Monitoring Indirect Contagion

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Assessing interconnectedness (BCBS GSIB framework)

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%

Interconnectedness and bank stress tests

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- *Static balance sheet assumption*: Stress tests assume 'passive' behaviour by banks. I.e no liquidations, no other distressed reactions.

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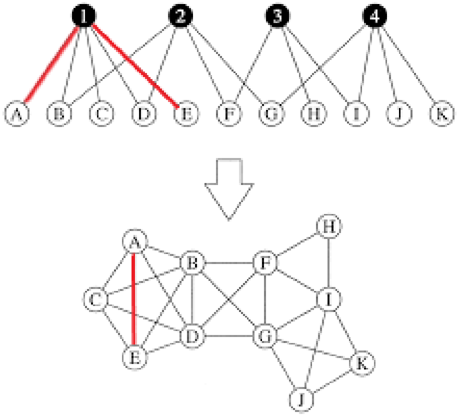
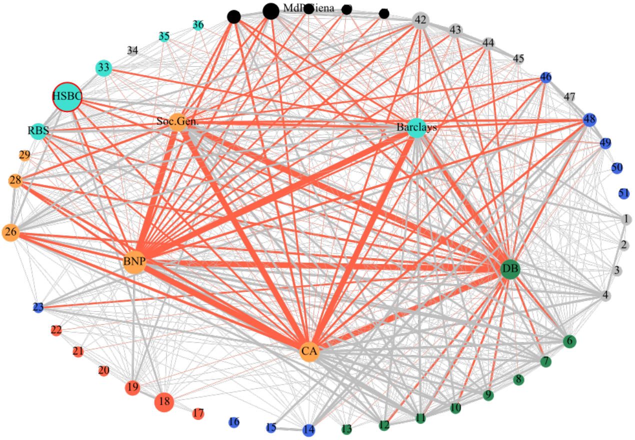
- *Static balance sheet assumption*: Stress tests assume 'passive' behaviour by banks. I.e no liquidations, no other distressed reactions.
- *Modular approach:* (i) When do institutions engage in distressed liquidations? (ii) How do they go about liquidating their portfolio? (iii) How do prices move due to fire sales?

Bipartite network of institutions and asset holdings



Indirect exposures across institutions through common asset holdings

The EU indirect contagion network (2016)



Literature

- **Portfolio overlaps** (Guo et al., 2015), (Braverman and Minca, 2016) (Beale et al., 2011), (Caccioli et al., 2015), (Getmansky et al., 2016a).
- **Stress testing** (Bookstaber et al., 2013), (Bookstaber et al., 2014), (Cont and Schaanning, 2016), (Breuer and Summer, 2017) (Calimani et al., 2016), (Anderson, 2016).
- **Market-based measures** (Adrian and Brunnermeier, 2016), (Brownlees and Engle, 2016), (Kritzman et al., 2011), (Acharya et al., 2017).

Portfolios and portfolio constraints

- 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- , capital- , liquidity ratio.
- Leverage ratio of i:

$$\lambda^i = \frac{Assets(i)}{C^i} = \frac{\Theta^i + \Pi^i}{C^i} \leq \lambda_{\max}$$

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- Initial/Direct loss of portfolio i: $L^i(\epsilon) = \epsilon.\Theta^i = \sum_\kappa \Theta^{i\kappa}\epsilon_\kappa$

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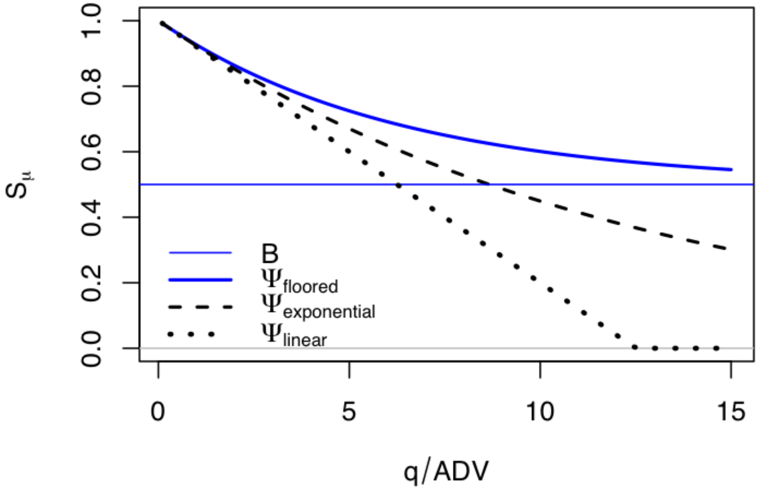
- Reaction: Proportional or optimised (loss-minimising) deleveraging.

Price impact as function of volume



Monitoring Indirect Contagion: The Endogenous Risk Index

Portfolio overlaps as drivers of price-mediated contagion

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

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

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 & Endogenous Risk Index

The 1st round fire-sales losses across the system are given by

$$FLoss = \Omega\Gamma.$$

If 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

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

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

We expect a slope 1 when regressing log fire-sales losses on $\log(u_i)$:

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

Define $ERI := u$.

Principal component analysis of portfolio holdings

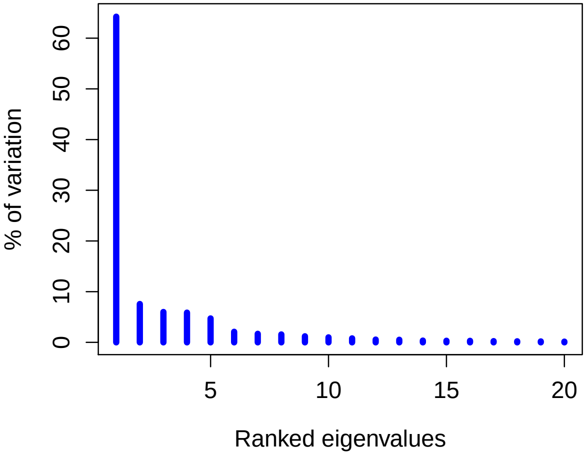


Figure: European banking system: Eigenvalues of matrix of liquidity-weighted overlaps. Source: EBA (public)

The Endogenous Risk Index (EBA 2016)

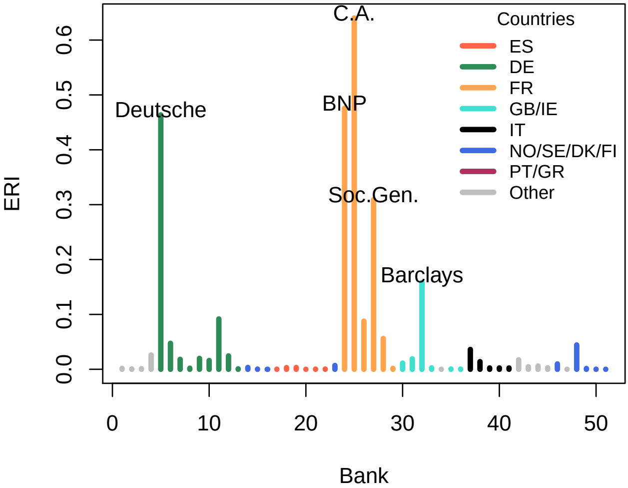
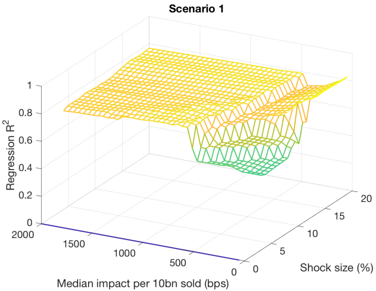


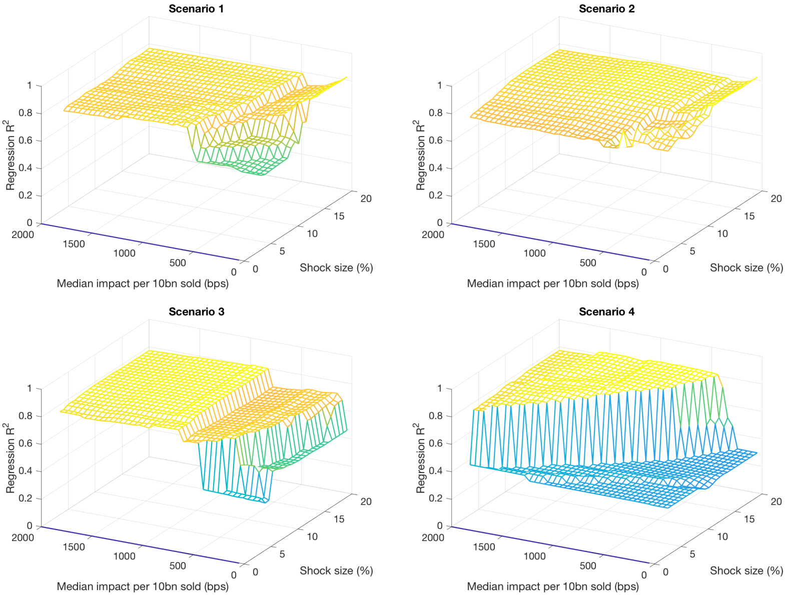
Table: Regression of bank-level fire-sales losses on the Endogenous Risk Index for all banks.

	Round 1	Round 2	Round 3	Round 4	All rounds
Slope	0.730***	0.795***	0.752***	0.516***	0.623 ***
	(0.072)	(0.060)	(0.068)	(0.112)	(0.055)
Intercept	10.5***	10.9***	10.7***	9.76***	11.1***
	(0.190)	(0.151)	(0.164)	(0.326)	(0.143)
n	51	49	41	30	51
R^2	0.68	0.79	0.76	0.43	0.73

Table: Regression of bank-level fire-sales losses on the Endogenous Risk Index for all banks with optimal bank responses.

	Round 1	Round 2	Round 3	Round 4	All rounds
Slope	0.614***	0.658***	0.600***	0.554***	0.613 ***
	(0.072)	(0.105)	(0.107)	(0.111)	(0.073)
Intercept	10.2***	8.75***	8.23***	7.76***	10.2***
	(0.190)	(0.281)	(0.288)	(0.301)	(0.191)
n	51	46	46	46	51
R^2	0.60	0.47	0.42	0.36	0.59


Scenario 1
Regression R^2
1
0.8
0.6
0.4
0.2
0
2000
1500
1000
500
0
Median impact per 10bn sold (bps)
0
5
10
15
20
Shock size (%)


Scenario 1
Scenario 2
Scenario 3
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Comparison with other measures

Size.

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

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

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$$\Omega_{Nominal} = \Pi\Pi^\top.$$

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Cosine Similarity. Getmansky et al. (2016b), 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

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

Similarity between overlap measures

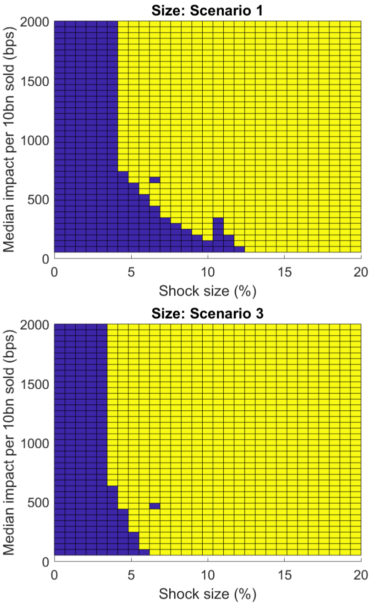
	ERI	Nom. Ov.	Cos. Sim.	Size
ERI	1	**0.68** (0.85)	-**0.13** (- 0.22)	**0.60** (0.80)
Nom. Ov.		1	-**0.14** (-0.22)	**0.78** (0.92)
Cos. Sim.			1	-**0.17** (-0.27)
Size				1

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).

Table: Size and *ERI* are retained as predictors for fire-sales losses.

	Model 1	Model 2	**Model 3**	Model 4
Size	–	–	0.58***	0.72***
ERI	–	–	0.27***	0.31***
Nom. Ov.	0.59***	–	–	-0.14
Cos. Sim.	–	-0.47**	–	-0.01
R^2	0.70	0.09	0.86	0.86
RMSE	0.38	0.66	0.27	0.27
n	51	51	51	51

*** for $p < 0.01$, ** for $p < 0.05$.


Size: Scenario 1
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Median impact per 10bn sold (bps)
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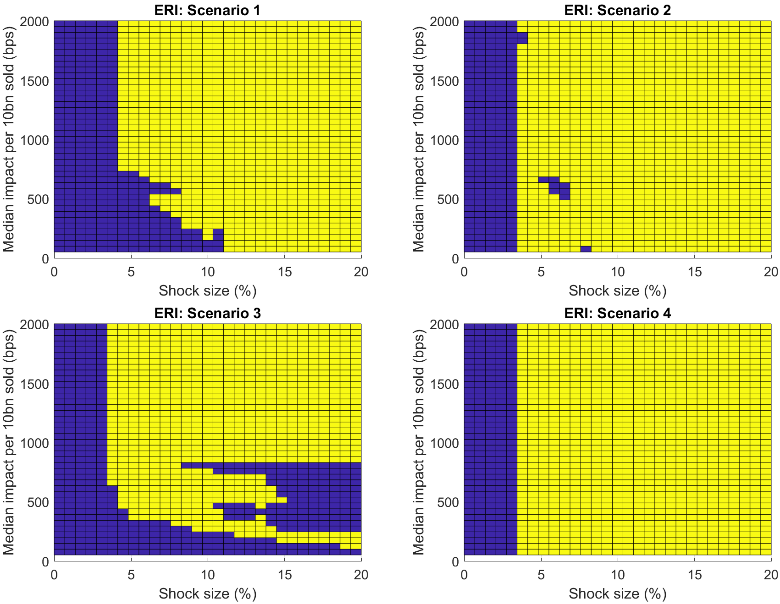
ERI: Scenario 1
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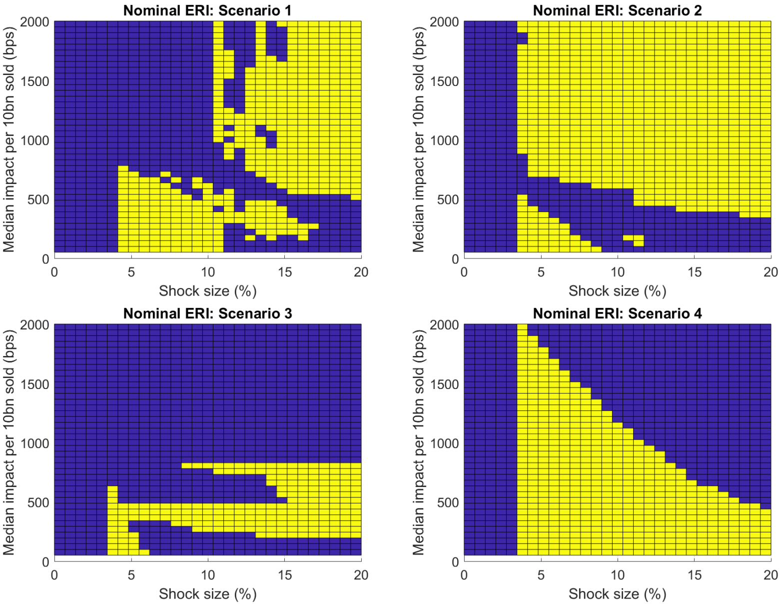
20


Nominal ERI: Scenario 1
Nominal ERI: Scenario 2
Nominal ERI: Scenario 3
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Median impact per 10bn sold (bps)
Shock size (%)
0
500
1000
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2000
0
5
10
15
20

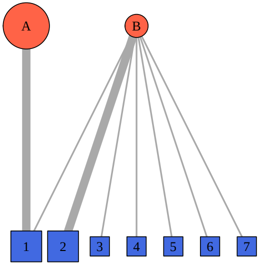
Inclusion of different predictors

Percentage of inclusion of predictors across scenarios, market impacts, and shock sizes:

- **Proportional response**: Size 96.5 %, *ERI* 91.9 %, Nom.Ov. 52.0 %, C.S. 6.5%.
- **Optimised response**: Size 78.5 %, *ERI* 42.1 %, Nom.Ov. 64.1 %, C.S $< 0.1\%$.

Self-inflicted losses & losses to *other* institutions

The Indirect Contagion Index (*ICI*) is the principal eigenvector of $\Omega_0 := \Omega - \text{diag}(\Omega_{11}, \ldots, \Omega_{NN})$.



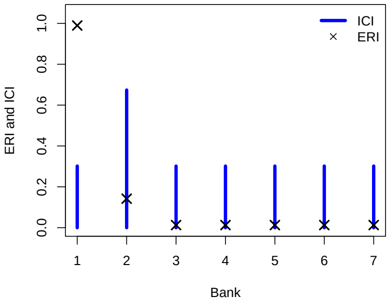


Figure: The (*ICI*) discounts self-inflicted losses compared to the losses caused to other participants relative to the *ERI*.

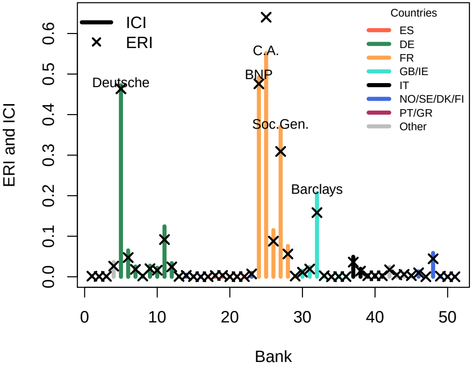


Figure: *ICI* and *ERI* (black crosses) for the European banking system. Data source: EBA 2016, Calculations: Authors.

Conclusions & Outlook

- 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.
- Our framework can be used to monitor large portfolios, and to make stress tests dynamic.
- The Endogenous Risk Index predicts fire-sales losses well, and can be used to quantify the systemicness of institutions.

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- Our framework can be used to monitor large portfolios, and to make stress tests dynamic.
- The Endogenous Risk Index predicts fire-sales losses well, and can be used to quantify the systemicness of institutions.
- The *ERI* provides additional information that is **not** captured by simple measures such as the size of portfolios.
- The modeling framework can be used to study worst-case scenarios given portfolio holdings.

Thank you!

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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Let $D_{\mu} = c\frac{ADV_{\mu}}{\sigma_{\mu}}\sqrt{\tau}$. Price move at k-th iteration of fire sales:

$$S_{k+1}^{\mu} = S_k^{\mu}\left(1 - D_{\mu}^{-1}\left(\sum_{j=1}^{N} \Pi_k^{j,\mu} \Gamma_{k+1}^{j}\right)\right),$$

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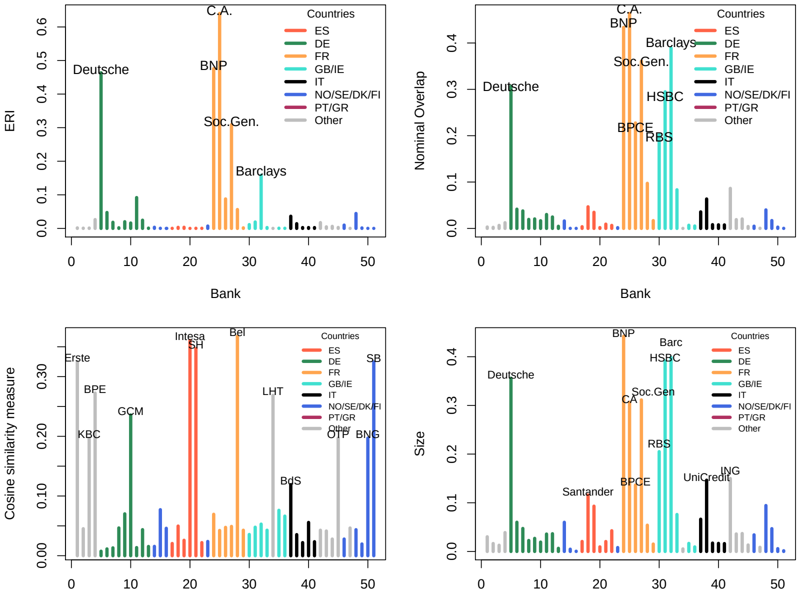
$$\Pi_{k+1}^{i,\mu} = \underbrace{\left(1 - \Gamma_{k+1}^i\right)}_{\text{Non-liquidated assets}} \overbrace{\Pi_k^{i,\mu}}^{\text{Previous value}} \underbrace{\left(1 - D_\mu^{-1}\left(\sum_{j=1}^{N} \Pi_k^{j,\mu}\Gamma_{k+1}^j\right)\right)}_{\text{Price impact on remaining holdings}}$$


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

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