NETWORK INDICATORS FOR MONITORING INTRADAY LIQUIDITY IN BOK-WIRE+

The Evolving Landscape of Payment Systems
Central Bank of Mexico, Mexico City
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Agenda

Problems

Which bank is important in an interbank payment system on a given moment of the day?
Which banks are most disrupted by a given initial problem?
Can we provide early warning on liquidity problems?

Objective

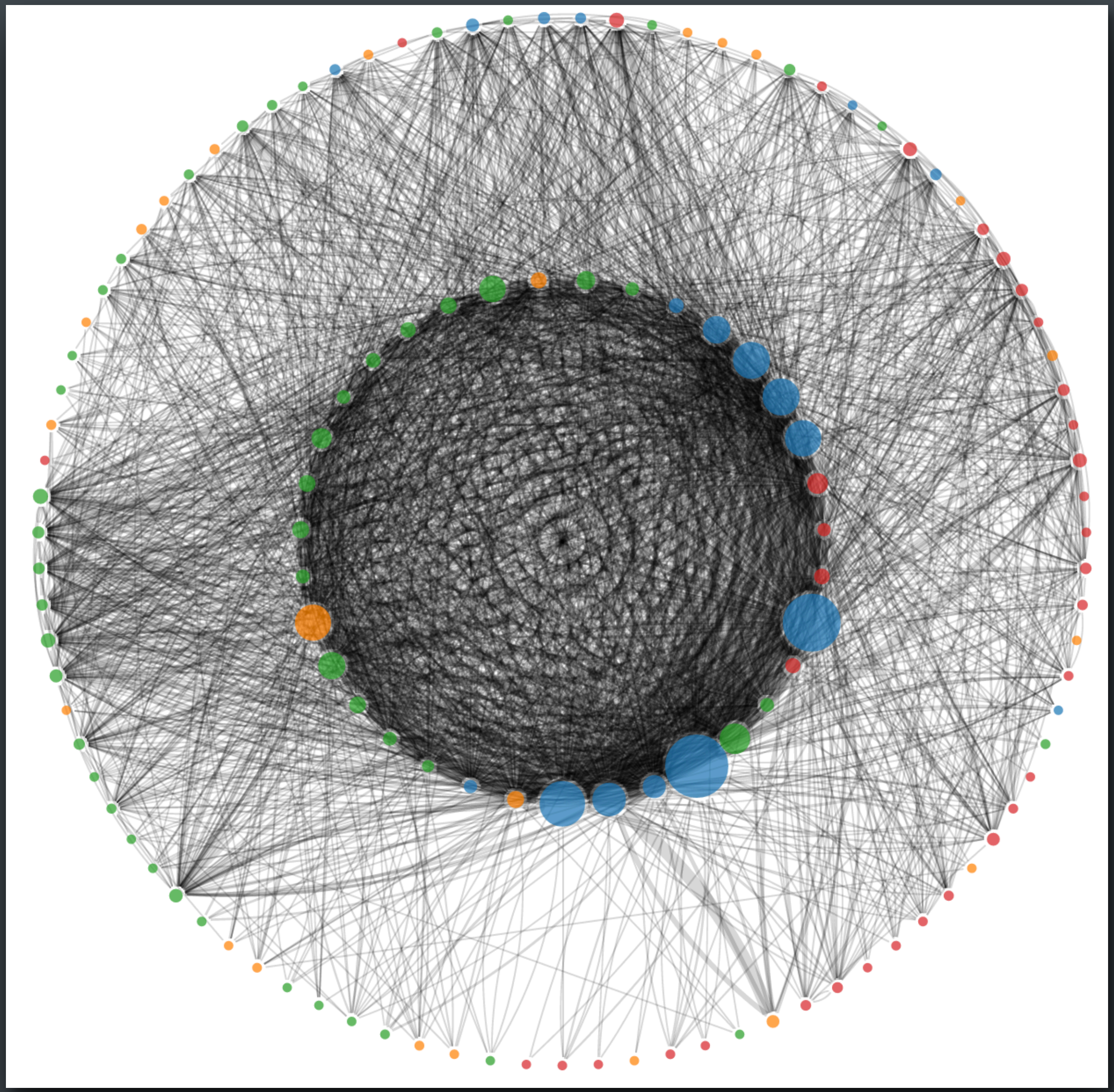
Develop analytics for a real-time monitoring system

Papers

“Algorithm for identifying systemically important banks in payment systems”, with Samantha Cook, Economics E-Journal, 2013.

“Network indicators for monitoring intraday liquidity in BOK-Wire+”, with Seungjin Baek and Yahoo Joon, Journal of Financial Market Infrastructures 2(3), 2014

BoK-Wire+



Banks are divided into core (inner circle) and periphery (outer circle) based on Craig and von Peter (2013).

We identify important banks with SinkRank algorithm by Soramaki and Cook (2014). They are shown with a larger node size in the visualization.

Node color reflects bank type:

- Blue=Domestic banks
- Green=Financial Intermediaries
- Red=Foreign Banks
- Orange=Other

Typical Payment Networks

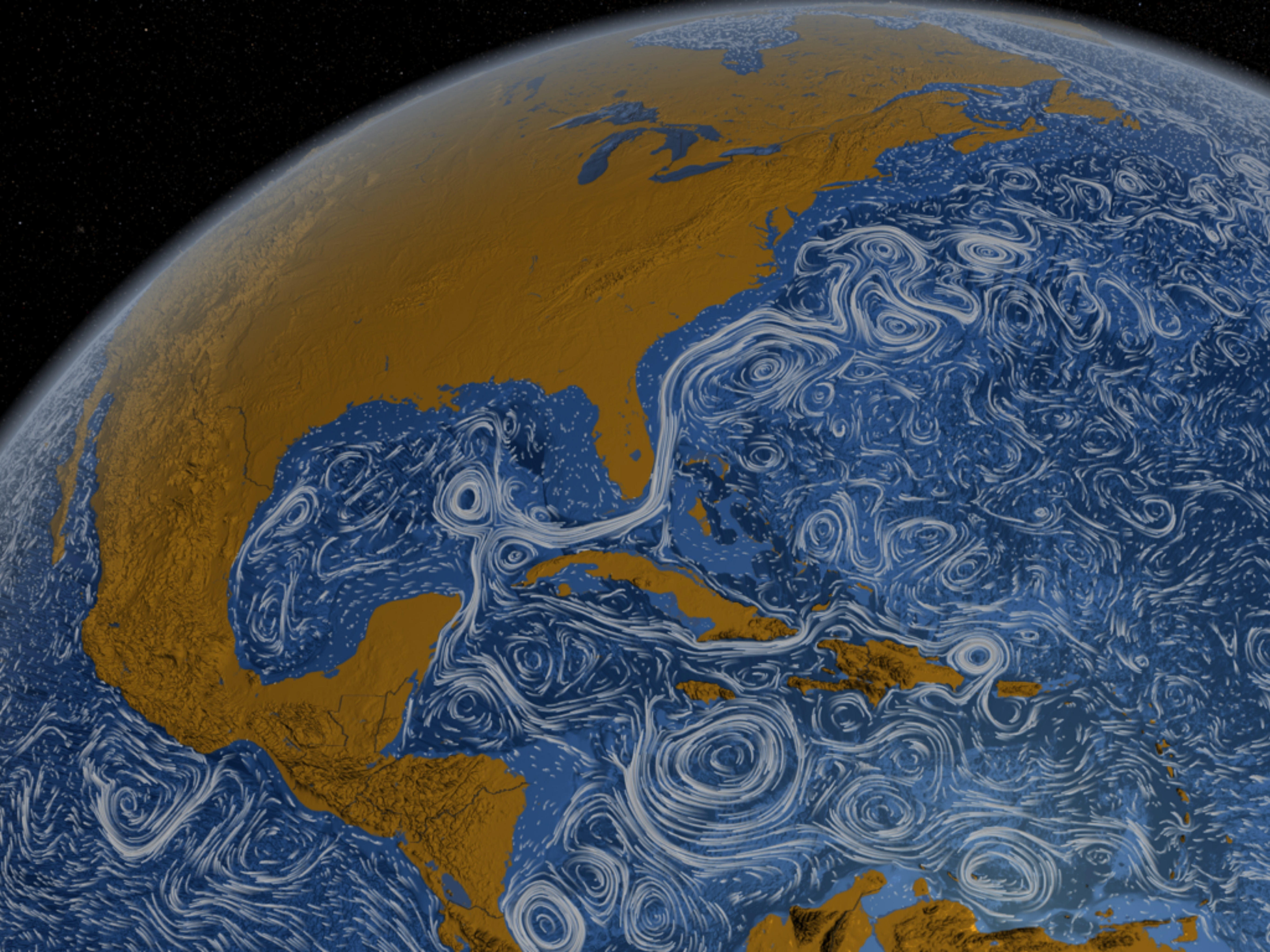
	System			
	BOK-Wire+ (Korea)	**LVTS (Canada)**	**TOP (Netherlands)**	**Fedwire (US)**
Period	Aug 2013	Apr 2004 –Dec 2008	Jun 2005 –May 2006	2005
Value	W190 tr	C$25.4 tr (pa)	€584 m	US$1.3 tr
Volume	11 672	4.4M (pa)	21 400	345 000
Number of nodes	122±5.9	14	155	5 086±123
Number of links	2871±471	N/A	1 182	76 614±6 151
Connectivity (%)	18.1±2.5	69.2±3.3	7.0	0.3±0.01
Degree (average)	45.4±6.9	N/A	9.2	15.2±0.8
Degree (maximum in)	84±8	N/A	N/A	2 097±115
Degree (maximum out)	86±10	N/A	N/A	1 922±121
Reciprocity (%)	58±6.0	89.3±2.5	63	21.5±0.03
Average path length	1.85±0.05	1.31±0.03	~2.3	2.62±0.02
Average eccentricity	2.9±0.1	1.84±0.07	~3.3	4.67±0.33
Average diameter	3.8±0.4	2.01±0.07	N/A	6.6±0.5
Clustering coefficient (%)	51.3±1.7	84.3±1.5	38.0	53.0±1

Generally
- Few very large banks
- Few very strong links
- High reciprocity
- High clustering
- Short path lengths

Large systems resemble scale free networks.

Very different from random or complete networks.

In small networks, information is on link weights.

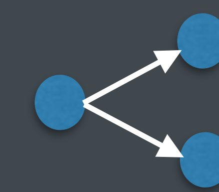


Modeling a Process in the Network

<u>Trajectory</u>

Geodesic paths (shortest paths)
Any path (visit no node twice)
Trails (visit no link twice)
Walks (free movement)

<u>Transmission</u>

Parallel duplication 

Serial duplication 

Transfer 

Table 1
Typology of flow processes

	Parallel duplication	Serial duplication	Transfer
Geodesics	<No process>	Mitotic reproduction	Package delivery
Paths	Internet name-server	Viral infection	Mooch
Trails	E-mail broadcast	Gossip	Used goods
Walks	Attitude influencing	Emotional support	Money exchange

Borgatti (2005)

SinkRank

Payments move liquidity.

Payments take place on links at some given frequency that can be measured.

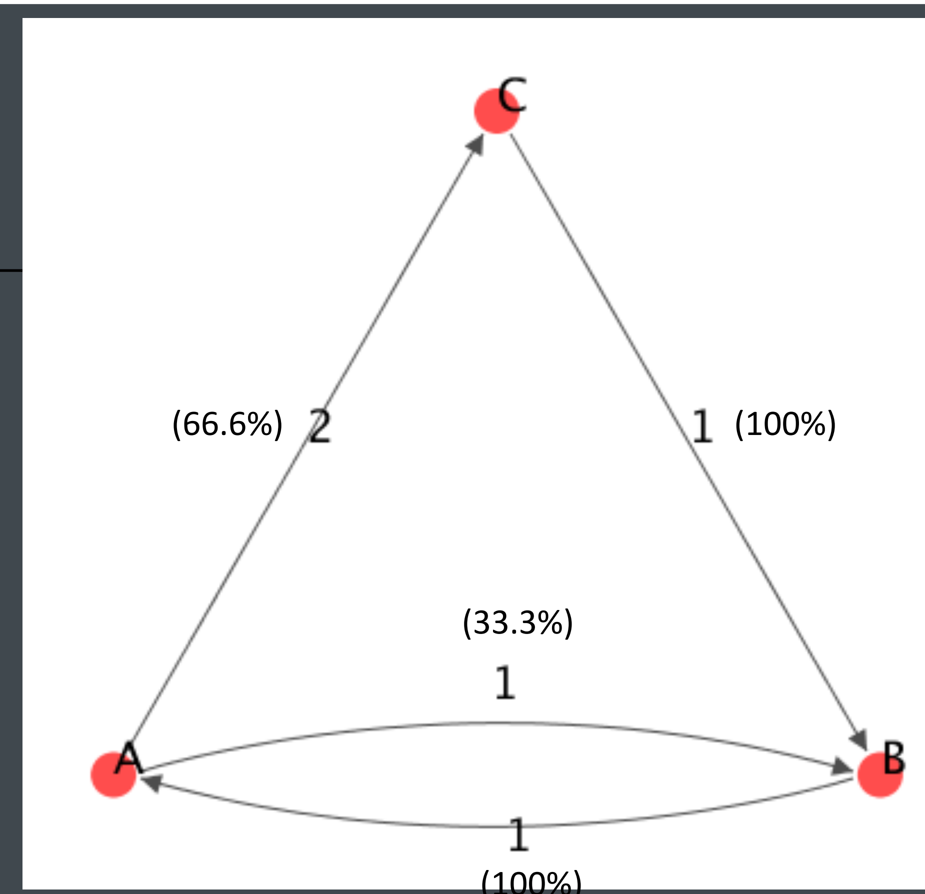
We are concerned on operational failures.The sink can receive payments but cannot send any.

Example:

Let's start by considering one unit of liquidity that is moved by payments in a simple system of three banks.

At the time of analysis, the unit of liquidity can be at either A, B or C.

What is the distance of the unit to the different 'sink nodes'?



To A	From B	1
	From C	2
To B	From A	$\frac{2}{3}\cdot 2+\frac{1}{3}\cdot 1=\frac{5}{3}$
	From C	1
To C	From A	$\sum_{i=1}^{\infty}(2i-i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=2$
	From B	$\sum_{i=1}^{\infty}(2i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=3$

Absorbing Markov Chains

SinkRank uses Absorbing Markov Chains to model the flow of liquidity to a sink.

SinkRank is the inverse of the average distance to a node via (weighted) walks from other nodes.

We can also calculate from which banks this liquidity comes from
-> most affected nodes

Transition Matrix P

$$P = \begin{bmatrix} S & T \\ 0 & I \end{bmatrix}$$

where *I* is an *m x m* identity matrix (*m* = the number of absorbing states), *S* is a square *(n - m) x (n - m)* matrix (*n* = total number of states, so *n - m* = the number of non-absorbing states), *0* is a zero matrix and *T* is an *(n - m) x m* matrix.

Fundamental Matrix Q

$$Q = (I - S)^{-1}$$

The *i,j*th entry of *Q* (q_{ij}) defines the number of times, starting in state *i*, a process is expected to visit state *j* before absorption.

SinkRank

$$\frac{n-m}{\sum_i \sum_j q_{ij}}.$$

Starting nodes are indexed by *i*, and nodes visited en-route to sink by *j*.

Liquidity Distribution

We need an assumption on the distribution of liquidity in the network at time of failure:

- Assume uniform
  -> unweighted average
  -> B is most important
- Estimate distribution
  -> Weight by steady state liquidity distribution that can be calculated by normal Markov Chains (PageRank)
  -> A and B are most important
- Use real distribution
  -> Weight by distribution from the system that is being modeled
  -> e.g. with A=5%,B=90%,C=5%, A is mot important

	Distribution	SinkRank
A	33.33%	0.67
B	33.33%	**0.75**
C	33.33%	0.40
A	37.5%	**0.71**
B	37.5%	**0.71**
C	25%	0.40
A	5%	**0.95**
B	90%	0.75
C	5%	0.34

=1/((1+2)/2) = 2/(1+2)

=1/
((1*0.375 + 2*0.25)/
(0.375 + 0.25))

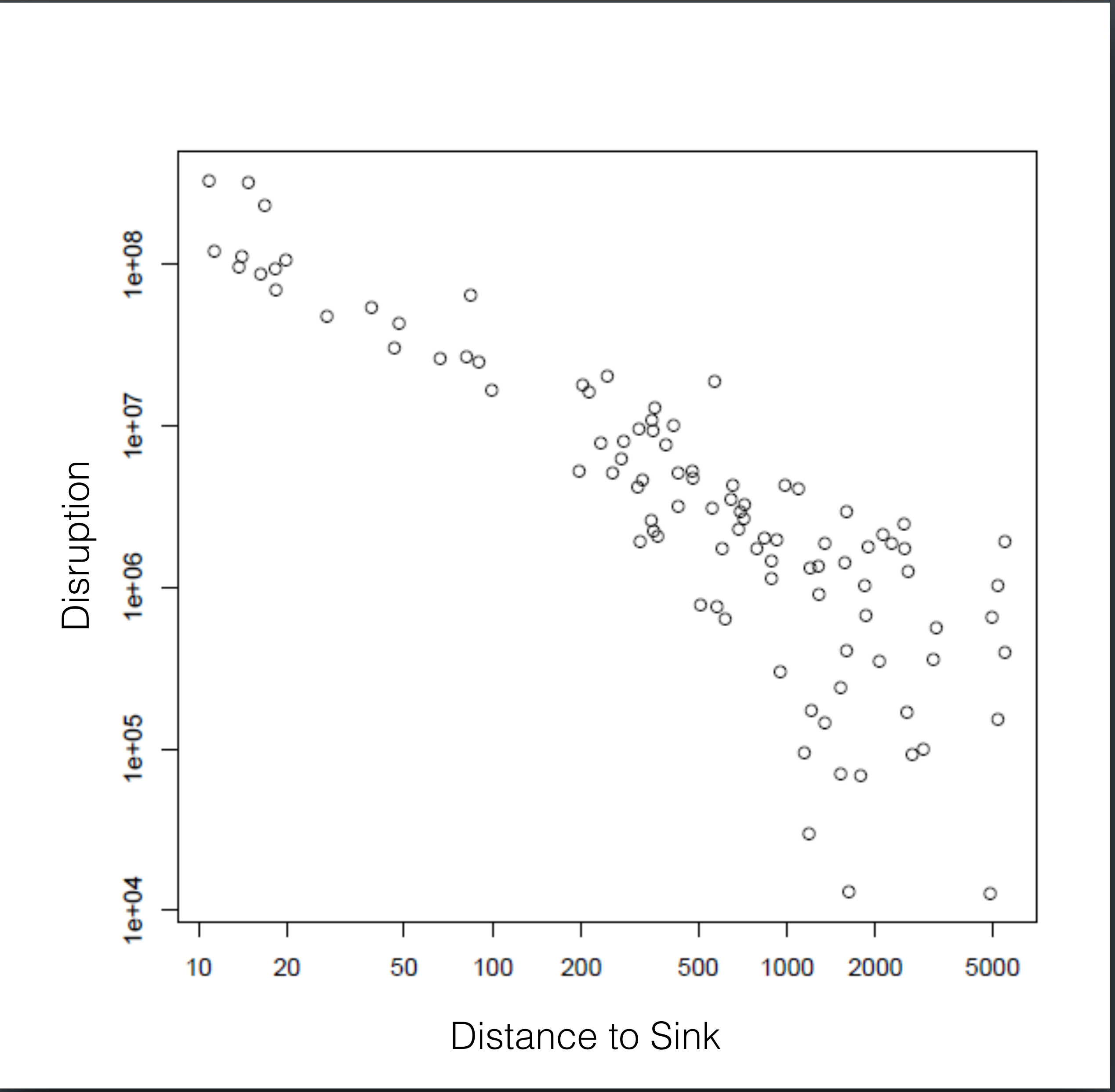
FNA PaymentSimulator

Simulation model for evaluating liquidity saving mechanisms and stress scenarios in payment systems.

Used e.g. in:

- Berge, T. O. and Christophersen, C. (2012). Operational problems in banks – Effects on the settlement of payments in Norges Bank. Norges Bank Economic Bulletin 83, 36–47.
- McLafferty, J. and Denbee, E. (2012). Liquidity saving in CHAPS: A Simulation Study.
- Soramaki, K and S. Cook (2013). “Algorithm for identifying systemically important banks in payment systems”, Economics E-Journal.
- Baek, S, J. Joon and K. Soramaki (2014) “Network indicators for monitoring intraday liquidity in BOK-Wire+”, Journal of Financial Market Infrastructures 2(3)

Distance to Sink



We carry out simulations with artificial payment data failing banks and comparing simulation results on disruption with Bank's Distance to Sink.

The chart shows the relationship between 'Distance to Sink' and Disruption when the bank with highest SinkRank fails.

We observe highest disruption to banks whose liquidity is absorbed first (i.e. which have low 'Distance to Sink').

Payment System Liquidity Indicator

PSLI is the ratio of projected liquidity demands and projected liquidity supply:

Debits so far

Payments pending/ queued

Expected debits for rest of the day

$$\mathrm{PSLI}_{ijt} = \frac{\mathrm{pending}_{ijt} + \mathrm{KRdebits}_{ijt} + \widehat{\mathrm{ERdebits}}_{ijt}}{\mathrm{balance}_{ijt} + \mathrm{limit}_{ijt} + \mathrm{KRcredits}_{ijt} + \widehat{\mathrm{ERcredits}}_{ijt}}$$

Balance now

Credits so far

Available overdraft facility

Expected credits for the rest of the day

Expected Debits & Credits

Expected credits and debits are estimated on the basis of a regression model.

The model takes into account the value already settled on the given day, effects related to reserve maintenance and to US holidays and the trade values of bonds and spot exchange.

The model has a good fit.

Model for credits

	Model 1			Model 2	
	Coefficient	*t*		**Coefficient**	*t*
tue	−0.2939**	−3.09	tue	−0.2692**	−3.49
wed	−0.5075***	−5.05	wed	−0.4879***	−5.67
thu	0.6049***	6.63	thu	0.6054***	7.93
fri	−0.0128	−0.14	—	—	—
reserve_check	−5.2343***	−35.43	reserve_check	−5.2310***	−35.50
us_hol	−1.0795***	−6.53	us_hol	−1.0934***	−6.82
bond	0.0037	0.87	—	—	—
fx	0.0001	0.04	—	—	—
_lreceiver_1	3.0615***	14.87	_lreceiver_1	3.1743***	31.34
_lreceiver_27	12.0550***	38.07	_lreceiver_27	12.1676***	130.47
_lreceiver_28	6.7873***	28.69	_lreceiver_28	6.9051***	80.15
_lreceiver_30	13.5095***	59.61	_lreceiver_30	13.6257***	87.87
_lreceiver_31	2.8790***	34.04	_lreceiver_31	2.9899***	32.92
_lreceiver_32	19.3134***	56.84	_lreceiver_32	19.4082***	89.10
_lreceiver_34	8.2016***	14.30	_lreceiver_34	8.3231***	118.77
_lreceiver_58	2.3454***	68.63	_lreceiver_58	2.4588***	26.63
_lreceiver_138	7.6201***	42.56	_lreceiver_138	7.7360***	87.08
_lreceiver_139	6.0048***	11.62	_lreceiver_139	6.1261***	56.87

Model 1	Model 2
Number of obs = 2 480	Number of obs = 2 490
$F(18,2462) = 4\,159.70$	$F(15,2475) = 5\,031.22$
Prob > F = 0.0000	Prob > F = 0.0000
R-squared = 0.9682	R-squared = 0.9682
Adj R-squared = 0.9679	Adj R-squared = 0.9681

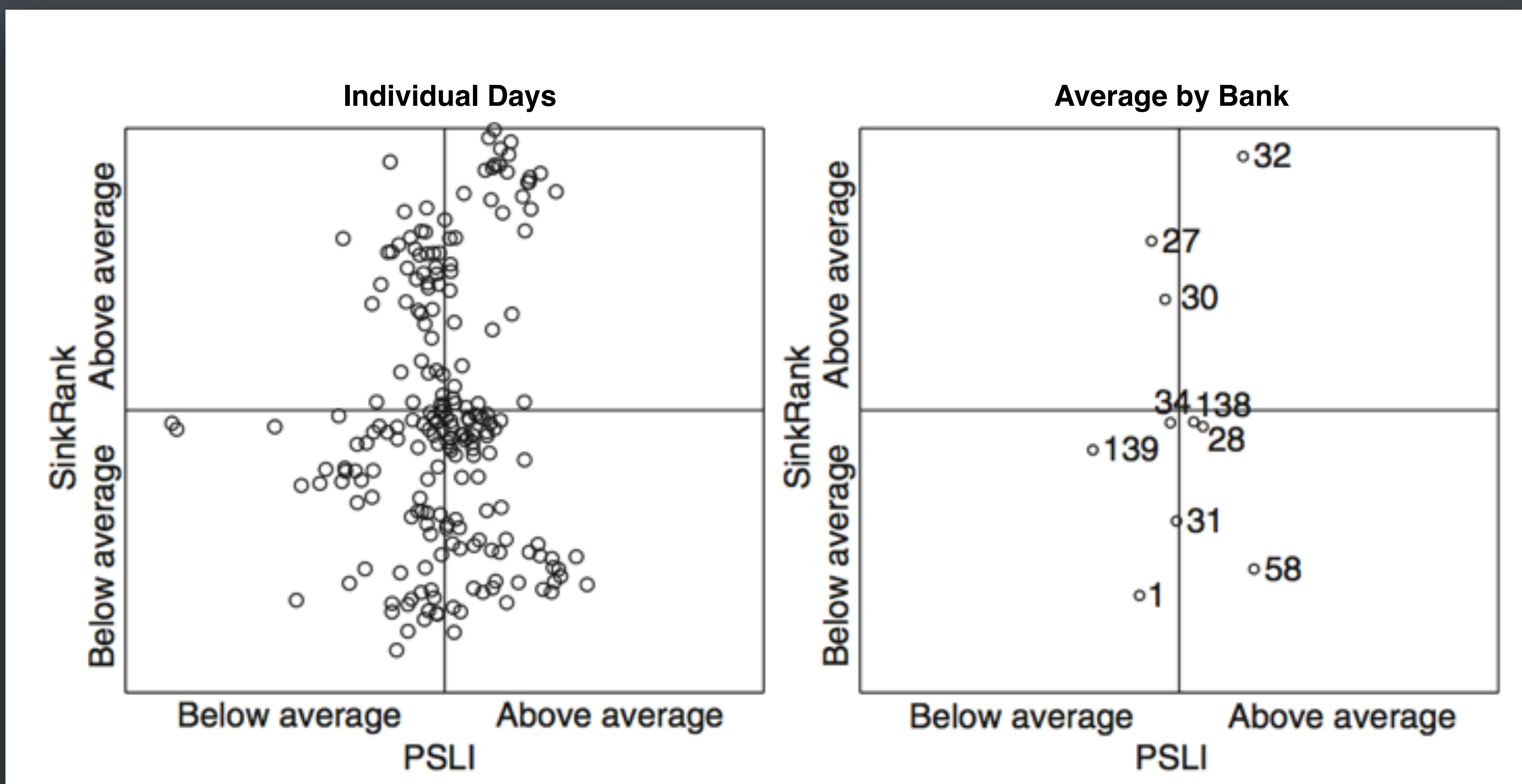
*, ** and *** represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Combining SinkRank and PSLI

We combine SinkRank with a measure on the banks' liquidity position (PSLI), here at 9am.

SinkRank measures systemic importance.

PSLI measures liquidity risk.



Conclusions

We developed an analytical framework for real-time monitoring of interbank payment systems

SinkRank measures systemic importance and identifies banks that are important due to their position in the network, and banks that are vulnerable to given disruptions

PSLI measures liquidity risk and identifies banks whose liquidity needs exceed their liquidity resources

Together they identify likely sources of disruption and the consequences of potential disruptions.

This allows for proactive oversight of interbank payment systems.

Thank You

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