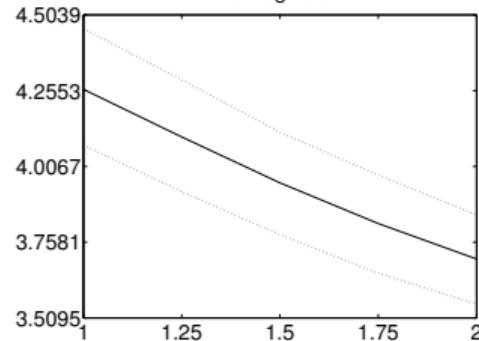
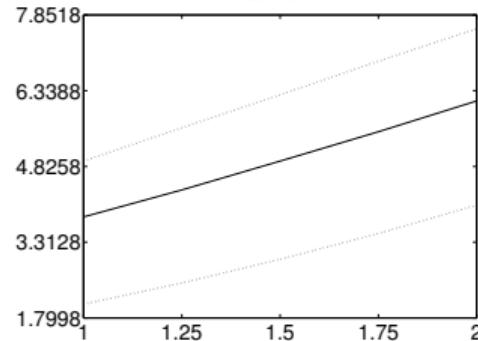
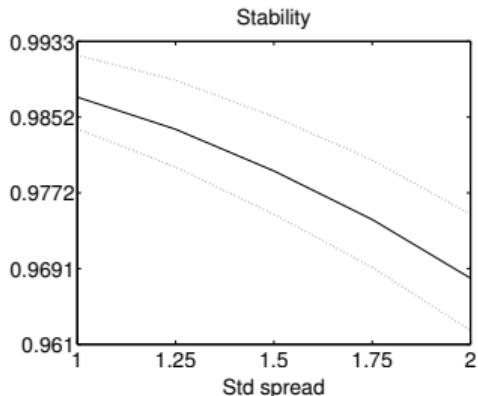
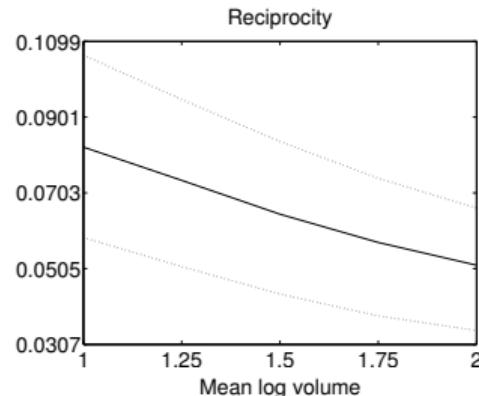
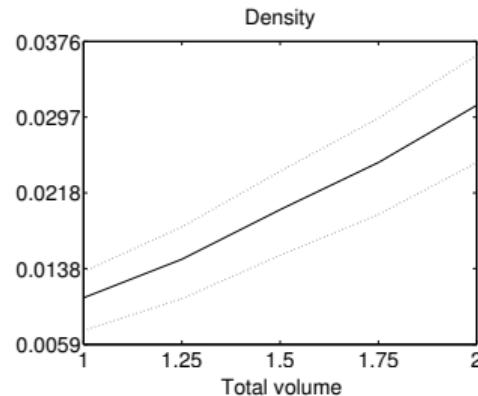
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Responses of Credit Conditions, Monitoring and Search

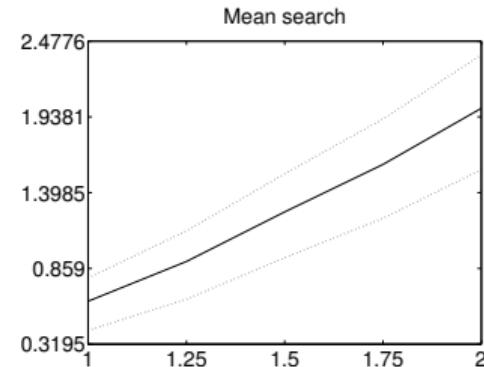
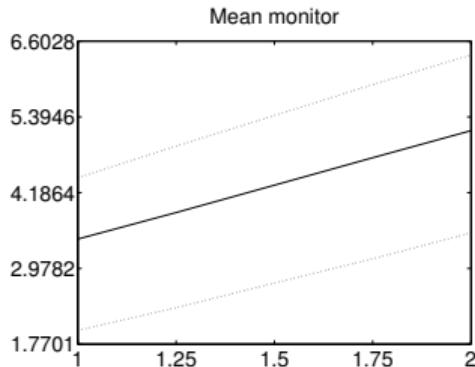


- ▶ What's the role of monetary policy on interbank network structure ?
- ▶ Focus on width of interest rate corridor as key parameter

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

- ▶ 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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