Money Illiquidity

Dmitry Livdan[1] Norman Schürhoff[2] Vladimir Sokolov[3]

[1]UC Berkeley, CEPR [2]University of Lausanne, SFI, CEPR

[3]ICEF, HSE Moscow

Economics of Payments X Conference

Payment disruptions cause "money illiquidity"

- Payment system is backbone of financial system
- Payment stress occurs regularly (09/11, 2019 repo blowup, March 2020)
- Payment system is assumed frictionless in traditional models of banking

Our approach

i. Equilibrium in endogenous production network with payment disruptions

ii. Evidence from granular payment system data with sender & receiver identifiers

- Exogenous shock to interbank loan market caused by banking panic in Russia
- Impact on payment system, firm-to-firm payments & firm growth

Main findings

- Money illiquidity impairs economic activity through two channels
  1. firms' direct loss of payment access, and
  2. payment network externality amplifies initial shock
- Payment shocks
  1. propagate upstream through firms' input-output network, and
  2. alter network structure (network structure adjusts endogenously)
     (Productivity shocks propagate downstream & do not alter network structure)
  3. Firms' resilience = elasticity of eigenvector centrality to payment shock
- Empirical estimates
  1. Payment shock originating at firm's own/supplier/customer banks reduces firm's revenue growth by 2.5%/3.1%/7%
  2. Upstream/downstream firms' resilience dampens payment shock pass-through by 0.61/0.26

Model of payment system disruptions

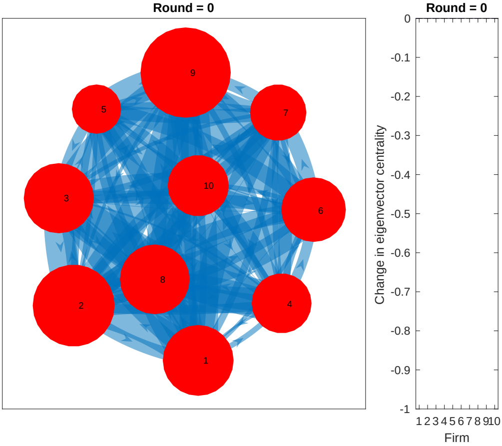
- Extension of Acemoglu et al. (2012) where N firms with CRS production subject to idiosyncratic productivity shocks & fixed network structure W
- 2 extensions
  1. Internal production factor k_{it}, independent of outside production factors
  2. Access-to-payment shocks z_{it} (M-shocks)

$$\text{Output: } x_{it} = e^{\varepsilon_{it}} \Big(\prod_{j=1}^{N} x_{ijt}^{w_{ij}} \Big)^{1-z_{it}} {k_{it}}^{z_{it}}, \qquad z_{it} \in [0,1],$$

- Leontief inverse $L_t = (I - \Sigma_t)^{-1} = I + \sum_{s=1}^{\infty} \Sigma_t^s$ and firms' eigenvector centralities $\delta_t = \frac{1}{N} L_t' 1$ depend on M-shocks

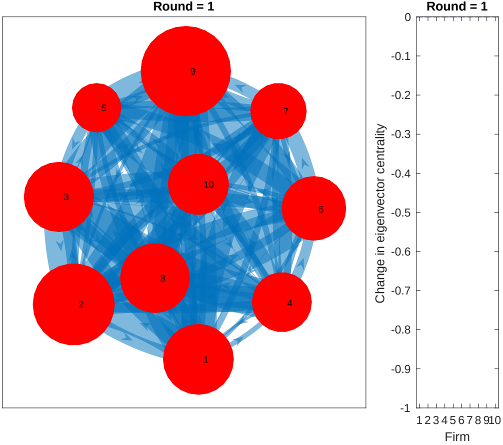
$$\Sigma_t = M_t * W = \underbrace{\begin{bmatrix} 1 - z_{1t} & 0 & \cdots & 0 \\ 0 & 1 - z_{2t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 - z_{Nt} \end{bmatrix}}_{\text{Payment shocks } M_t} * W$$

Propagation of payment shocks



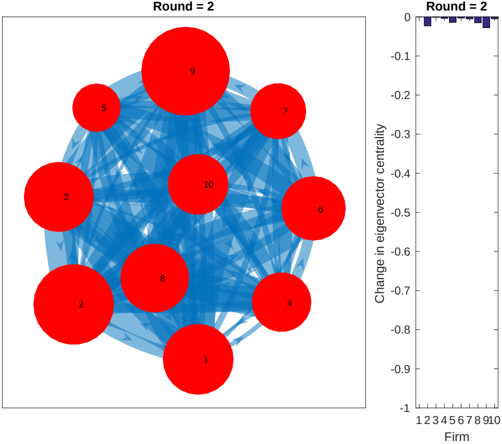
- Random network of $N = 10$ firms where firm revenues & firm-to-firm flows
- Payment shock originates at (customer) firm 1: $z_1 = 1$

Propagation of payment shocks



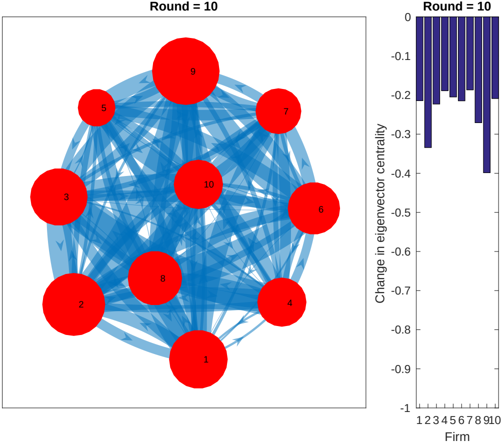
- Direct impact of payment shock $z_1 = 1$ realized after round 1
- Network structure unchanged ($\Delta\delta_{it} = 0$); effect not very big

Propagation of payment shocks



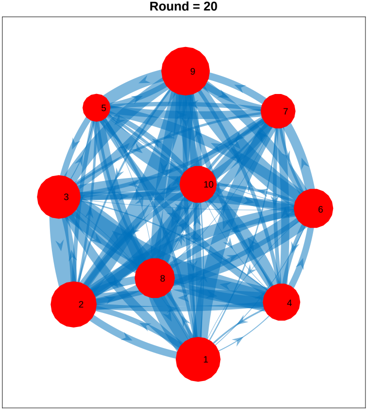
- Indirect impact of payment shock $z_1 = 1$ propagation starts in round 2
- Network structure changes ($\Delta\delta_{it} < 0$)

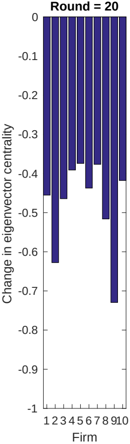
Propagation of payment shocks



- Most firm revenues & firm-to-firm flows decline
- Network structure continues to change ($\Delta\delta_{it} < 0$)

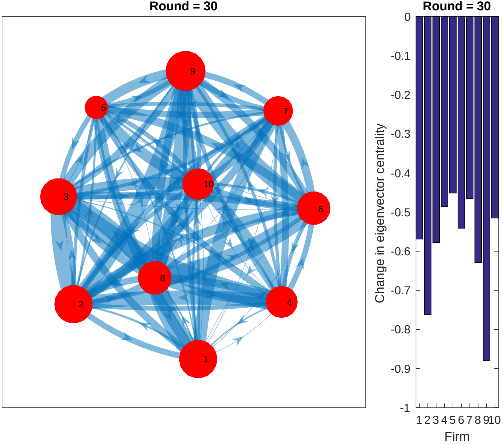
Propagation of payment shocks





- Network structure continues to change ($\Delta\delta_{it} < 0$)

Propagation of payment shocks



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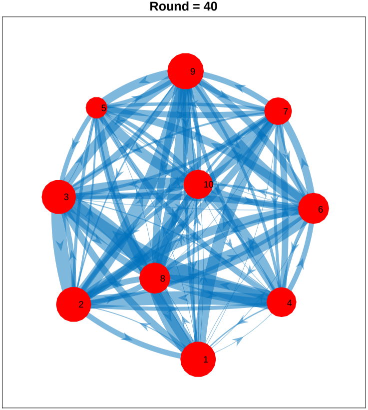
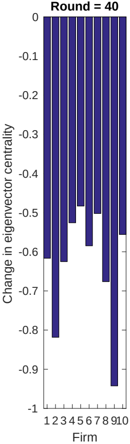
Propagation of payment shocks





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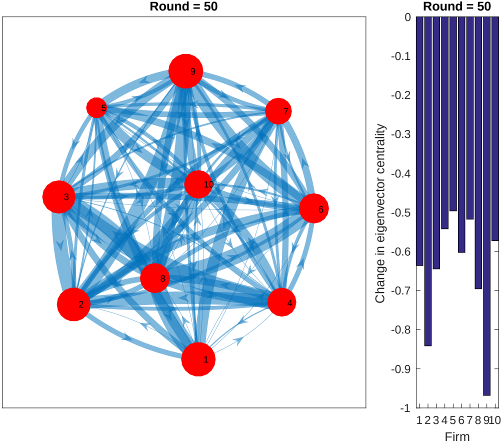
Propagation of payment shocks



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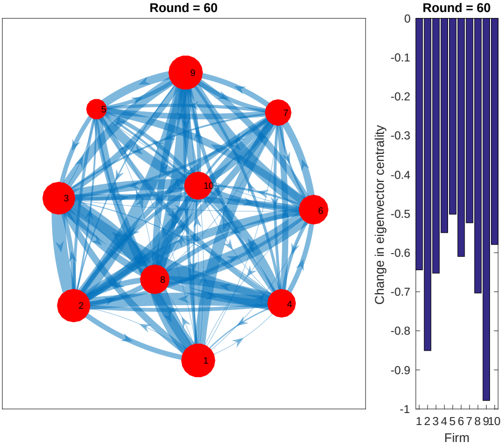
Propagation of payment shocks



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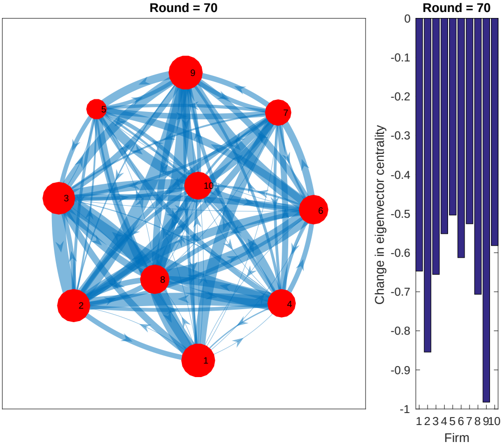
Propagation of payment shocks



- Network stabilizes after about 70 rounds (power series expansion)
- Least (Most) resilient are firms 2 & 9 (5 & 7); hit harder than firm 1

Testable predictions

PREDICTION 1

Firms' payment network centrality declines after a payment shock.

PREDICTION 2

Firm growth declines with its own payment shocks z_{it}.

PREDICTION 3

Payment shocks propagate upstream. Firm growth declines with payment shocks of the customers (more than suppliers).

PREDICTION 4

More eigenvector-central firms are more sensitive to payment shocks.

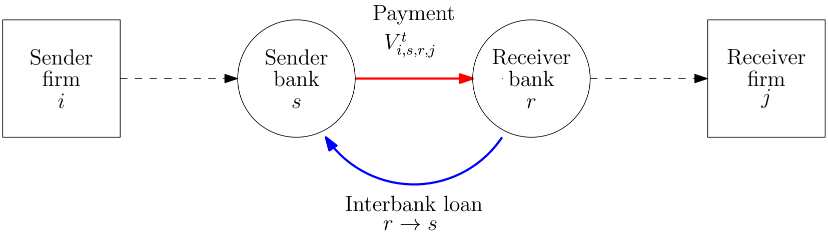
PREDICTION 5

The firm-to-firm payment growth is negatively impacted by own and other firms' payment shocks. More resilient firms have higher $\mathcal{R}_t$ and are less affected by payment shocks including shocks originated at different firms.

Description of Russian payment system data

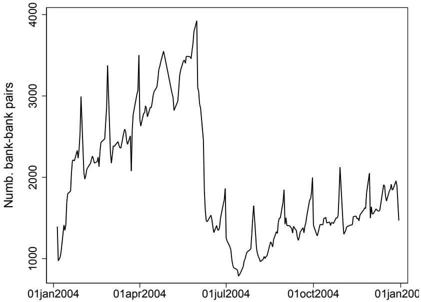
- Payment system data usually unavailable → Money illiquidity is hard to study empirically
- Back in 2004, data on all firm-firm payments conducted by banks through the Central Bank of Russia (CBR) Moscow branch got available
  - A few researchers had looked into this data in other contexts: Mironov (JF, 2013); Mironov and Zhuravkaya (AEJ Policy, 2016)
- Daily 2004 data contains 133.4 mln. payment orders
- 1.168 mln. unique paying entities and 1.245 mln. unique receiving entities. These include firms, individuals, banks, municipalities, etc.
- Payment network contains 1,413 bank senders, 1,418 bank recipients and 637,081 bank sender-recipient pairs

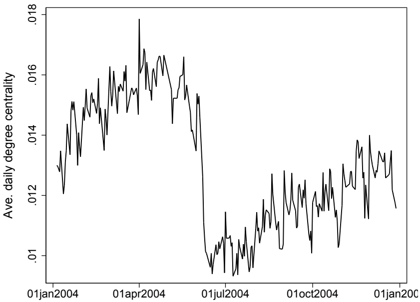
Payment system disruptions



- Payment system is maintained by banks (s, r)
- Red arrow: Payment $V^t_{i,s,r,j}$ from paying firm i through sender bank s and receiver bank r to receiving firm j, where t is payment instruction date
- Blue arrow: Interbank loan between banks r and s with r being the originator bank to offset liquidity imbalance
- Banking panic causes ~~blue arrow~~ causes ~~red arrow~~ to fail/be delayed

Interbank loan market panic



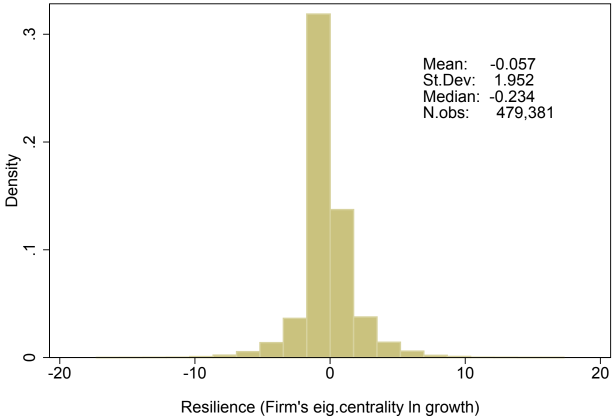


- On May 13, 2004 the CBR unexpectedly withdrew licences of *Sodbiznesbank* and *Credittrust* blaming them for money laundering (Degryse et al. (2019))
- In the last week of May 2004, the Head of the Federal Financial Monitoring Service made a statement that "there are at least ten other banks that are about to lose their banking licences for money laundering reasons"

Density plot of eigenvector centrality growth

PREDICTION 1

Firms' payment network centrality declines after a payment shock.



Testing the model predictions

PREDICTION 2

Firm growth declines with its own payment shocks Z_i.

$$\mathrm{Y}_i = \alpha_I \times \alpha_{PC} + \beta \times \mathrm{Z}_i + \gamma' \boldsymbol{X}_i + \varepsilon_i,$$

PREDICTION 3

Payment shocks propagate upstream. Firm growth declines with payment shocks of the customers Z_i^d (more than suppliers Z_i^u).

$$\mathrm{Y}_i = \alpha_I \times \alpha_{PC} + \beta_1 \times \mathrm{Z}_i + \beta_2 \times \mathrm{Z}_i^{\mathrm{d}} + \beta_3 \times \mathrm{Z}_i^{\mathrm{u}} + \gamma' \boldsymbol{X}_i + \varepsilon_i.$$

- where α_I and α_{PC} are industry and postal code fixed effects, respectively. $\boldsymbol{X}_i$ are firm level and averaged for a firm bank level controls. Standard errors are double-clustered at the firm industry and postal code levels.

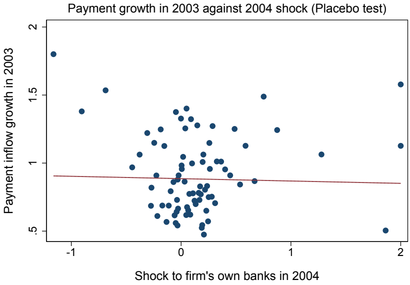
Firm revenue growth and its own payment shock (P2)

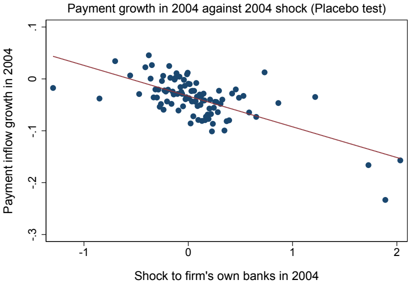
Standard errors are clustered at firm-firm pair level. Significance levels are * 5%, ** 1%, *** 0.1%.

Dependent variable:	Payment inflow (revenue) growth		
	(1)	(2)	(3)
Shock to firm's own banks Z_i	-0.082***	-0.106***	-0.038***
	(0.008)	(0.008)	(0.007)
Firm controls	NO	YES	YES
Bank controls	NO	NO	YES
Industry*Postal code FE	YES	YES	YES
Num. Industry*Postal code	9,252	9,252	9,252
Observations	792,283	790,641	790,641
Adj. R-squared	0.023	0.033	0.508

- In agreement with the model the coefficient on the payment shock is negative, statistically significant at 1%, and equal to -0.082/-0.106/-0.038.

Binscatterplots for Placebo test and for Prediction 2 result





- The left-hand side figure illustrates the *placebo test* where all firms are assigned the payment shock that occurred to them in 2004. We plot bin values of this shock against the bin values of firm's payment growth between half-year periods of 2003
- The right-hand side figure illustrates the main result on *prediction 2*. Firms are assigned the payment shock that occurred to them in 2004 and plot bin values of this shock against the bin values of firm's payment growth between half-year periods of 2004

Upstream propagation of payment shocks (P3)

Standard errors are clustered at firm-firm pair level. Significance are *5%, **1%, ***0.1%.

Dependent variable:	Payment inflow (revenue) growth		
	(1)	(2)	(3)
Shock to firm's own banks Z_i	-0.025***	-0.038***	-0.025***
	(0.005)	(0.006)	(0.005)
Shock to downstream firms' banks Z_i^d	-0.071***		-0.070***
	(0.005)		(0.005)
Shock to upstream firms' banks Z_i^u		-0.042***	-0.031***
		(0.010)	(0.009)
Firm and Bank Controls	YES	YES	YES
Industry*Zip FE	YES	YES	YES
Num. Industry*Postal code	9,252	9,252	9,252
Adj. R-squared	0.615	0.508	0.615
Observations	790,641	790,641	790,641

- In agreement with the model prediction 3, shocks to payer firms' banks have much larger effect on the supplier firm *i*'s revenue growth, $\beta_2 = -0.071$, than shocks to its own banks have, $\beta_1 = -0.025$.

Eigenvector-centrality and sensitivity to payment shocks

PREDICTION 4

More eigenvector-central firms are more sensitive to payment shocks.

$$\mathrm{Y}_i = \alpha_I \times \alpha_{PC} + \beta_1 \times \mathrm{Z}_i + \beta_2 \times \log \delta_i^{Pre} + \beta_3 \times (\mathrm{Z}_i \times \ln \delta_i^{Pre}) + \gamma' \boldsymbol{X}_i + \varepsilon_i.$$

- where: δ_i is an eigenvalue centrality of a firm during the pre-panic period weighted by the volume of payment

PREDICTION 5

More resilient firms have higher $\mathcal{R}_t$ and are less affected by the payment shocks including shocks originated at different firms.

$$\mathrm{Y}_i = \alpha_I \times \alpha_{PC} + \beta_1 \times \mathrm{Z}_i + \beta_2 \times \widehat{\mathrm{Resilience}}_i + \gamma' \boldsymbol{X}_i + \varepsilon_i,$$

- where: $\widehat{\mathrm{Resilience}}_i(\text{sym. growth}) = \frac{\delta_i^{Post} - \delta_i^{Pre}}{\frac{1}{2}(\delta_i^{Post} + \delta_i^{Pre})}$

Eigenvector-centrality and payment shocks (P4)

Standard errors are clustered at firm-firm pair level. Significance levels: *5%, **1%, ***0.1%.

Dependent variable:	Payment inflow (revenue) growth		
	(1)	(2)	(3)
Shock to firm's own banks Z_i	-0.145***	-0.142***	-0.109***
	(0.033)	(0.036)	(0.030)
Firm's eig. centrality $\ln \delta_i$	-0.083***	-0.085***	-0.086***
	(0.016)	(0.016)	(0.016)
$Z_i \times \ln \delta_i$	-0.012***	-0.011***	-0.011***
	(0.004)	(0.004)	(0.004)
Firm Controls	NO	YES	YES
Bank Controls	NO	NO	YES
Industry*Postal code FE	YES	YES	YES
Num. Industry*Postal code	8,701	8,701	8,701
Observations	601,037	601,037	601,037
Adj. R-squared	0.240	0.247	0.249

- More pre-panic central firms experience more reduction in revenue growth than less central firms when hit by the same shock to their own banks, Z_i.

Resilience to payment shocks (P5)

Standard errors are clustered at firm-firm pair level. Significance levels: *5%, **1%, ***0.1%.

Dependent variable:	Payment inflow (revenue) growth	
	Full sample	Active firms in both periods
	(1)	(2)
$\widehat{\text{Resilience}}_i$ (Firm's eig. centrality, symmetric growth)	0.841***	
	(0.036)	
$\widehat{\text{Resilience}}_i$ (Firm's eig. centrality, ln-growth)		0.057***
		(0.001)
Shock to firm's own banks Z_i	-0.023***	-0.016***
	(0.006)	(0.004)
Controls	YES	YES
Industry*Zip FE	YES	YES
Adj. R-squared	0.747	0.459
Observations	790,641	431,221

- $\beta_2 = 0.845$ in Column 1 translates into 10% increase in resilience leads to 0.0845 increase in the revenue growth.

Conclusion

- We modify the static I-O production network of Acemoglu et al. (2012) by introducing an internal factor independent of the outside factors into the production technology and allowing for **access-to-payment shocks**
- Using CBR payment level data we provide **causal evidence on how disruption of interbank market network affects payment flows between firms**
- We show that payment system disruptions propagate upstream and diminish firm growth and distort the network structure of firm-to-firm payment flows
- Firms with larger eigenvector centrality are more exposed to payment shocks and are hurt more
- More resilient firms, as captured by the firm's change in eigenvector centrality, are less affected, as predicted by the model