

Smart Systemic-Risk Scores

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How to measure systemic risk

Two main approaches (for a survey, see Benoit *et al.*, RoF, 2017):

- ① A first family of papers derives **global measures of systemic risk**, potentially encompassing all the mechanisms studied in the systemic-risk literature and *often based on market data* (e.g. MES, SRISK, and ΔCoVaR).
- ② A second family of papers looks at specific sources of systemic risk (**systemic risk-taking**, **contagion**, **amplification**) relying sometimes on theoretical models and *often based on supervisory data* (e.g. Greenwood, Landier and Thesmar, JFE, 2015; **Scoring approach**).

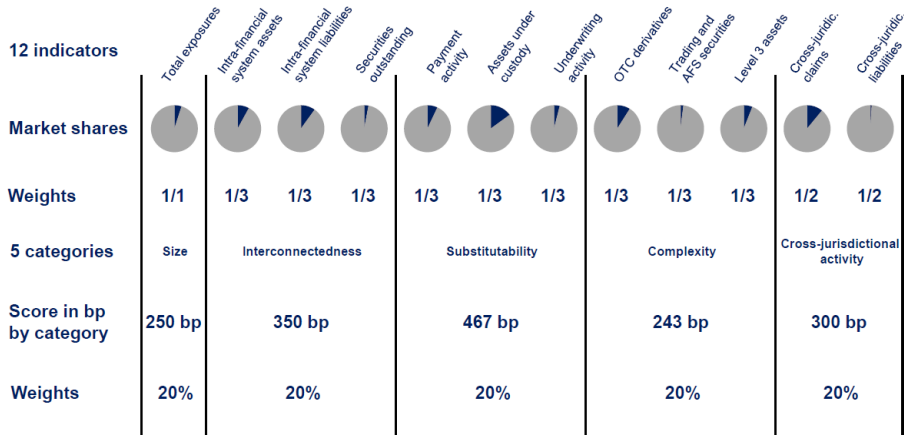
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Identify and impose higher capital requirements to systemically important financial institutions (SIFIs)

Presentation of the current methodology



➡ **Systemic score = 322 bp** (bucket 2, surcharge = 1.5% of RWA)

SIFI list (2017)

Bucket	Additional Capital	BCBS Score (30)
5 [530-629]	3.5%	Empty
4 [430-529]	2.5%	JP Morgan Chase* (468/588)
3 [330-429]	2.0%	HSBC (411) Citigroup* (410/452) Bank of America (340) Deutsche Bank (334)
2 [230-329]	1.5%	BNP Paribas (312) Barclays (292) Mitsubishi UFJ FG (287) ICBC (268) Goldman Sachs (255) China Construction Bank (252) Wells Fargo (243) Bank of China (232)
1 [130-229]	1.0%	Credit Suisse (229) Morgan Stanley (214) Société Générale (200) Santander (193) Mizuho FG (187) UBS (185) Sumitomo Mitsui FG (181) Agricultural Bank of China (176) Groupe Crédit Agricole (161) ING Bank (160) Bank of New York Mellon* (153/215) State Street* (149/171) Royal Bank of Canada (145) Unicredit Group (135) Standard Chartered (133) Royal Bank of Scotland* (128) Nordea* (115)
Total extra capital requirement		EUR 304.15 billion

This paper

How to aggregate categories? Which weights?

- In order to give the same importance to each category, the BCBS considers an **equally weighted score** where $\bar{\omega} = 1/K$:

$$\bar{S} = X \bar{\omega}.$$

- The current aggregation technique **distorts incentives** for banks to reduce risk (Benoit, Hurlin and Pérignon, JFI, 2018)
 - Incentive to reduce risk in volatile risk categories
 - Incentive to increase risk in low volatile risk categories

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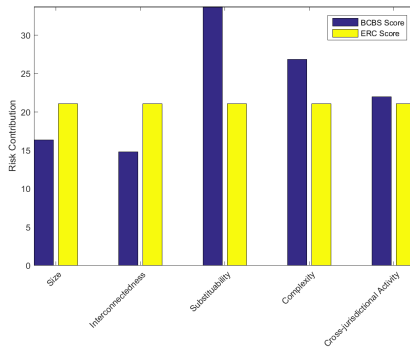
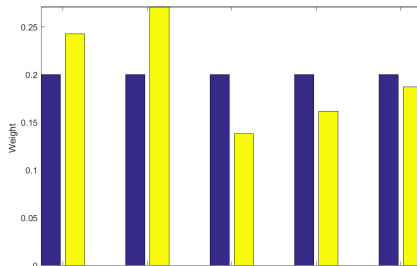
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We propose an alternative to the naive equally-weighted average of categories (indicators) to compute systemic-risk score

Equally-weighted risk contribution method (1/3)



Equally-weighted risk contribution method (2/3)

The **cross-sectional volatility of the systemic-risk score** is given by $\sigma_S = \sqrt{\omega' \Omega \omega}$ where ω is the column vector of weights. This risk can be decomposed as the sum of the **risk contributions** of the K categories:

$$\sigma_S = \sum_{k=1}^K \underbrace{(\omega_k \times \delta_{\omega_k} \sigma_S)}_{\text{Risk Contribution}}$$

where the **marginal risk contribution** for the k^{th} category is defined as:

$$\delta_{\omega_k} \sigma_S = \frac{\partial \sigma_S}{\partial \omega_k} = \frac{\omega_k \sigma_k^2 + \sum_{l \neq k} \omega_l \sigma_{kl}}{\sigma_S}$$

The **marginal risk contribution** of category k gives the change in volatility of the score induced by a small increase in the weight of this component.

Equally-weighted risk contribution method (3/3)

In the **ERC** strategy, the **risk contribution** of each category k is equal to the same target b . Thus, the optimal weights satisfying the following constraints:

$$\hat{\omega} = \left\{ \omega \in]0, 1]^K : \sum_{k=1}^K \omega_k = 1, \underbrace{\omega_k \times \delta_{\omega_k} \sigma_S}_{\text{Risk Contribution}} = b = \frac{\sigma_S}{K} \quad \forall k \in [1, \dots, K] \right\}$$

The *smart* systemic-risk score is given by:

$$\hat{S} = X \hat{\omega}.$$

An Axiomatic Approach to Systemic Risk (1/3)

Which column vector of weights ω should be preferred by the regulator to aggregate systemic-risk categories?

$$\begin{array}{c}
N \text{ Banks} \\
\left\{ \begin{array}{c} \left[\begin{array}{cccccc} S_1^{\theta_1} & S_1^{\theta_2} & \dots & S_1^{\theta_t} & \dots & S_1^{\theta_T} \\ S_2^{\theta_1} & S_2^{\theta_2} & \dots & S_2^{\theta_t} & \dots & S_2^{\theta_T} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ S_i^{\theta_1} & S_i^{\theta_2} & \dots & S_i^{\theta_t} & \dots & S_i^{\theta_T} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ S_N^{\theta_1} & S_N^{\theta_2} & \dots & S_N^{\theta_t} & \dots & S_N^{\theta_T} \end{array} \right] \end{array} \right. \\
\left. \begin{array}{c} \left[\begin{array}{cccccc} \hat{S}_1^{\theta_1} & \hat{S}_1^{\theta_2} & \dots & \hat{S}_1^{\theta_t} & \dots & \hat{S}_1^{\theta_T} \\ \hat{S}_2^{\theta_1} & \hat{S}_2^{\theta_2} & \dots & \hat{S}_2^{\theta_t} & \dots & \hat{S}_2^{\theta_T} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{S}_i^{\theta_1} & \hat{S}_i^{\theta_2} & \dots & \hat{S}_i^{\theta_t} & \dots & \hat{S}_i^{\theta_T} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{S}_N^{\theta_1} & \hat{S}_N^{\theta_2} & \dots & \hat{S}_N^{\theta_t} & \dots & \hat{S}_N^{\theta_T} \end{array} \right] \end{array} \right\} \\
T \text{ Scenarios}
\end{array}$$

An Axiomatic Approach to Systemic Risk (2/3)

A **global systemic-risk measure** is a function $\rho : \mathbb{R}^{|\mathcal{B}| \times |\Theta|} \rightarrow \mathbb{R}$ that satisfies the following conditions, for all systemic-risk scores of a given economy exposed to several scenarios $S, \hat{S}, \bar{S} \in \mathbb{R}^{|\mathcal{B}| \times |\Theta|}$:

- (i) *Monotonicity*;
- (ii) *Positive homogeneity (of degree one)*;
- (iii) **Preference consistency**: Define a partial order \succeq_ρ on cross-sectional score profiles as follows: $S^\theta \succeq_\rho \hat{S}^\theta$, i.e., \hat{S}^θ is preferred to S^θ .
Suppose that $\forall \theta \in \Theta, S^\theta \succeq_\rho \hat{S}^\theta$. Then, $\rho(S) \geq \rho(\hat{S}) \geq \rho(\mathbf{1}_{\mathcal{S}})$.
- (iv) *Convexity*:
 - ① *Outcome convexity*;
 - ② *Risk convexity*.
- (v) *Normalization*: $\rho(\mathbf{1}_{\mathcal{S}}) = 0$.

An Axiomatic Approach to Systemic Risk (3/3)

Theorem

$\rho : \mathbb{R}^{|\mathcal{B}| \times |\Theta|} \rightarrow \mathbb{R}$ admits a decomposition equivalent to the choice of a **base (univariate) risk measure** $\eta : \mathbb{R}^{|\Theta|} \rightarrow \mathbb{R}$, and of an **aggregation function** $\Lambda : \mathbb{R}^{|\mathcal{B}|} \rightarrow \mathbb{R}$:

$$\rho(S) = (\eta \circ \Lambda)(S) \triangleq \eta \left[\Lambda \left(S^{\theta_1} \right), \Lambda \left(S^{\theta_2} \right), \dots, \Lambda \left(S^{\theta_T} \right) \right], \quad \forall S \in \mathbb{R}^{|\mathcal{B}| \times |\Theta|}.$$

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$$\rho(S) = (\eta \circ \Lambda)(S) \triangleq \eta \left[\Lambda \left(S^{\theta_1} \right), \Lambda \left(S^{\theta_2} \right), \dots, \Lambda \left(S^{\theta_\tau} \right) \right], \quad \forall S \in \mathbb{R}^{|\mathcal{B}| \times |\Theta|}.$$

As a consequence, the Basel Committee must deal with both
(i) the cross-sectional profile of scores across banks (aggregation function),
and (ii) the distribution of aggregated outcomes across scenarios
(individual risk measure).

Preferences based on cross-sectional dispersion

A natural candidate for being the *global* systemic-risk measure is **the expectation of the cross-sectional volatility of SR scores across scenarios**:

$$\rho_{Disp.}(S) = \eta_{Exp.} \left[\Lambda_{Disp.} \left(S^{\theta_1} \right), \Lambda_{Disp.} \left(S^{\theta_2} \right), \dots, \Lambda_{Disp.} \left(S^{\theta_T} \right) \right],$$

$$\rho_{Disp.}(S) = \mathbb{E} \left[\sigma_{S^{\theta_1}}, \sigma_{S^{\theta_2}}, \dots, \sigma_{S^{\theta_T}} \right], \quad \forall S \in \mathbb{R}^{|\mathcal{B}| \times |\Theta|}.$$

- $\sum_{i=1}^N S_i = \sum_{i=1}^N \bar{S}_i = \sum_{i=1}^N \hat{S}_i = 10,000.$
- The volatility is a coherent measure of risk (Artzner *et al.*, 1999).

Preferences based on cross-sectional dispersion

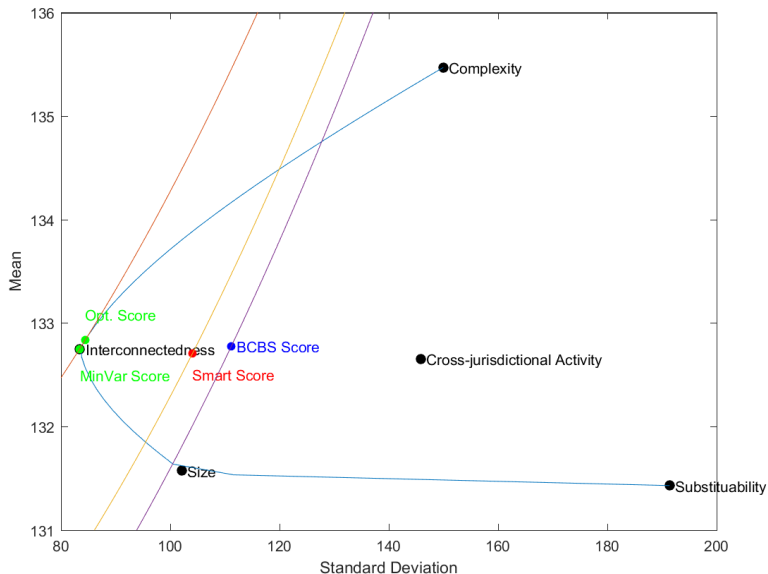
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The **smart Score** \hat{S} will be located between the **BCBS score** \bar{S} and the **minimum-variance score** (irrelevant alternative; Kreps, 1988).

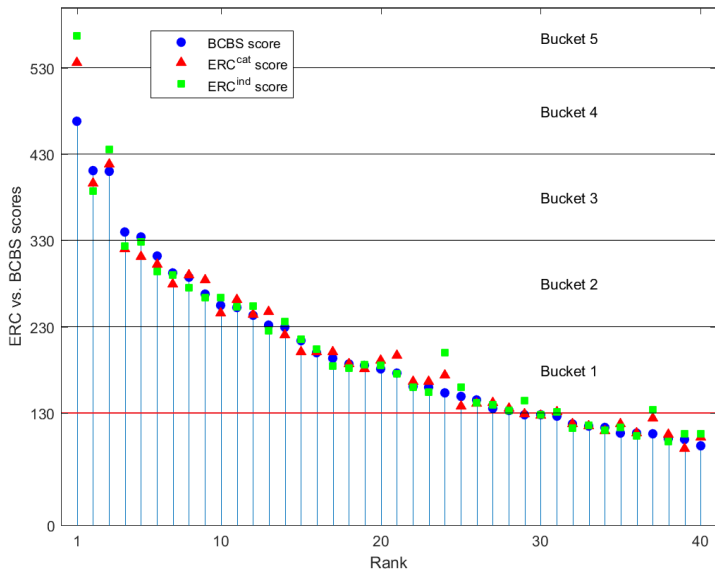
Mean-variance representation (2017)



Empirical analysis

- Regulatory data on systemic-risk have become public since 2014.
- We collect **systemic-risk indicators** of international banks from regulators and banks' websites (go to <http://sifiwatch.fr/>).
- **Two smart SR scores** can be computed by using
 - (i) SR categories (ERC^{cat} Score), or (ii) SR indicators (ERC^{ind} Score).
- What is the impact of these new *smart* scores on:
 - ① The identification of SIFIs
 - ② The total extra capital requirement
 - ③ The cross-sectional volatility

SIFI rankings (2017)



Comparing SIFI lists: current vs. *smart* (2017)

Bucket	Additional Capital	BCBS Score (30)	ERC ^{cat} Score (29)	ERC ^{ind} Score(31)
5 [530-629]	3.5%	Empty	JP Morgan Chase (536 ↑)	JP Morgan Chase (567 ↑)
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A coherent alternative to the official list of SIFIs

Aggregate regulatory capital surcharge:

	2014	2015	2016	2017
BCBS Score (uncapped)	247.39	279.13	313.33	323.39
BCBS Score	221.76	261.90	298.87	304.15
ERC ^{cat} Score	241.57	285.65	301.83	309.61
ERC ^{ind} Score	215.68	271.10	312.60	318.89

Cross-sectional volatility and *global* systemic-risk measure:

	2014	2015	2016	2017	$\rho_{Disp.}(S)$
BCBS Score (uncapped)	132	125	119	114	123
BCBS Score	120	114	109	105	112
ERC ^{cat} Score	120	116	110	105	113
ERC ^{ind} Score	127	121	115	108	118

Conclusion

The expectation of the cross-sectional volatility of SR scores across scenarios can be used to express supervisor preferences among systemic-risk scores.

Systemic-Risk Score based on the ERC methodology:

- Does not require data transformation;
- Produces no incentive for banks to increase risk in low volatile systemic-risk categories anymore;
- Equalizes the risk contribution of each SR component to the cross-sectional volatility of SR scores;
- Identifies the same SIFIs than the current systemic-risk score but leads to higher aggregate capital surcharge.