Reconstructing and Stress Testing Credit Networks

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- Stress tests are an important tool to assess the vulnerability of financial networks.
- Given its importance, finding a robust methodology of stress test is of considerable interest to regulators and practitioners.
- However, there is a gap in the literature for what concerns the empirical comparison of the proposed methodologies.
- We focus on the network reconstruction aspect of stress test: so that the outcome of stress test on the reconstructed networks is reliable.

Even among the world's largest banks, data on their bilateral exposures to one another remains partial and patchy... (Haldane, 2015).

Contributions

This paper:

- Data on bank-firm credit interactions in Japan (different aggregation level) from the Nikkei NEEDS database for the period 1980 2013.
- A horse race between reconstruction methods that have been found to be of importance for unipartite networks, adjusted for bipartite networks.
- Two different dimensions of horse race:
 - In term of reproducing the actual topological features, and
 reproducing the actual systemic risk.
- Some methods that we explore require different amount of information, to understand which partial information is actually needed.
- Finally, we look at different policies to improve the networks' robustness.

On the Network Reconstruction

Methodology

1 Original network

2 Compute the total strength (or degree)

3 "Forget" actual network

4 Reconstruct network

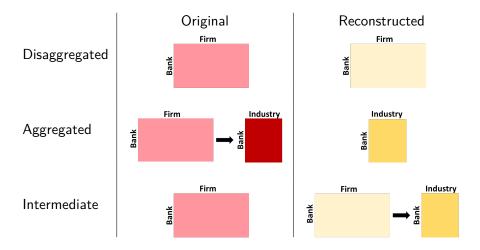
5 Compare the reconstructed with the actual











Year	Size	Volume	Banks'	Firms'	Density	Assorta-
	Size	(trillion)	Degree	Degree	Density	tivity

Disaggregated level (Bank-Firm networks)

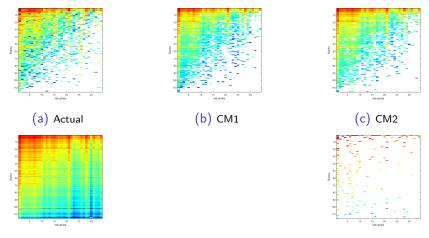
1995	145 imes 1734	70	141	12	0.08	-0.30
2010	116×2296	28	96	5	0.04	-0.21

Aggregated level (Bank-Industry networks)

1995	145×33	70	17	75	0.52	-0.34
2010	116×34	28	16	53	0.46	-0.33

Code	Authors	Short Description
CM1	Squartini and Garlaschelli (2011),	A configuration model determines the likelihood of linkages by satisfying degree sequences, and exposures are allocated via MaxEntropy. Required info: degree sequences.
CM2	Musmeci et al. (2013)	A fitness model determines the likelihood of linkages, and exposures are allocated via MaxEntropy. Required info: aggregate positions & density.
MaxEntropy	Upper and Worms (2004)	Simple implementation of standard max. entropy approaches. Required info: aggregate positions
MinDensity	Anand et al. (2015)	Minimises the number of links necessary for distributing a given volume of loans. Required info: aggregate positions

Weighted credit networks



(d) MaxEntropy

(e) MinDensity

Figure: Weighted credit network bank-industry in 2010 and one realization for each of the four reconstruction methods. Data are log transformed. Warmer colors indicate stronger links, and white dots correspond to the absence of a link.

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Horse racing results

Aggregated	Assorta- tivity	Cluster- ing	Ave Degree Bank	Ave Degree Firm	Density	Nested- ness
$W^{I}(116 \times 34)$	0.461	16	53	-0.330	0.134	0.819
CM1	0.460	16	53	-0.370	0.136	0.821
CM2	0.461	16	54	-0.248	0.131	0.704
MaxEntropy	1.000	34	116	NaN	1.000	0.000
MinDensity	0.038	1	4	-0.224	0.000	0.044

	L	ink similarit	у	Weight similarity			
Aggregated	Accuracy	Sensitiv- ity	Speci- ficity	L ₁ -error	RMSE	Cos-Sim	
CM1	0.781	0.762	0.798	0.015	2.527	0.915	
CM2	0.711	0.687	0.732	0.018	2.555	0.914	
MaxEntropy	0.461	1.000	0.000	0.000	2.572	0.914	
MinDensity	0.558	0.061	0.982	0.000	8.607	0.532	

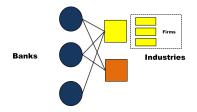
Horse racing results

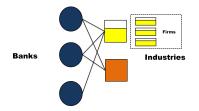
Rank	Disaggregated		Aggregat	ted	Intermediate	
Nalik	Null mode	rk	Null model	rk	Null model	rk
1	CM1	2.22	CM1	1.44	CM1	2.00
		(1.02)		(0.40)		(1.18)
2	CM2	2.33	CM2	2.44	CM2	2.11
		(0.67)		(0.40)		(0.51)
3	MinDensity	2.67	MinDensity	3.00	MinDensity	2.89
		(0.58)		(0.30)		(0.17)
4	MaxEntropy	2.78	MaxEntropy	3.11	MaxEntropy	3.00
		(1.35)		(0.85)		(1.00)

Table: Rank of the null models in term of reproducing the observed credit network toplogy at different aggregation levels. Rank 1 corresponds to the best null model. rk corresponds the average value for the three categories under study (standard deviation in brackets): network characteristics, link similarity, and weight distribution.

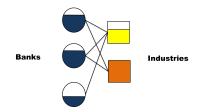
- The winner depends on the assumed criterion of interest.
- In the absence of specific preferences (or weights), CM1 and CM2 consistently perform best.

On the Systemic Risk Analysis

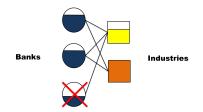




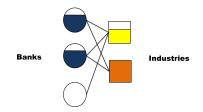
Initial shocks: reduce market value of asset *j* to a fraction *p* ∈ [0,1] of its original value. For disaggretion level, *j* is all firms that belongs to the same indutry.



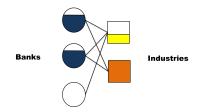
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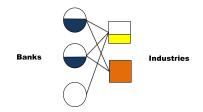
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 $r_j = rac{n_j^{Bdefault}}{2}$

$$P_d = rac{\sum_{j=1}^{n'} r_j}{n'} \leftarrow ext{Our systemic risk measure}$$

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P_d over time

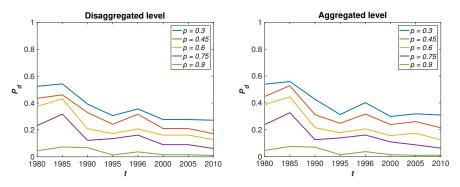


Figure: Yearly data for realistic market impact ($\alpha = 0.1$).

• The level of systemic risk have been reduced over time.

Relative difference of P_d between actual and reconstructed networks

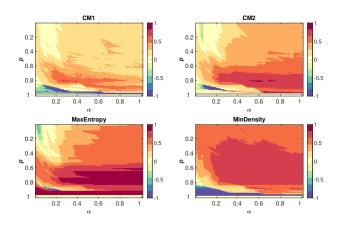
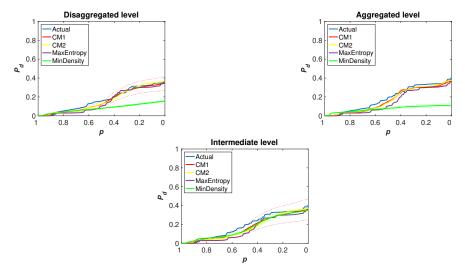


Figure: Relative difference of P_d. Data for year 2010. Warm color indicates an underestimation of the actual risk, while cold color indicates an overestimation.
The actual network displays the highest level of systemic risk.

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P_d as the function of initial shock (p) when lpha=0.1



• The choice of aggregation level of financial networks matters for stress testing.

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Reconstructing and Stress Testing

Horse racing results

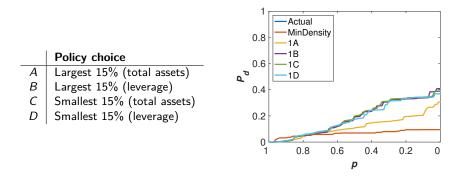
Rank	Disaggregated		Aggrega	ated	Intermediate	
Nalik	Null mode	$\overline{P_d}$	Null model	$\overline{P_d}$	Null model	$\overline{P_d}$
1	Actual	0.393	Actual	0.360	Actual	0.360
		(0.254)		(0.230)		(0.230)
2	CM1	0.301	CM1	0.218	MinDensity	0.358
		(0.202)		(0.156)		(0.217)
3	CM2	0.243	CM2	0.217	CM1	0.275
		(0.176)		(0.157)		(0.182)
4	MaxEntropy	0.190	MinDensity	0.202	CM2	0.241
		(0.149)		(0.122)		(0.174)
5	MinDensity	0.140	MaxEntropy	0.190	MaxEntropy	0.190
		(0.096)		(0.149)		(0.149)

Table: Rank of the actual networks and the corresponding null models at different aggregation levels. Rank 1 corresponds to the most risky network. $\overline{P_d}$ denotes the average (standard deviation in brackets) across all possible parameter values, $p \in \{0, 0.01, 0.02, \dots, 1\}$ and $\alpha \in \{0, 0.01, 0.02, \dots, 1\}$.

- To formally test whether the difference between each reconstructed network's P_d is significant, we run a two-sided Wilcoxon signed rank test on each pair of methods.
- The test results suggest that the systemic risk level of CM1 and CM2 is similar, which implies that CM2 (which requires only the information on aggregate positions of each institution and network density) is more appealing.
- The horse race ranking of: first dimension (topological properties) vs second dimension (systemic risk level) is not always consistent. This leads to our future research.

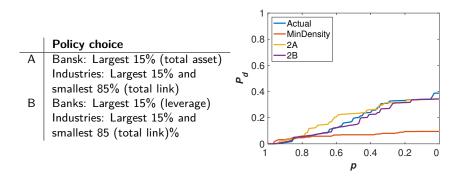
On the Policy Experiment

Policy 1 - Banks merger



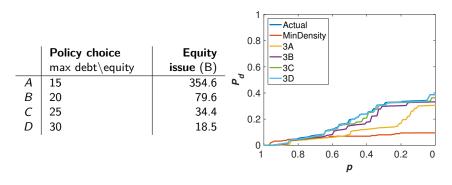
• Merging largest banks in term of total assets (A) decreases P_d .

Policy 2 - Banks break-up



• Breaking up banks does not lower P_d as effective as merging banks. Splitting banks with large assets (A) in fact increases P_d .

Policy 3 - Leverage cap



- Tighter contraints of leverage cap yielding lower P_d values.
- However, for modest constraint (e.g. (D)) the P_d remains largely unaffected.
- This suggests that a substantial part of the observed vulnerability is due to the high levels of portfolio overlap.

- Two dimensions of horse race: (1) reproducing the actual topological features, (2) reproducing the actual systemic risk.
- Results on the first dimension: the winner depends on the assumed criterion of interest.
- Results on the second dimension:
 - Actual network is still the riskiest.
 - Among all methods, CM2 (which requires only the information on the aggregate positions of each institution and network density) is more appealing.
 - Aggregation level of financial networks matters for stress testing.
- Policy experiment: Banks merger and leverage cap may make the network more robust, while banks break up do not.

Thank you for your attention!