Measuring systemic risk: The Indirect Contagion Index

Rama Cont
Imperial College London
CNRS

Eric Schaanning
RiskLab Switzerland, ETH Zürich
Norges Bank

Wirtschaftsuniversität Wien
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Based on:
Rama Cont and Eric Schaanning (2016)
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- So: B experiences a loss following a large shock to the illiquid asset: B has an (indirect) exposure to an asset it does not hold!
- Magnitude of this indirect exposure is directly linked to the overlap between B and institutions holding this asset.
- Large diversified institutions increase overlaps across system and become nodes for price-mediated contagion.

Losses arising from indirect exposures

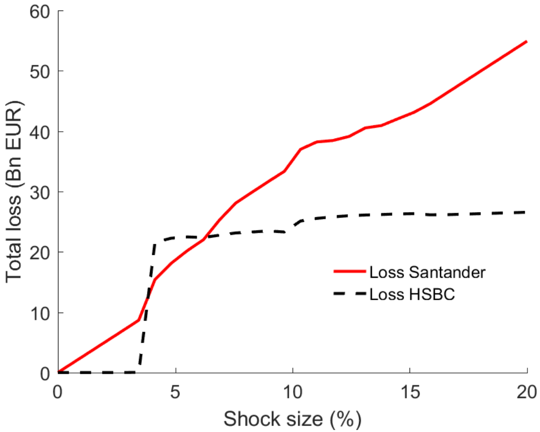

Figure: Losses of HSBC and Banco Santander as a function of losses in the Southern European real estate sector.

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- Given institutions' portfolio holdings, are the stress scenarios that we consider the right ones?
- How can we **quantify** the notion of "interconnectedness" for Global systemically important banks (GSIBs)?
- Can regulators disseminate a metric that would allow institutions to quantify their exposures to price-mediated contagion?

Bank stress tests and interconnectedness assessments

- Bank stress tests have become an essential component of bank supervision (EU-wide EBA stress tests, Dodd-Frank tests (DFAST, CCAR)).
- *Static balance sheet assumption*: Stress tests assume 'passive' behaviour by banks.
- BCBS 2015: "Stress tests conducted by bank supervisors still lack a genuine macro-prudential component": "*endogenous reactions* to initial stress, loss amplification mechanisms and *feedback effects*" are missing.
- Currently *"interconnectedness"* in the GSIB methodology is based on (i) intra-financial system assets, (ii) intra-financial system liabilities, (iii) securities outstanding.

Channels of loss amplification in the financial system

1. Counterparty Risk: balance sheet contagion through asset devaluation
2. Funding channel: balance sheet contagion through withdrawal of funding (bank runs by depositors, institutional bank runs by lenders)

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3. **Feedback effects from fire sales**: loss contagion through mark-to-market losses in common asset holdings

Research on financial networks and their use in macroprudential regulation has focused on direct contagion mechanisms (1+2). Regulatory measures have focused on 1 (large exposure limits, central clearing, CVA, ring-fencing) or 2 (LCR, NSFR).

Modeling fire sales

Systemic stress testing with endogenous effects

Ingredients:

1. Data: Portfolio holdings of financial institutions by asset class: N institutions, K *illiquid* asset classes, M *marketable* asset classes $\rightarrow N \times (M + K)$ portfolio matrix (network)

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5. Mark-to-market accounting: transmits market impact to all institutions $\rightarrow$ may lead to feedback if market losses large

Balance sheets: illiquid and marketable assets

Illiquid assets
Residential mortgage exposures
Commercial real estate exposure
Retail exposures: Revolving credits, SME, Other
Indirect sovereign exposures in the trading book
Defaulted exposures
Residual exposures

Marketable assets
Corporate bonds
Sovereign debt
Derivatives
Institutional client exposures: interbank, CCPs,...

Table: Stylized representation of asset classes in bank balance sheets. (Data: European Banking Authority)

- Illiquid holdings of institution i: $\Theta^i := \sum_{\kappa=1}^{K} \Theta^{i\kappa}$.
- Marketable Securities held by i: $\Pi^i := \sum_{\mu=1}^{M} \Pi^{i\mu}$.
- Equity (Tier 1 capital): C^i

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- Financial institutions are subject to various **one-sided** portfolio constraints: leverage ratio, capital ratio, liquidity ratio.
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- A stress scenario is defined by a vector $\epsilon \in [0,1]^K$ whose components ϵ_κ are the percentage shocks to asset class κ.
- Initial/Direct loss of portfolio i: $L^i(\epsilon) = \epsilon.\Theta^i = \sum_\kappa \Theta^{i\kappa}\epsilon_\kappa$

Deleveraging

Deleveraging assumption: if following a loss L^i in asset values the leverage of bank i exceeds the constraint

$$\lambda^i = \frac{\Theta^i + \Pi^i - L^i}{C^i - L^i} > \lambda_{\max}$$

bank deleverages by selling a proportion $\Gamma^i \in [0,1]$ of assets in order to restore a leverage ratio $\lambda_b^i \leq \lambda_{\max}$:

$$\frac{(1-\Gamma^i)\Pi^i + \Theta^i - L^i}{C^i - L^i} = \lambda_b^i \leq \lambda_{\max} \quad \Rightarrow \Gamma^i = \frac{C^i(\lambda^i - \lambda_b^i)}{\Pi^i} \mathbf{1}_{\lambda^i > \lambda_{\max}}$$

Develeraging in response to a loss

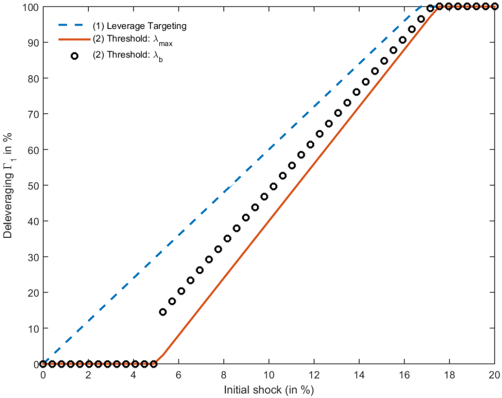
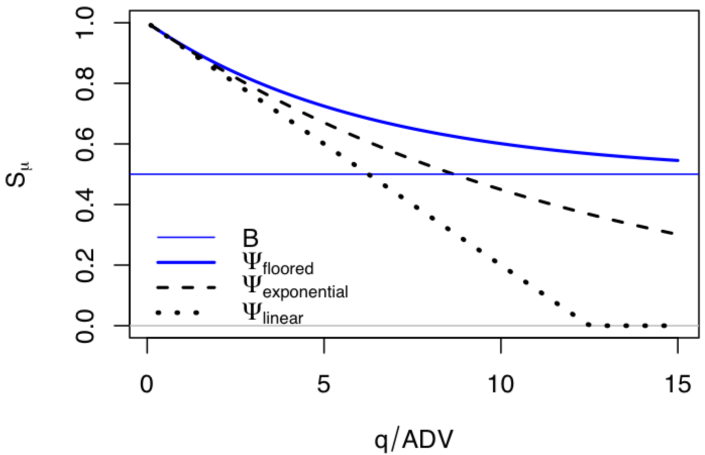


Figure: Percentage of marketable asset deleveraged in response to a shock to assets (circles) for a leverage constraint of 20. Leverage targeting (dotted blue) would lead to a linear response.

Market impact function



Market impact function and market depth

The impact of a total distressed liquidation volume q is modelled by a *level-dependent market impact function*

$$\Psi_\mu(q, S) = \left(1 - \frac{B_\mu}{S}\right)\left(1 - \exp\left(-\frac{q}{D_\mu}\right)\right),$$

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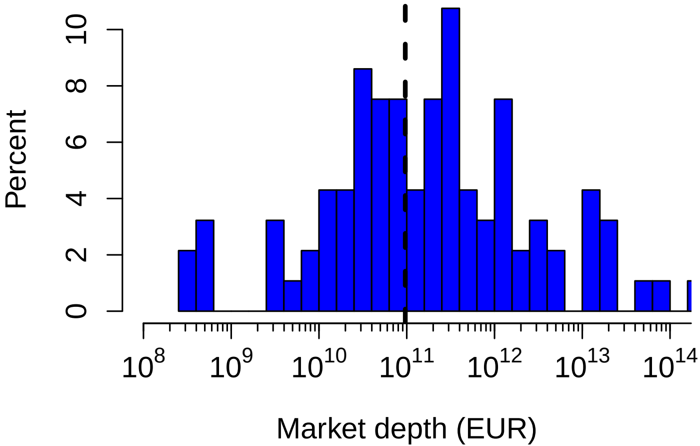
where

$$D_\mu = c\frac{ADV_\mu}{\sigma_\mu}\sqrt{\tau},$$

- $S \geq B_\mu$ where B_μ is the price-floor
- ADV: average daily volume, σ_μ: daily volatility of asset
- $c \approx 0.25$, a coefficient to make Ψ_μ consistent with empirical estimates of the linear impact model for small volumes q.
- τ is the liquidation horizon

Estimated market depth



Market impact and feedback effects

Total liquidation in asset μ at k-th round: $q^{\mu} = \sum_{j=1}^{N} \Pi_k^{j,\mu} \Gamma_{k+1}^{j}$

$$\text{Market impact}: \quad \frac{\Delta S^{\mu}}{S^{\mu}} = -\Psi_{\mu}(q^{\mu}),$$

Impact/ inverse demand function: $\Psi_{\mu} > 0, \Psi'_{\mu} > 0, \Psi_{\mu}(0) = 0.$

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Price move at k-th iteration of fire sales:

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$$\Pi_{k+1}^{i,\mu} = \underbrace{\left(1 - \Gamma_{k+1}^i\right)}_{\text{Non-liquidated assets}} \overbrace{\Pi_k^{i,\mu}}^{\text{Previous value}} \underbrace{\left(1 - \Psi_\mu\left(\sum_{j=1}^N \Pi_k^{j,\mu} \Gamma_{k+1}^j\right)\right)}_{\text{Price impact on remaining holdings}}$$

Fire sales losses

- Mark to market loss:

$$M^i_{k+1} := \sum_{\mu=1}^{M} \left((1 - \Gamma^i_{k+1}) \Pi^{i\mu}_k - \Pi^{i\mu}_{k+1} \right)$$

$$= (1 - \Gamma^i_{k+1}) \sum_{\mu=1}^{M} \Pi^{i\mu}_k \Psi_\mu \left(\sum_{j=1}^{N} \Pi^{j\mu}_k \Gamma^j_{k+1} \right)$$

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- Realised loss (implementation shortfall / slippage):

$$R^i_{k+1} := \alpha \Gamma^i_{k+1} \sum_{\mu=1}^{M} \Pi^{i\mu}_k \Psi_\mu \left(\sum_{j=1}^{N} \Pi^{j\mu}_k \Gamma^j_{k+1} \right)$$

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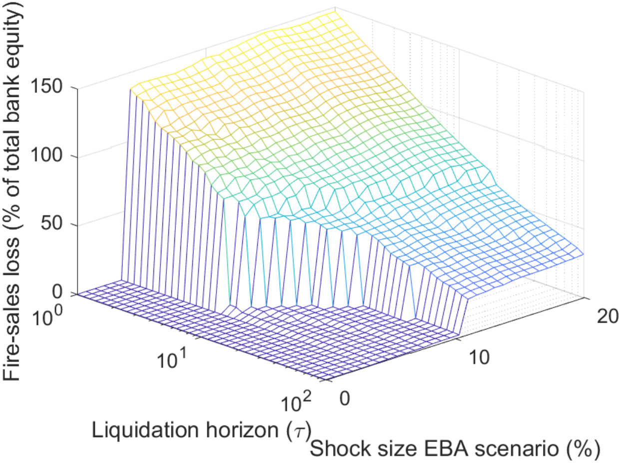
- Fire sales loss:

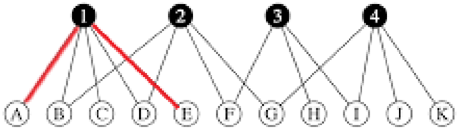
$$L^i_k = (1 - (1-\alpha) \Gamma^i_{k+1}) \sum_{\mu=1}^{M} \Pi^{i\mu}_k \Psi_\mu \left(\sum_{j=1}^{N} \Pi^{j\mu}_k \Gamma^j_{k+1} \right)$$

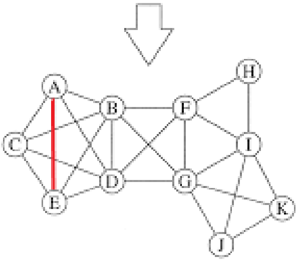
Estimated fire-sales losses EBA scenario



Monitoring systemic risk: The Indirect Contagion Index

Bipartite network of asset holdings





Indirect exposures across institutions through common asset holdings

Portfolio overlaps as drivers of price-mediated contagion

For $\alpha = 1$ and $\Psi_\mu(x) = \frac{x}{D_\mu}$ with $D_\mu = c\frac{ADV_\mu}{\sigma_\mu}\sqrt{\tau}$, the indirect loss of bank i resulting from deleveraging by other banks becomes:

$$L^i = \sum_{j=1}^{N} \underbrace{\sum_{\mu=1}^{M} \frac{\Pi^{i\mu}\Pi^{j\mu}}{D_\mu}}_{\Omega_{ij}} \Gamma^j = \sum_{j=1}^{N} \Omega_{ij}\Gamma^j,$$

where Ω_{ij} is the **liquidity-weighted overlap** between portfolios i and j (Cont & Wagalath 2013):

$$\Omega_{ij} = \sum_{\mu=1}^{M} \frac{\Pi^{i\mu}\Pi^{j\mu}}{D_\mu} \qquad D_\mu = \text{market depth for asset } \mu$$

Ω_{ij} = exposure of marketable assets of i to deleveraging by j.
$\Rightarrow$ loss contagion = contagion process on network defined by $[\Omega_{ij}]$

Indirect contagion

The first round fire-sales losses across the banking system are thus given by

$$FLoss = \Omega\Gamma.$$

When the liquidity-weighted overlap network is close to a 1-factor model

$$\Omega \approx \lambda_1 u u^\top,$$

then the first round fire sales loss of i is

$$\log(Floss^i) = \log(\lambda_1 u_i \sum_{j=1}^{N} u_j \Gamma_j(\epsilon)),$$

and we expect a slope 1 when regressing the log fire-sales losses on the log ICI:

$$\log(Floss^i) = 1 \times \log(u_i) + \log(\lambda_1) + \log(< u, \Gamma(\epsilon) >).$$

Indirect Contagion Index Construction

1. Collect portfolio holdings $\Pi^{i,\mu}$ by asset class for each financial institution in the network, at the granularity level corresponding to bank stress tests.
2. Estimate a market depth parameter $D_\mu \propto \frac{ADV_\mu}{\sigma_\mu}$ for each asset class.

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4. Compute the "Perron eigenvector" $u = (u_i, i = 1...N)$ of the matrix of liquidity-weighted overlaps $\Omega(\Pi) = \Pi D^{-1} \Pi^\top$ (SVD of $\Pi\sqrt{D^{-1}}$).

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5. The Indirect Contagion Index is the Perron eigenvector, $ICI = u$, whose component $ICI(i) = u_i$ provides a measure of centrality of the node i in the network whose links are weighted by the overlap matrix Ω.

Principal component analysis of portfolio holdings

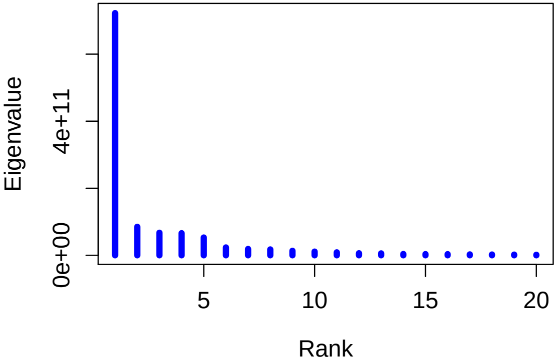
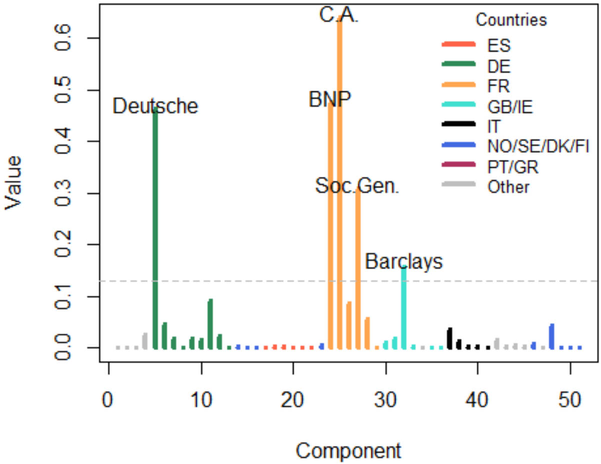
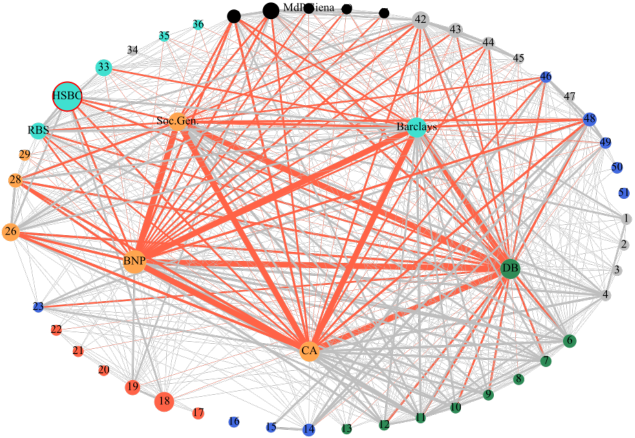


Figure: European banking system: Eigenvalues of matrix of liquidity-weighted overlaps. Source: EBA (public)

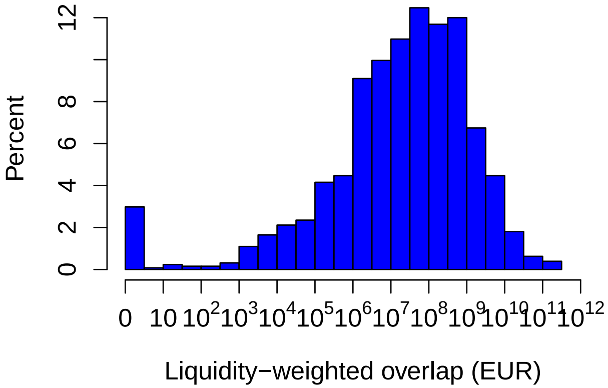
The Indirect Contagion Index (EBA 2016)

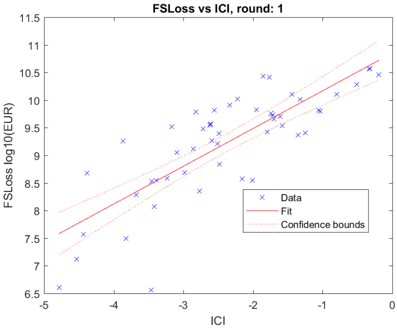


The EU indirect contagion network (2016)



Portfolio overlaps, Ω_{ij}, across EU banks (EBA 2016)





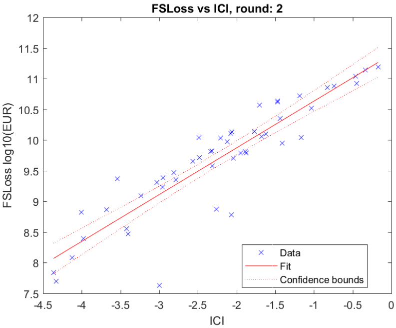


Figure: Bank-level fire-sales losses regressed on the ICI.

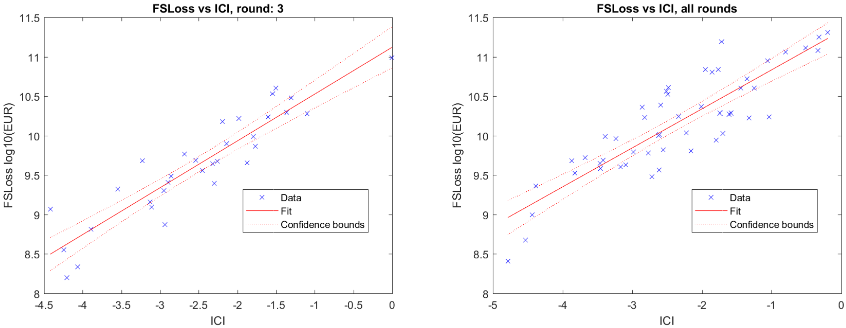


Figure: Bank-level fire-sales losses regressed on the ICI.

Table: Regression of bank-level fire-sales losses on the Indirect Contagion Index for all banks.

	Round 1	Round 2	Round 3	Round 4	Total
Slope	0.684***	0.762***	0.594***	0.10	0.490 ***
	(0.072)	(0.052)	(0.047)	(0.168)	(0.040)
Intercept	10.85***	11.39***	11.12***	9.06***	11.4***
	(0.190)	(0.130)	(0.128)	(0.411)	(0.106)
n	51	49	32	16	51
adj. R^2	0.64	0.82	0.83	-0.04	0.74

Table: Regressing fire-sales losses on the *ICI*. *** denotes significance $p < 10^{-4}$.

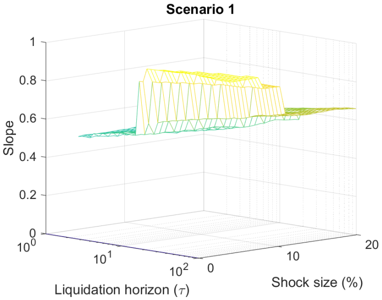


Figure: Slope of the regression of fire-sales losses on the ICI, as a function of the shock size and market depth.

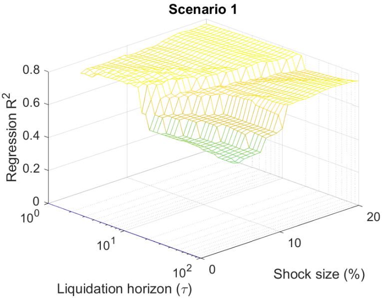


Figure: R^2 of the regression of fire-sales losses on the ICI, as a function of the shock size and market depth.

Robustness checks

Nominal overlaps. Perron eigenvector of

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Cosine Similarity. [Getmansky et al., 2016], Portfolio weights:

$$w_i := \frac{1}{\sum_{\mu=1}^{M} \Pi^{i,\mu}} (\Pi^{i,1}, \ldots, \Pi^{i,M})^{\top}.$$

Cosine similarity: Perron eigenvector of $\Omega_{C.S.}$ given by

$$\Omega_{C.S.}^{ij} = \frac{< w_i, w_j >}{||w_i||_2||w_j||_2} \in [-1, 1] \, .$$

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Size.

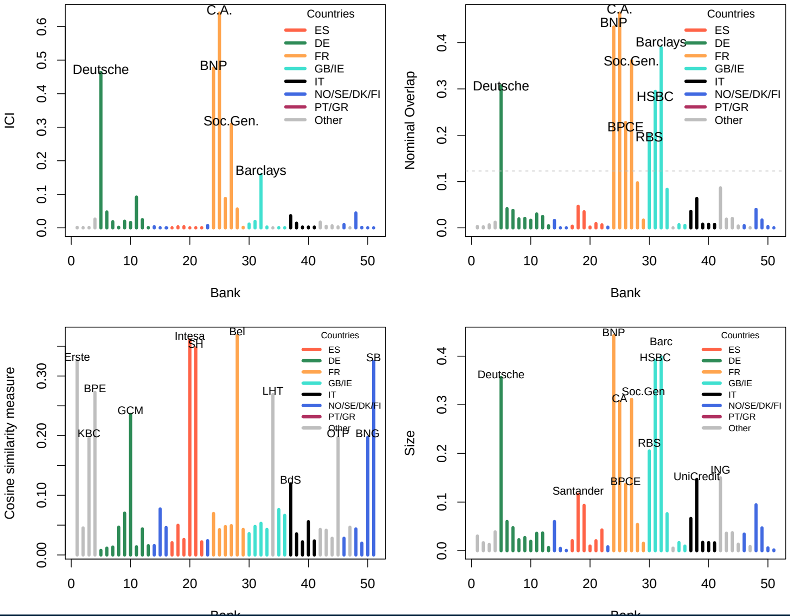
$$size = \frac{(\Pi^1, \ldots, \Pi^N)}{||(\Pi^1, \ldots, \Pi^N)||_2},$$

where $\Pi^i := \sum_{\mu=1}^{M} \Pi^{i,\mu}$.

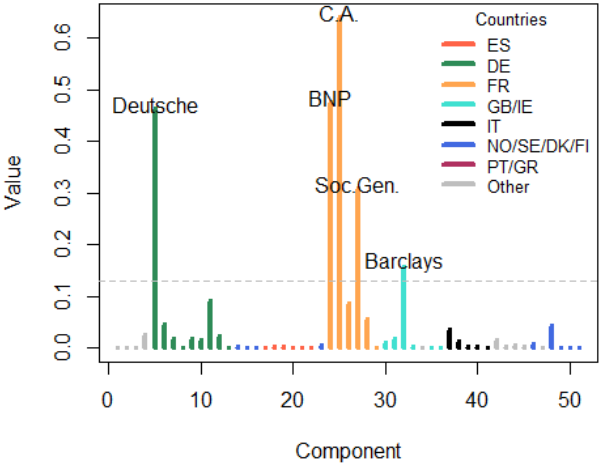
Similarity between overlap measures

	ICI	Nom. Ov.	Cos. Sim.	Size
ICI	1	**0.68** (0.85)	-**0.13** (- 0.22)	**0.60** (0.80)
Nom. Ov.		1	-**0.14** (-0.22)	**0.78** (0.92)
Cos. Sim.			1	-**0.17** (-0.26)
Size				1

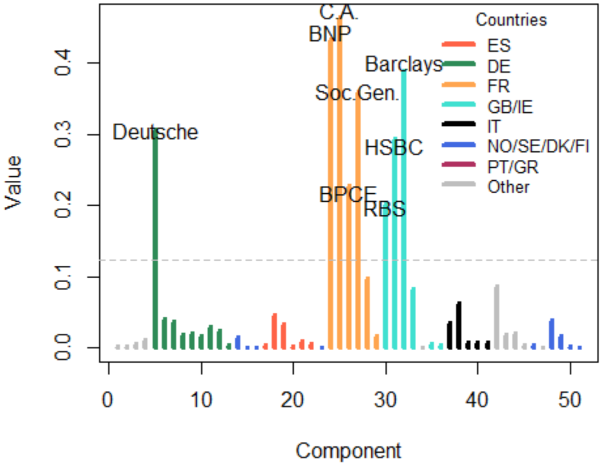
Table: Similarity between the various overlap measures: The bold numbers are rank-correlations (Kendall's τ), while the numbers in brackets are linear correlations (Spearman's ρ).


ICI
Bank
Deutsche
BNP
C.A.
Soc.Gen.
Barclays
Nominal Overlap
Deutsche
C.A.
BNP
Barclays
Soc.Gen.
HSBC
BPCE
RBS
Cosine similarity measure
Erste
BPE
KBC
GCM
Intesa
SH
Bel
LHT
BdS
OTP
BNG
SB
Size
Deutsche
BNP
Barc
HSBC
CA
Soc.Gen
RBS
BPCE
Santander
UniCredit
ING
Countries
ES
DE
FR
GB/IE
IT
NO/SE/DK/FI
PT/GR
Other

Liquidity-weighted overlaps



Nominal overlaps



$$\log_{10}(FSLoss^i) = b_1 \log_{10}(X) + b_0 + \epsilon$$

	ICI	Nominal overlap	Total Assets	Similarity
Slope	0.684***	0.742***	71.4***	-0.627**
	(0.072)	(0.089)	(14.9)	(0.295)
Intercept	10.85***	10.68***	-505***	8.49***
	(0.190)	(0.190)	(107)	(0.395)
n	51	51	51	51
adj. R^2	0.64	0.31	0.57	0.07

Table: Regression of bank losses on the Indirect Contagion Index and other measures (X) for all banks. First round only.

$$\log_{10}(FSLoss^i) = b_1 \log_{10}(ICI) + b_2 \log_{10}(N.Ov.) + b_3 \log_{10}(Size) + b_0 + \epsilon.$$

Dependent Variable	Estimate	Std. dev.	p-value
ICI	0.22***	(0.062)	9.34E-4
Nominal Overlap	0.22***	(0.080)	5.97E-3
Size	22***	(7.09)	3.20E-3
Intercept	-147***	(51)	5.90E-3
	n = 51	adj. $R^2 = 0.84$	

Global systemically important banks

Indicator-based measurement approach — Table 1

Category (and weighting)	Individual indicator	Indicator weighting
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio	20%
Interconnectedness (20%)	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Securities outstanding	6.67%
Substitutability/financial institution infrastructure (20%)	Assets under custody	6.67%
	Payments activity	6.67%
	Underwritten transactions in debt and equity markets	6.67%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%
	Level 3 assets	6.67%
	Trading and available-for-sale securities	6.67%

Figure: BCBS GSIB Indicator measurement approach. Source: Basel Committee on Banking Supervision (2013).

“Spillover"-*ICI*: Discount self-inflicted losses

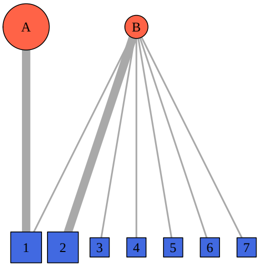
Consider a portfolio network given by:

$$\Pi = \begin{pmatrix} 1000 & 0 & 0 & 0 & 0 & 0 & 0 \\ 100 & 1100 & 100 & 100 & 100 & 100 & 100 \end{pmatrix}^{\top}$$

$$D = (1000, 2000)^{\top}.$$

- Compute $\Omega = \Pi D^{-1} \Pi^{\top}$, as before.
- Compute the principal (largest) eigenvalue and the corresponding eigenvector (the “Perron eigenvector") of $\Omega_0 := \Omega - \text{diag}(\Omega_{11}, \ldots, \Omega_{NN})$.

ICI and ICI_0



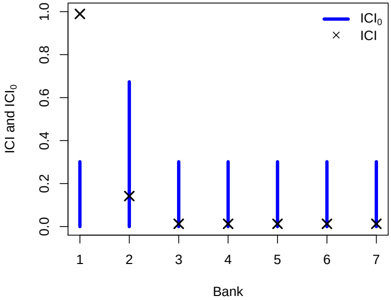
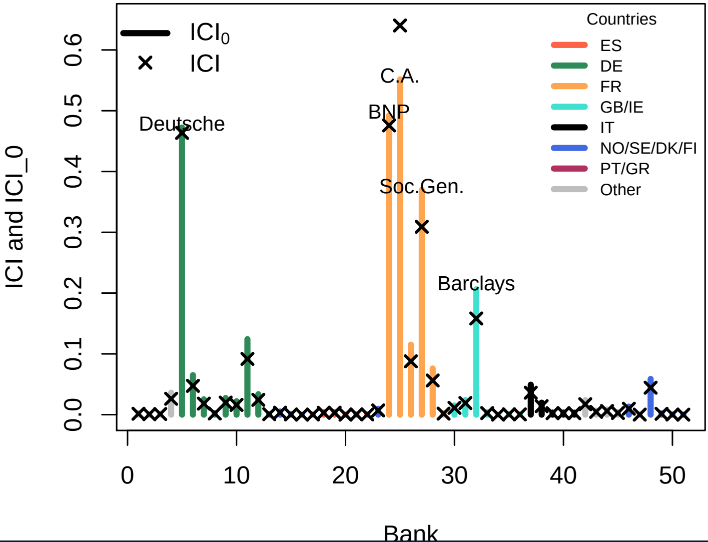


Figure: Illustrative example showing how the ICI_0 discounts self-inflicted losses compared to the losses caused for other participants relative to the *ICI*.

ICI_0


ICI₀
ICI
Countries
ES
DE
FR
GB/IE
IT
NO/SE/DK/FI
PT/GR
Other
Deutsche
C.A.
BNP
Soc.Gen.
Barclays
ICI and ICI_0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0
10
20
30
40
50
Bank

Scenario design

Motivation

- Currently, the starting point for stress scenario design is often based on macroeconomic- and broader financial developments.
- The stress test scenario is often defined in terms of macroeconomic variables, which banks map to specific risk factors.
- Portfolio holdings and exposures do not play a large role, if any, in constructing the scenario.

Motivation

- Currently, the starting point for stress scenario design is often based on macroeconomic- and broader financial developments.
- The stress test scenario is often defined in terms of macroeconomic variables, which banks map to specific risk factors.
- Portfolio holdings and exposures do not play a large role, if any, in constructing the scenario.

Reverse stress testing and scenario design: First collect portfolio holdings and identify the main exposures/vulnerabilities. This has two advantages:

- For a given scenario, we can assess how “close" it is to a worst-case scenario in terms of contagion effects.
- The scenario can be designed such that particular weaknesses of the system are tested. This ensures that the scenario is “relevant".

Worst-case contagion scenario

Assume that the deleveraging of institutions is proportional to their resilience $R_i \in [0, 1]$. The weakest bank has resilience $R_i = 1$; a bank which is “fully" resilient and generates no fire sales has $R_i = 0$.

Worst-case contagion scenario

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View Ω as a map from deleveraging proportions/shock to fire-sales losses:

$$\Omega : [0,1]^N \mapsto \mathbb{R}_+^N.$$

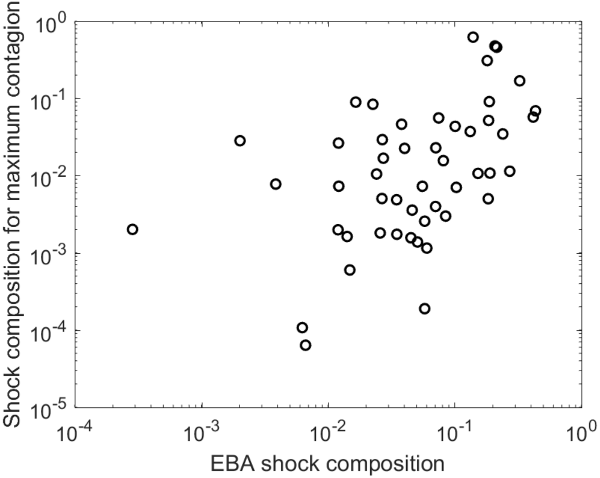
We want to find the scenario which maximizes

$$\max_{||x||_2 \leq 1} \left\{ \mathbf{1}^\top \Omega x \right\} = \max_{||x||_2 \leq 1} \left\{ f^\top x \right\},$$

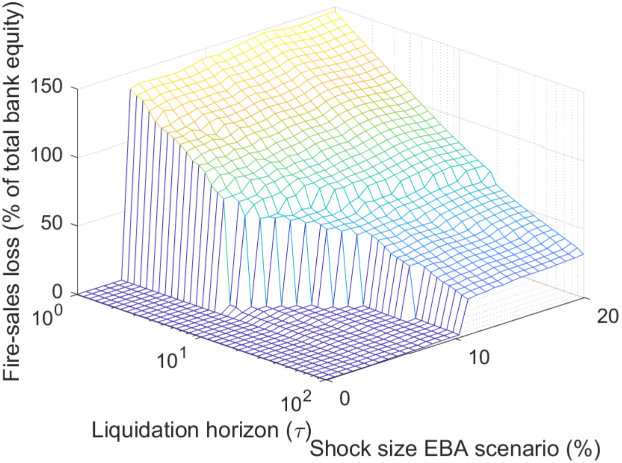
where $f := \mathbf{1}^\top \Omega R$. The worst-case scenario, which follows immediately from Cauchy-Schwarz, is

$$x^* = \frac{f}{||f||_2}.$$

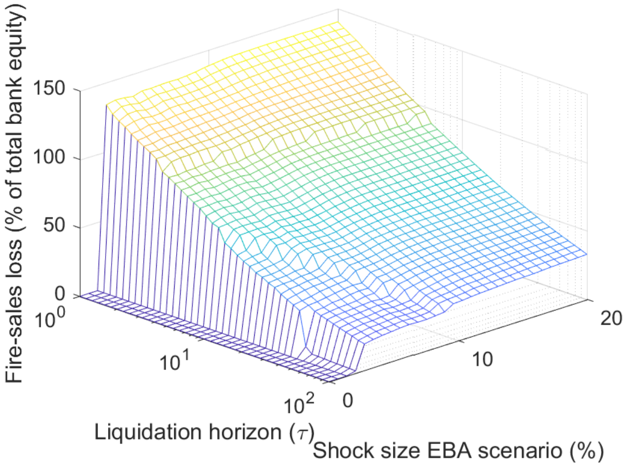
EBA 2016


Shock composition for maximum contagion
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-4}
10^{-3}
10^{-2}
10^{-1}
10^{0}
EBA shock composition

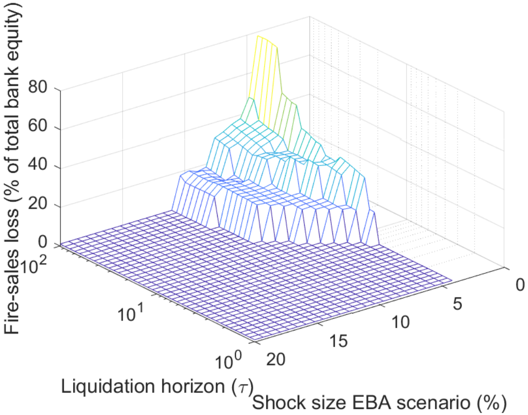
Estimated fire-sales losses EBA scenario



Worst-case fire-sales losses



Ratio of EBA FSLoss to worst-case FSLoss



Further work

The problem

$$\max_{||x||_2 \leq 1} \left\{ \mathbf{1}^\top \Omega x \right\} \qquad (1)$$

only looks at the fire-sales losses. It (i) ignores losses suffered on illiquid assets, and (ii) implicitly assumes a leverage targeting behaviour instead of a threshold behaviour.

Further work

The problem

$$\max_{||x||_2 \leq 1} \left\{ \mathbf{1}^\top \Omega x \right\} \tag{1}$$

only looks at the fire-sales losses. It (i) ignores losses suffered on illiquid assets, and (ii) implicitly assumes a leverage targeting behaviour instead of a threshold behaviour.
Ideally, we would like to find scenarios $\epsilon \in [0,1]^{M+K}$ as shocks to asset classes, that maximize

$$\max_{||\epsilon||_2 \leq 1} \mathbf{1}^\top A\epsilon + \mathbf{1}^\top \Omega \Gamma(A\epsilon), \tag{2}$$

where $A = (\Theta, \Pi)$, $\Gamma : \mathbb{R}^N \to \mathbb{R}^N$ is the threshold deleveraging function, and ϵ is potentially subject to further restrictions. This is a concave minimization.

Conclusions

- Overlapping portfolios give rise to an indirect contagion network. Under stress, the risk of a portfolio thus depends on the distress that similar portfolio-holders suffer.
- The indirect contagion index predicts fire-sales losses well, and can be used to quantify the systemicness of institutions.

Conclusions

- Overlapping portfolios give rise to an indirect contagion network. Under stress, the risk of a portfolio thus depends on the distress that similar portfolio-holders suffer.
- The indirect contagion index predicts fire-sales losses well, and can be used to quantify the systemicness of institutions.
- From the liquidity-weighted overlap network, we can derive a “worst-case" contagion scenario via a simple optimisation problem. This can be used both for benchmarking current stress scenarios, and for designing relevant future scenarios.
- The worst-case contagion scenario leads to a “perfect-storm" contagion, where the weaknesses of the system are specifically targeted.

References

- R Cont and E Schaanning. Fire sales, indirect contagion and systemic stress testing, http://ssrn.com/abstract=2541114
- R Cont and E Schaanning. Measuring systemic risk: The Indirect Contagion Index, Working paper.

Adrian, T. and Shin, H. S. (2010).
Liquidity and leverage.
Journal of Financial Intermediation, 19(3):418–437.

Anderson, R. W. (2016).
Stress testing and macroprudential regulation: A transatlantic assessment.
Systemic Risk Center, Financial Markets Group & CEPR Press.

Basel Committee on Banking Supervision (2015).
Making supervisory stress tests more macroprudential: Considering liquidity and solvency interactions and systemic risk.
BIS Working Paper.

- Bookstaber, R., Cetina, J., Feldberg, G., Flood, M., and Glasserman, P. (2013).
  Stress tests to promote financial stability: Assessing progress and looking to the future.
  Journal of Risk Management in Financial Institutions, 7(1):16–25.

- Bookstaber, R., Paddrik, M., and Tivnan, B. (2014).
  An agent-based model for financial vulnerability.
  Office for Financial Research Working Paper.

- Calimani, S., Halaj, G., and Zochowski, D. (2016).
  Simulating fire-sales in banking and shadow banking system.
  Mimeo.

Cont, R. and Wagalath, L. (2013).
Running for the exit: Distressed selling and endogenous correlation in financial markets.
Mathematical Finance, 23:718–741.

Cont, R. and Wagalath, L. (2016).
Fire sales forensics: Measuring endogenous risk.
Mathematical Finance, 26:835–866.

Duarte, F. and Eisenbach, T. M. (2013).
Fire sale spillovers and systemic risk.
Federal Reserve Bank of New York Staff Report, 645.

Duffie, D. (2010).
How Big Banks Fail and What to Do About It?
Princeton University Press.

ECB, E. C. B. (2013).
A macro stress testing framework for assessing systemic risk in the banking sector.
ECB Occasional Paper Series.

Getmansky, M., Girardi, G., Hanley, K. W., Nikolova, S., and Pelizzon, L. (2016).
Portfolio similarity and asset liquidation in the insurance industry.
SSRN Working paper.

Greenwood, R., Landier, A., and Thesmar, D. (2015).
Vulnerable banks.
Journal of Financial Economics, 115(3):471 – 485.