Discussion of:

"Choosing Stress Scenarios for Systemic Risk Through Dimension Reduction"

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Outline

1. In A Nutshell

2. In- vs Out-degree Systemic Risk

3. But this paper is right...

In A Nutshell

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 $F \in \mathbb{R}^n$, $n << m$ 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.

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Aside: aggregate effects modelled linearly up to an ad hoc – state invariant – nonlinear transformation of X (m should be huge)

$\Rightarrow$ 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) $\Rightarrow$ the MLE constraint.

So: gaussian world with linear dynamics, constant volatility, single state variable for banks $\Rightarrow$ a thin tailed safe world.

Reality: non gaussian, non-linear dynamics, time varying volatility (correlations spike in crises!), complex state vector $\Rightarrow$ makes dimension m enormous $\Rightarrow$ 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 $\Rightarrow$ underestimate risk.

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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 ⇒ what is a tail event is per-se endogenous.

Examples:
- portfolio holdings/fire-sale/price impact/externality ⇒ shocks amplification (e.g. Greenwood et al. (2015))
- interbank borrowing and landing: individual shocks transmitted/dampened/amplified through the network (Denbee et al. (2014))
- liquidity holding externalities (e.g. Bhattacharya and Gale (1987))
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All ⇒ networks transform fundamental shocks.

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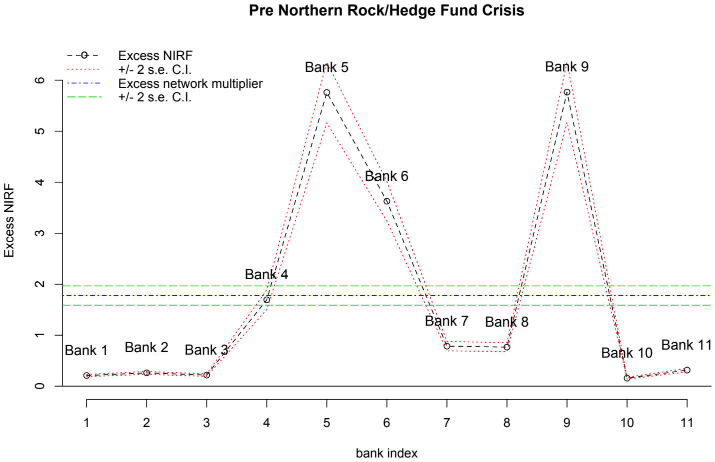
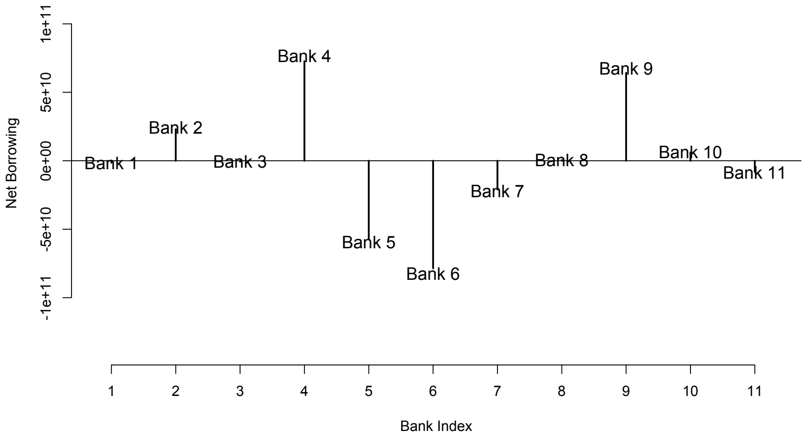
The *out-degree* in (some) data – Liquidity Risk Key Players



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

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

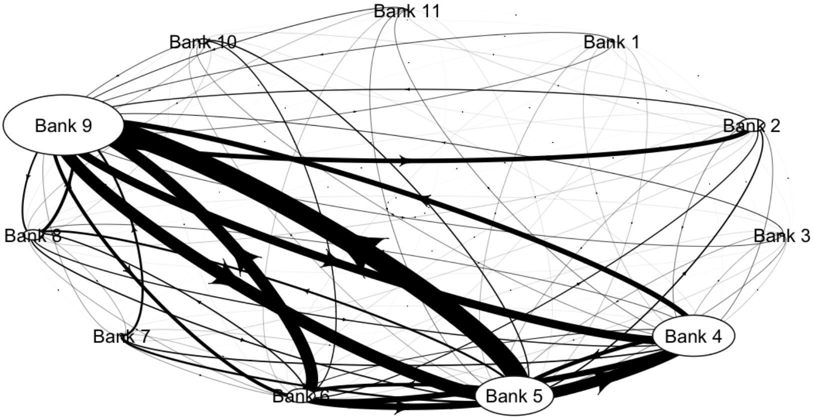
Only one state variable to explain risk?



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

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

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



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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
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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)).
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