BANK OF ENGLAND

2018 RiskLab/BoF/ESRB
Conference on Systemic Risk Analytics
Bank of Finland – Helsinki
29th May 2018

Multiplex network analysis of the UK OTC derivatives market

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Info

- Any views expressed are solely those of author(s) and so cannot be taken to represent those of the Bank of England or to state Bank of England policy.
- More details on the Bank of England Staff Working Paper: https://papers.ssrn.com/abstract=3180709

Summary

- We use Trade Repository data to construct the multi-layered network of exposures in the IR, CD, and FX markets
- We use a multiplex extension of the PageRank centrality to rank the most vulnerable institutions in our network and we compare it with the multiplex extension of the eigenvector centrality
- Then we test the potential for liquidity contagion after a VM shock:
  - We estimate the deficiencies in payments faced by each institution
  - We compare the rankings of deficiencies with the rankings of vulnerabilities computed using the centrality measures

Data

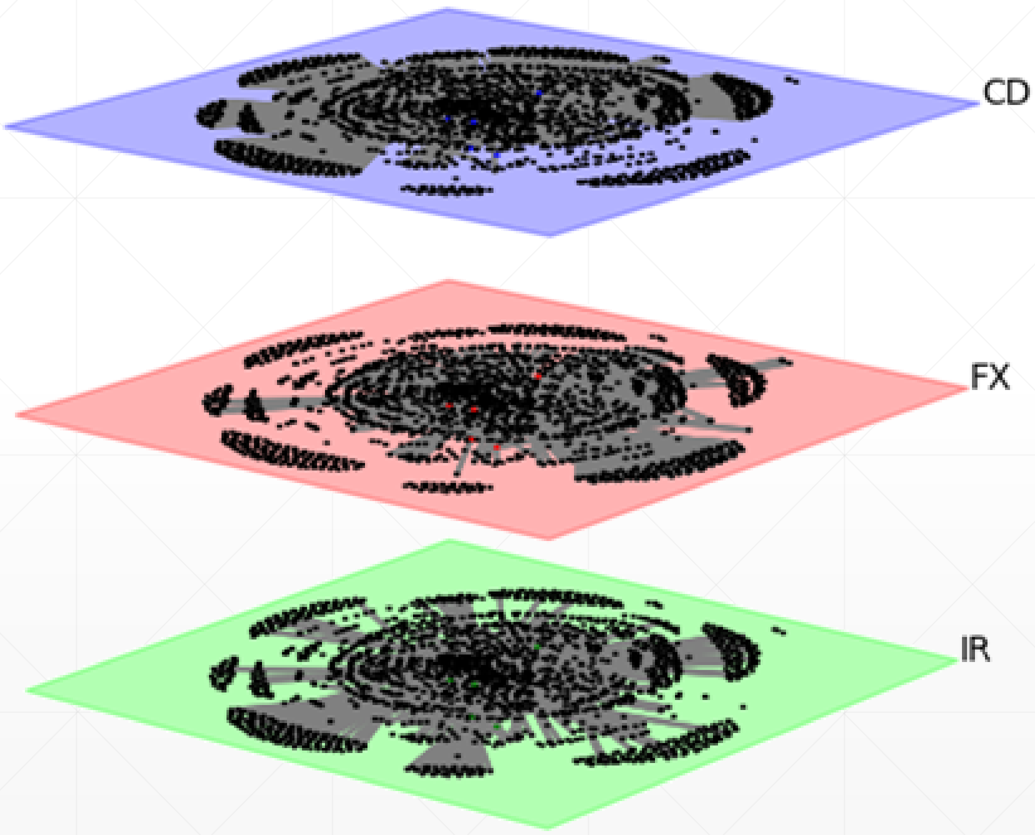
- Our source is the Trade Repository[1], all transactions:
  - Through a CCP in the UK
  - In which one of the counterparties is located in the UK
  - For which the underlying is a UK entity
  - For GBP denominated contracts
- We use a snapshot of the open positions on 30th June 2016 for:
  - Interest rate derivatives: 80%
  - FX derivatives: 10%
  - Credit Default Swaps: 2%
- All transactions of clearing members (both centrally cleared and not centrally cleared)

[1]DTCC and UnaVista

Data

	Notional (USD bn)	Trades	Cleared	Cleared notional (USD bn)
IR	264 000	3 674 857	68.69%	210 000
CD	110 000	1 033 158	8.47%	2 870
FX	69 000	5 975 179	0.92%	3 260

Data



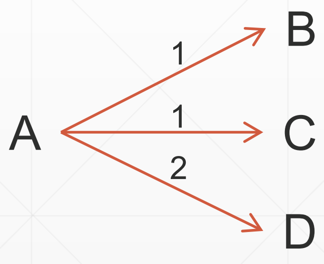
- Exposures: aggregate net MtM value of outstanding contracts
- $N = 2174$

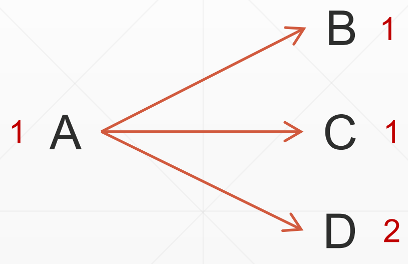
	Active nodes	Average degree
IR	473	7.99
CD	1 469	4.91
FX	553	3.58

	Active nodes
1 layer	89.3%
2 layers	6.6%
3 layers	4.1%

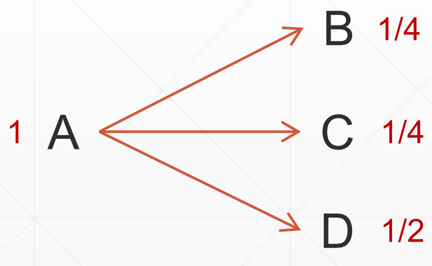
Centrality: Intuition

- The centrality of each node depends on the centrality of other nodes
- Therefore, centralities are computed as fixed points
- One can interpret centralities’ algorithms as the propagation of shocks





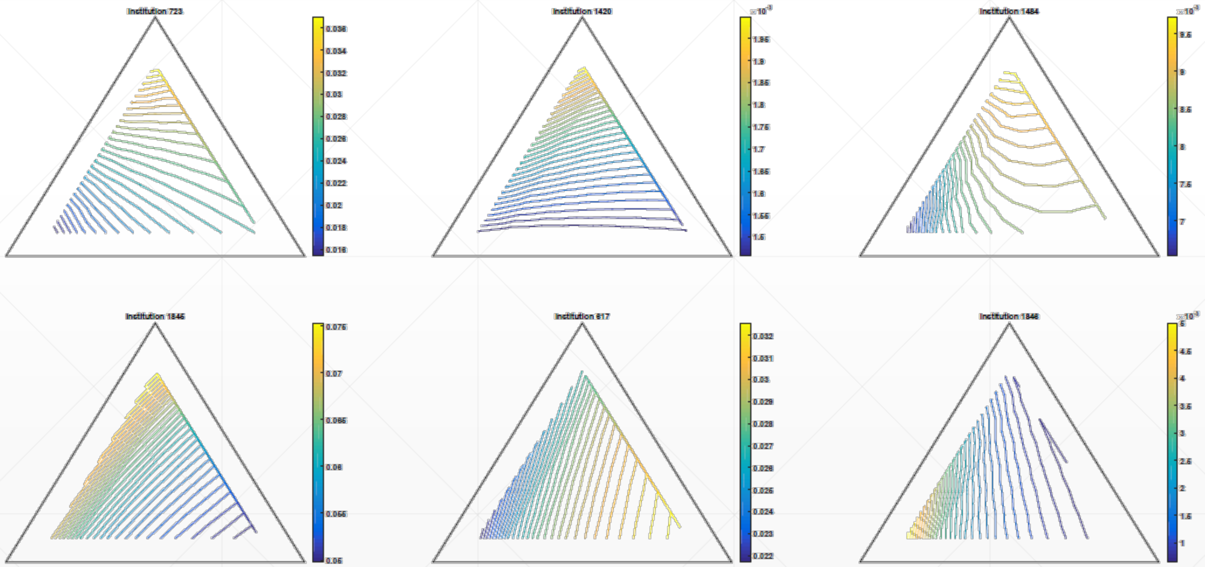
Eigenvector centrality



PageRank centrality

Centrality: Multiplex

- The most general extension of such centralities[1] to multiplex networks is done by assigning weights (influences) to each layer



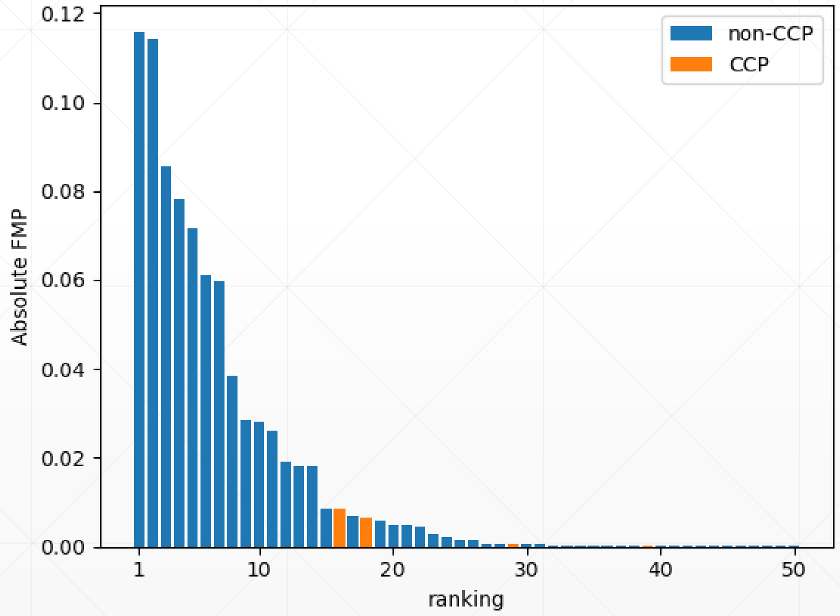
[1]Iacovacci et al. (2016). EPL **116**(2), 28004

Centrality: Multiplex

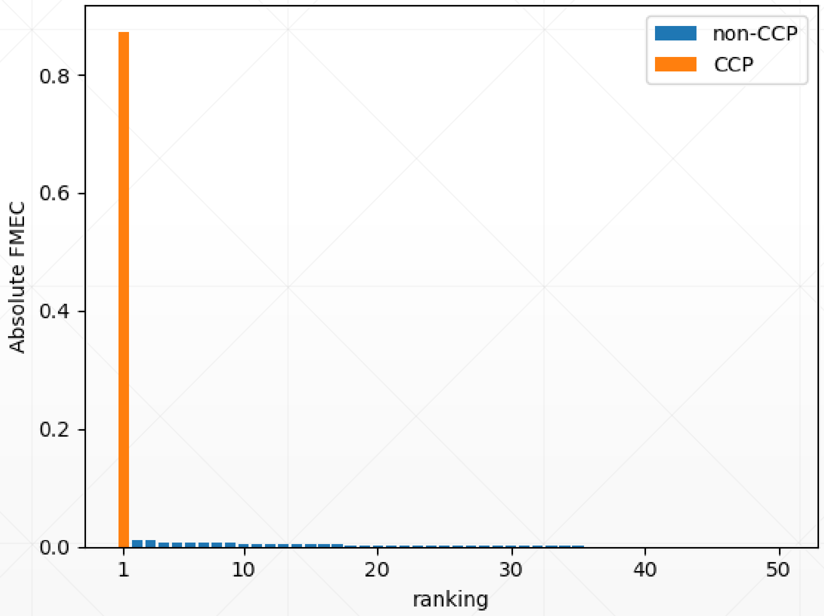
- The most general extension of such centralities to multiplex networks is done by assigning weights (influences) to each layer
- This allows to explore the vulnerability of the system under different assumptions on how relevant each layer is
- We compute:
  - The average over all influences: “Unconditional” vulnerabilities
  - The maximum over all influences: Worst case scenario

Centrality: Results

Multiplex PageRank (Average)



Multiplex Eigenvector (Average)



Liquidity contagion: Basics

- Price movements imply that institutions will have to post variation margins (VMs)
- Institutions will receive incoming payments and will have to make outgoing payments
- However, for some incoming payments + liquid asset buffers might not be enough to cover their outgoing payments
- As a consequence neighbouring institutions might face shortfalls themselves, and so on…

Liquidity contagion: Caveats

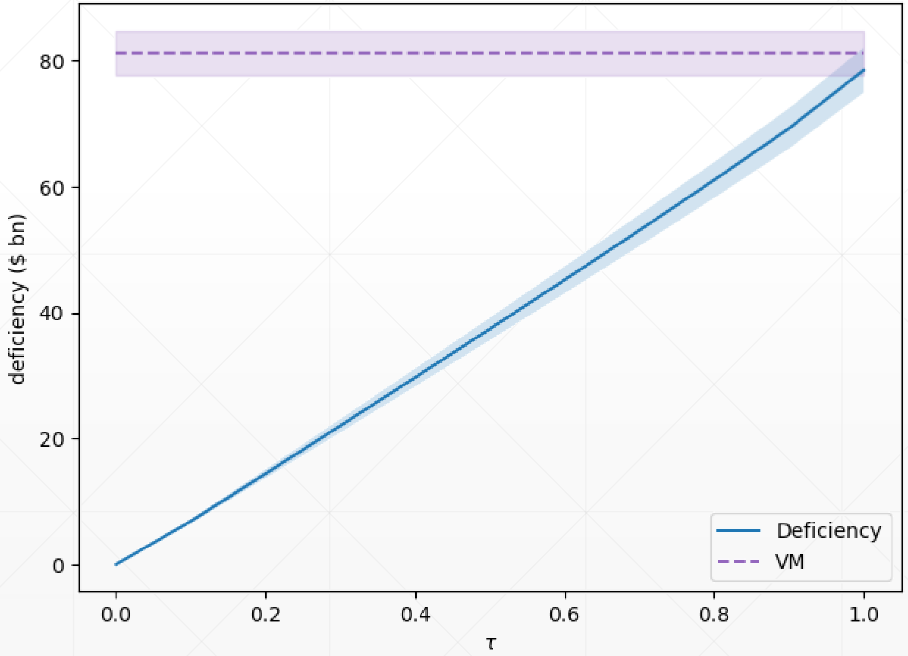
- Initial shocks are random:
  - $\bar{p}_{ij}^{\alpha} \sim A_{ij}^{\alpha}\mathcal{N}(0, \sigma_{\alpha}^{2})$
  - Same as Heath et al. (2016)
- Liquid asset buffers:
  - Not easy to quantify for most institutions
  - Proportional transmission as in Paddrick et al. (2016)
- Solvency vs Liquidity:
  - No initial margins
  - No default waterfalls for CCPs

Liquidity contagion: Mechanism

Liquid asset buffers known	Liquid asset buffers unknown
$$s_i = \sum_{j,\alpha} \bar{p}_{ij}^{\alpha} - \sum_{j,\alpha} p_{ij}^{\alpha} - \gamma_i$$	$$s_i = \sum_{j,\alpha} \bar{p}_{ij}^{\alpha} - \sum_{j,\alpha} p_{ij}^{\alpha}$$
Obligations · **Incoming payments** · **Liquid buffer**	
$$p_{ij}^{\alpha} = \left[\bar{p}_{ij}^{\alpha} - L_{ij}^{\alpha} s_i\right]_+$$	$$p_{ij}^{\alpha} = \left[\bar{p}_{ij}^{\alpha} - \tau_i L_{ij}^{\alpha} s_i\right]_+$$
Relative liability matrix	**Transmission factor**
Eisenberg and Noe (2001)	Paddrick et al. (2016)

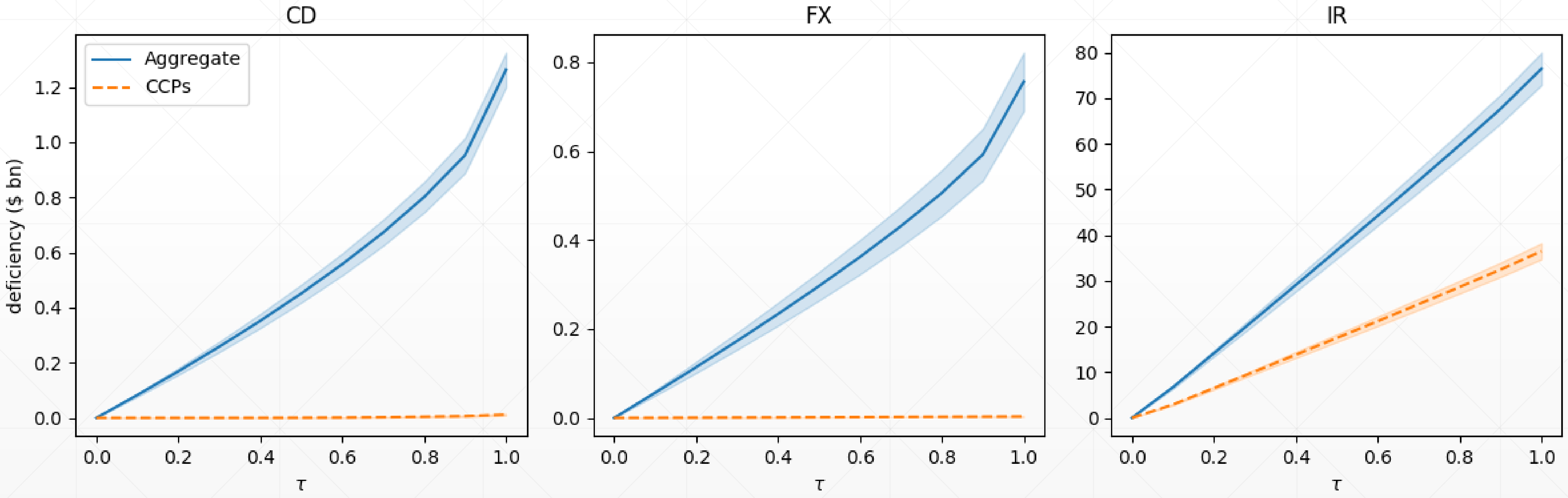
Liquidity contagion: Results

- We measure the aggregate deficiencies in payments as a function of the transmission factor τ



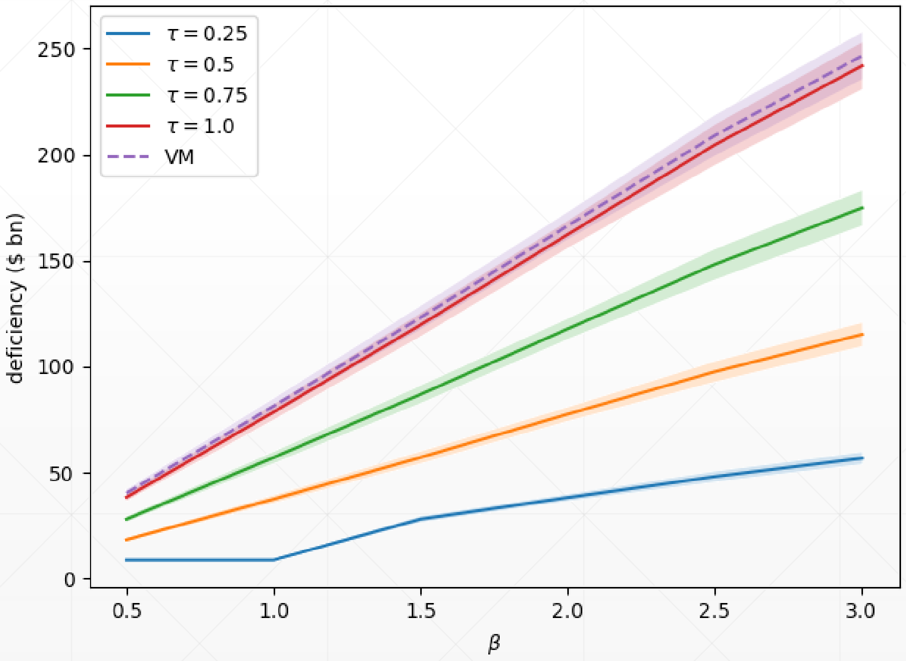
Liquidity contagion: Results

- We disaggregate by layers and we isolate the deficiencies of CCPs



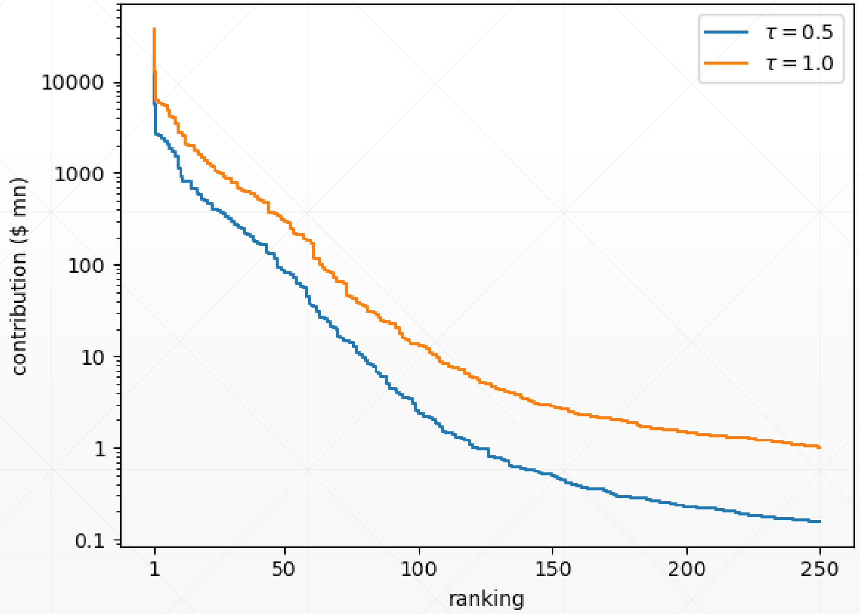
Liquidity contagion: Results

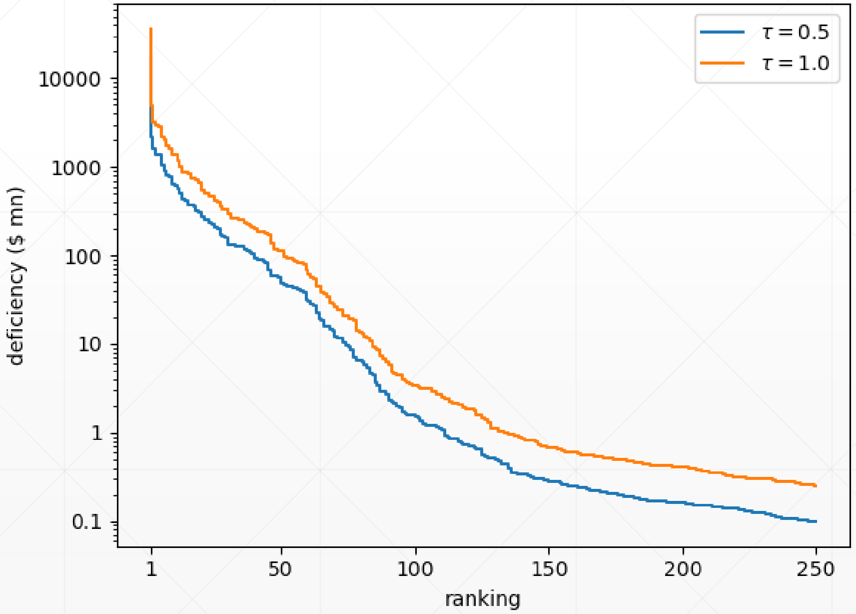
- What happens if we change the size of the shock? Here we scale the standard deviation of shocks with β



Liquidity contagion: Results

- The contribution of a single institution is the difference in aggregate deficiency between the baseline scenario and the scenario in which that institution has an infinite liquid asset buffer





Liquidity contagion: Results

- We compare the ranking of institutions experiencing the largest deficiencies with the ranking of most vulnerable institutions according to centrality measures
- We focus on the top 50 institutions

τ	FMT	FMEC
0.1	0.510	0.373
0.2	0.495	0.324
0.3	0.497	0.325
0.4	0.497	0.328
0.5	0.503	0.335
0.6	0.503	0.335
0.7	0.503	0.338
0.8	0.508	0.343
0.9	0.508	0.346
1.0	0.515	0.320

Conclusions

- Between 0.3% and 0.6% institutions experience materially large deficiencies
- Between 0.5% and 1.2% institutions contribute to materially large deficiencies
- Rankings of vulnerabilities computed with Functional Multiplex PageRank (averaged over influences) correlate reasonably well rankings of deficiencies computed via the contagion algorithm
- Next steps:
  - VMs computed by repricing all contracts after a shock
  - Liquid asset buffers in place of transmission factors