

Discussion of:
“Choosing Stress Scenarios for Systemic Risk
Through Dimension Reduction”

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- 1 In A Nutshell
- 2 In- vs Out-degree Systemic Risk
- 3 But this paper is right...

A clever idea ... but with BIG caveats

The (apparently) simple recipe:

- 1 Simulate observable economic "characteristics" $X \in \mathbb{R}^m$, from **joint distribution**.

But: m is huge ("2015 CCAR stress scenario for 6 largest banks trading book positions stresses tens of thousand of variables")

⇒ curse of dimensionality i.e. can't really estimate the necessary joint distributions – the world is not *iid*.

⇒ no model uncertainty ⇒ risk of not knowing the risks.

- 2 "PC" projection of X (or a function of) on $F \in \mathbb{R}^n$, $n \ll m$
projection gives a linear mapping from F to X .

- 3 Assume gaussian+homoscedastic shocks: the F_{MLE} , given the estimated mapping coefficients from simulated data, selects the X scenarios.

Note: in this case, the (constrained) MLE has actually a maximum entropy rationale.

In A Nutshell cont'd

- Aside:** aggregate effects modelled linearly up to an ad hoc – state invariant – nonlinear transformation of X (m should be huge)
⇒ systemic risk just a size weighted "average" of capital ratios (or a linear approximation of this)
- Policy:** keep this "average" above some threshold (make sense in a world in which the intermediation services produced are just proportional to assets) ⇒ the MLE constraint.
- So:** gaussian world with linear dynamics, constant volatility, single state variable for banks ⇒ a thin tailed safe world.
- Reality:** non gaussian, non-linear dynamics, time varying volatility (correlations spike in crises!), complex state vector ⇒ makes dimension m enormous ⇒ can't fit/draw from joint distribution of X without "heroic" assumptions.
- Even if** one could draw from the distribution of X , model uncertainty would not be taken into account ⇒ underestimate risk.

This paper: an *in-degree* view of systemic risk

- **Systemic risk:** the sum of the individual loadings on an aggregate, low dimensional, set of shocks (spanned by) F .
- Some truth to that in some states (e.g. oil price shocks).

But accurate approximation only for small shocks/perturbations (linearity+gaussianity) i.e. the safest states.

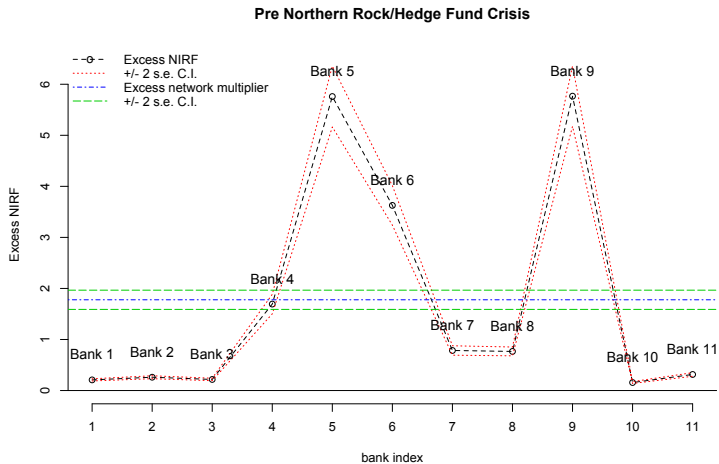
No *Out-Degree* systemic risk: i.e. disregards how individual shocks are transformed by the networks of contracts & holdings – networks that also change dynamically.

Theory: time varying network generates time varying volatility for the system \Rightarrow what is a tail event is per-se endogenous.

- Examples:**
- portfolio holdings/fire-sale/price impact/externality \Rightarrow shocks amplification (e.g. Greenwood et al. (2015))
 - interbank borrowing and lending: individual shocks transmitted/dampened/amplified through the network (Denbee et al. (2014))
 - liquidity holding externalities (e.g. Bhattacharya and Gale (1987))
 - building the network of contracts, and the market structure, is a profit maximizing activity (Moore (2012))

All \Rightarrow networks transform fundamental shocks

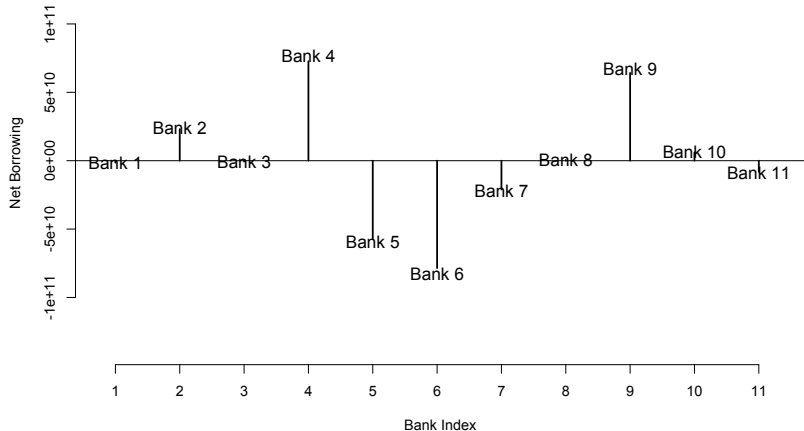
The *out-degree* in (some) data – Liquidity Risk Key Players



Network (excess) Impulse-Response Functions to unit bank specific liquidity shock

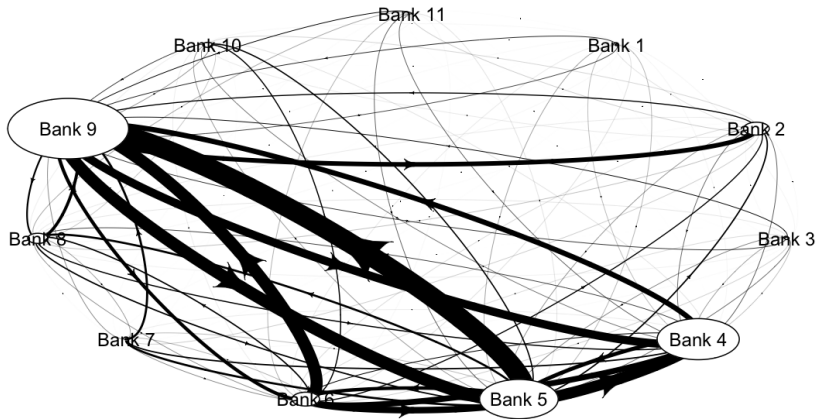
(source: Denbee, Julliard, Li, Yuan (2014))

Only one state variable to explain risk?



... maybe, but not an obvious one (and not the capital ratio...)

Not surprising: it's the business model/network!



(source: Denbee, Julliard, Li, Yuan (2014))

But this paper is right....

Can we really write full blown (non trivial) equilibrium models of the financial micro and macro structure, estimate them structurally, and estimate both in-degree and out-degree risk?

- not yet, but we can do a decent job in modelling subparts (e.g. linear quadratic games with shocks) that we can both solve and estimate, sometimes in real time (flow/transaction data are crucial).

But often need more info to trace the network topology.

⇒ use “inversion” techniques (e.g. de Paula (2015)) and more data collection/integration – YOU, can!

But we don't have “A” model yet ... and want answers now.

⇒ need some sort of feasible “reduced form” approach that:

- ① encodes both in & out degree risk
- ② can approximate well non-linearities
- ③ has time varying volatility
- ④ includes the risk of not knowing the risks (aka model uncertainty).

Two modest proposals

I. The MacGyver approach

- 1 very large scale VARs with dimension reduction via e.g. “lasso” methods.

Note: e.g. 6-variables-5-lags VAR can fit a $(6 \times 5 - 1)$ th-order polynomial in t without residual error

- “easy” to include time varying vol (e.g. Primiceri (2005)) as theory requires.
 - can include regime shifts (e.g. Sims and Zha (2006)).
 - generalised impulse responses (e.g. Diebold and Yilmaz (2009, 2014)) to identify large risks (albeit not their sources) scenarios.
- 2 draw tail scenarios (for chosen dimension(s)) from the (well defined) posterior distributions \Rightarrow accounts for parameter uncertainty.
 - 3 take scenarios from the tails we are worried about...
... and maybe give them at random: “stress test snooping” or 2 vs 3 σ put options.

II. Stress testing = poor man's robust control

- do it formally (DGPs, priors, loss functions to start, build models and games within to grow).

Conclusion

- a good starting point for thinking about formalising/optimizing stress test scenarios selection...
- ... but very far from a silver bullet.